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China and the World Bank: How Contrasting Development Approaches Affect the Stability of African States

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Abstract

China's development model challenges the approaches of traditional, Western donors like the World Bank. We argue that both aim at stability, but differ in the norms propagated to achieve that. Using fixed effects and IV estimations, we analyze a broad range of subnational stability measures in Africa. Aid by both the World Bank and China does not increase outright conflict nor any type of citizen protest, on average. Both even reduce outright conflict by governments against civilians. Still, Chinese aid is associated with more government repression and an increased acceptance of authoritarian norms, while World Bank projects strengthen democratic values.

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

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1 Introduction

As part of what the Economist describes as the "The new scramble for Africa," emerging donors, in particular, China (Dreher and Fuchs, 2015; Dreher et al., 2018), are challenging the predominance of traditional donors in affecting African development. The big question is whether this time, as the magazine asks, African countries will be the benefactors of foreign engagement? Africa is a central focus of traditional donors as well as a key target region for China. While there was a considerable drop in global poverty rates thanks to rapid growth, mostly in Asian countries, many African states lag behind. In particular conflict-prone states plagued by re-igniting battles pose a challenge, which is why those are also labeled as the "new frontier of development".[1]

While the literature on the growth effects of aid converges towards an on average small, positive effect (Clemens et al., 2011; Dreher and Langlotz, 2019; Galiani et al., 2017; Kilby, 2015), researchers are divided about the impact of aid on stability and conflict (e.g., Bluhm et al., 2016; Child, 2018; Crost et al., 2014; Nunn and Qian, 2014). Some perceive Chinese aid as a crucial step forward that brings growth and stability to Africa, while others regard it as a big risk that narrowly focuses on Chinese self-interest, enriches elites (Dreher et al., 2019), fosters conflict, and exports repression, along with surveillance tactics and autocratic norms (Kishi and Raleigh, 2016).[2] We are shedding light on this crucial question by systematically contrasting the Chinese approach to development with that of the World Bank (WB), one of the most important traditional donors, and analyzing their effect on stability in recipient regions.

Moving beyond the partly subjective public rhetoric, we argue that Chinese foreign aid needs to be considered with all its nuances. China's "no strings attached" approach to development differs sharply from the expert-driven, conditional approach of traditional donors like the WB and many other Western DAC donors. Both donors are interested in growth. While the World Bank regards democracy, transparency, and human rights as a critical part of prosperity, the Chinese model highlights social and political stability as the key ingredient to development. To comprehensively understand the impact of these approaches, requires

[1] See The Economist (2019) and The Economist (2017), accessed 30.01.2019.

[2] See Washington Post Monkey Cage and Council on Foreign Relations for the direct citation, accessed 31.04.2019. See Freedom House on East African states adapting Chinese internet censorship policies, The New York Times on exporting the surveillance state, and US News about China's web surveillance model, and Council on Foreign Relations about Zimbabwe using Chinese large-scale facial recognition software in its capital Harare. See The Economist about China training foreign officials and bureaucrats, and promoting "their political model" as an alternative to democracy. All accessed 31.04.2019.

a holistic definition of stability. This paper defines stability as a broad continuum ranging from outright conflicts with at least a certain number of battle-related deaths, to lower level-conflict events like citizen protests and government repression, as well as attitudes related to stability.

Although the more economic growth and stability-oriented perspective of China and the rule- and expert-based democratic perspective of the World Bank might be seen as two ends of the spectrum of development policies, their impact on stability is complex. Even if its motive would be mere self-interest, China also has an incentive to protect its investments as well as its workers in Africa. One should not expect China to turn a blind eye on recipient governments starting outright conflicts. Both donors will try to stop recipient governments from engaging in conflicts that they deem avoidable or unnecessary, and given their size have some leeway over recipient governments.[3] At the same time, when regarding stability more broadly than just focusing on the outright conflicts, China is likely to build on its own domestic development experience, which combines growth with an autocratic and stability-oriented rule. Therefore, there are good reasons to believe that China would be more willing to accept recipient governments' use of autocratic policies and non-lethal repression to enhance stability, while the WB emphasizes democracy and humanitarian values more strongly. This paper does not take a normative stance which approach is ultimately superior from the perspective of a developing country. But it carefully carves out the most important conceptual differences between the two donors and their potential effect on state stability.

To then investigate the causal effects of the two donors on stability, we precisely link new detailed geo-referenced datasets on development projects by China (Strange et al., 2017) and the WB (Dreher et al., 2017b) with geo-referenced measures of stability at the sub-national level in Africa. Our dataset allows us to match the location of aid projects and conflicts more precisely than earlier studies, and enables us to flexibly eliminate potential biases arising from, for instance, unobserved conflict trends, region-specific time-invariant factors, and country-level time-varying factors. Moreover, our identification strategy adapts an established instrumental variable (IV) approach by Nunn and Qian (2014). Our instrument is the interaction between exogenous temporal variation in the WB's IDA liquidity (Dreher et al., 2017b) and in Chinese domestic (over-)production of commodities with the pre-determined

[3] Based on the different approaches, the distribution of aid also differs. Chinese aid goes more often directly to governments and the home regions of ethnic leaders (Dreher et al., 2019). Its distribution is associated with more corruption (Isaksson and Kotsadam, 2018a) and weaker labor unions (Isaksson and Kotsadam, 2018b). Still, its less bureaucratic approach was also found to lead to more evenly distributed economic activity within countries (Bluhm et al., 2018).

probability of a region to receive aid with (Bluhm et al., 2018; Dreher et al., 2017a).

Our results provide several important insights. First, a wide range of fixed effects (FE) and IV specifications reject the idea that aid by either donor, on average, fuels conflict at the sub-national level. In the FE specification, a one standard deviation change in WB aid decreases the conflict likelihood by about 1.6 percentage points. The effect remains negative and of similar magnitude, but becomes statistically insignificant when using IV. When studying China, both strategies yield negative and small, insignificant coefficients.

We move beyond this main IV effect by considering the actors involved in and responsible for a conflict. Both WB and Chinese engagement consistently leads to a reduction in lethal violence by governments against civilians. For both donors, we also find no positive effect on protest events like demonstrations, riots, and strikes. At the same time, there are crucial differences concerning how stability is secured. Among the two, only Chinese aid is associated with more government repression in recipient regions. Afrobarometer responses suggest that both donors have different effects on measures of security, democratic norms and attitudes, as well as on perceptions of government behavior. While WB aid is linked to higher perceived security and stronger support for democratic values, Chinese aid tends to result in a stronger emphasis on rule following behavior and a higher acceptance of autocratic regimes.

This paper contributes in several ways to better understand the role of donors in influencing recipient country stability, as well as the channels and mechanisms linking aid to various types of conflict. We combine the strengths of existing approaches on the country level (e.g., Bluhm et al., 2016; Nielsen et al., 2011; Nunn and Qian, 2014), with the advantages of studies focusing on sub-national aid data in specific sectors in selected countries (e.g., Berman et al., 2011; Child, 2018; Crost et al., 2016; Sexton, 2016; Van Weezel, 2015). The aim is to deliver the best possible compromise between using micro-data with causal identification strategies and estimating externally valid results for more than one country. Truly randomly allocated aid projects in individual countries possess a higher internal validity. Still, their findings could be driven by the particular country context or the specific type of aid, and it is impossible to replicate them at large scale for a full continent. We apply identification strategies that are well established in the literature. We consider a broad set of all aid-eligible countries. Our results can be meaningfully interpreted beyond the context of an individual country.

Besides using new data and providing more precise estimates about the causal effect of aid on more comprehensive measures of stability, we want to emphasize three main contributions.

First, our paper adds to the scarce evidence on the incentives for different actors and their choices created by development projects. Crost et al. (2014), for instance, focus on how aid changes the incentives for rebel groups.[4] Our finding of a significant reduction in lethal violence enacted by recipient governments against civilians supports the idea of the "cost of shame" (Lebovic and Voeten, 2009). The fear of losing aid money changes the incentives of recipient notably.

Second, we shed some light on the hopes and fears associated with emerging donors (Asmus et al., 2017; Fuchs and Vadlamannati, 2013). In particular, China's increased global engagement, like the Belt and Road initiative and the intense China-Africa Cooperation, is one of the crucial geopolitical changes in the last two decades. These changes will continue to create tensions in the future. Existing papers have either focused on outright conflict, or the impact of, for instance, Chinese aid in Latin America on attitudes towards China (Brückner et al., 2018). Still, convincing causal evidence that provides a comprehensive picture of the impact of Chinese aid on stability in a broad sense was missing.

Third, by contrasting Chinese aid with the World Bank as a prototypical example of a traditional, multilateral donor that involves development experts and accounts for democracy and humanitarian values, we provide a useful reference point. Western newspapers and NGOs have widely complained about the active export of Chinese surveillance technology and policies, as well as about the potentially detrimental impact that the apparent success of the Chinese approach to development has on developing countries. Our results paint a more nuanced picture. China's engagement is not associated with an increase in outright conflict, and even with more stability when considering less-lethal conflicts by governments against civilians. Still, it comes along with increased government repression and a higher prevalence of autocratic norms. Hence, the approach makes a difference in some critical dimensions. How to assess these differences depends on the normative perspective of the observer.

The paper proceeds as follows. Section 2 summarizes the existing literature and how the two approaches are linked to different measures of stability. 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.

[4] As a robustness test, we also show results on sectoral differences, which augment previous results on intersectoral differences within specific countries (e.g., Child, 2018; Crost et al., 2016; Berman et al., 2011).

2 Theoretical considerations and existing literature

This section first defines our concept of stability, and then contrasts the policies by China and the WB, and how they may affect outright conflict as well as individual dimensions of stability. To understand the impact of the two approaches to development in a comprehensive way requires a holistic definition of stability. More specifically, we think of outright conflict as a lethal fight that caused at least a specific number of battle-related deaths. Besides the average effects on conflict, we distinguish between the actors involved in a conflict, either government-related or non-state actors like rebels. Each of those can be engaged in a two-sided conflict with the respective other group, or start a one-sided conflict against civilians. Besides these lethal conflict events, lower-level conflicts like citizens protests against governments, and government policies against potential rebels or other minority groups in the country also characterize stability. Finally, attitudes are both reflecting the results of these other events, but are also themselves signs of stability, for instance, beliefs about the quality of democratic processes or rule-following behavior.

Outright conflict: Aid can lower conflict if it raises income and hence, the opportunity costs of fighting. In that regard, 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. Berman et al. (2013) hypothesize that projects are more successful in reducing violence if they require the integration of development experts. Minasyan et al. (2017) demonstrate the importance of donor quality. The WB built up large expertise over the decades since its foundation, which may increase the effectiveness of its projects in raising income.

At the same time, traditional donors have also been criticized for lack of "ownership" and underutilizing local knowledge in recipient countries. Scholars writing about emerging donors like India (Fuchs and Vadlamannati, 2013) and China (Humphrey and Michaelowa, 2018) also highlight less complicated, bureaucratic processes with quicker implementation times. Hence, China's flexibility and emphasis on economic "mutual benefits" may boost growth even more than the WB approach (Dreher et al., 2017b). Thus, in these dimensions both donors could reduce the incentives to engage in conflict by fostering growth in their own ways.[5]

Besides growth effects, the distribution of potential gains is vital as the literature on resource-related income shocks highlights (e.g., Berman et al., 2017; Dube and Vargas, 2013; Gehring et al., 2018). 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. If the projects contribute to rising inequality, this could trigger conflicts. WB projects were found to be less politically motivated than other types of aid (e.g., Dreher et al., 2009). The Bank aims for aid allocation in line with conflict prevention policies accounting for humanitarian aspects and security. In contrast, Dreher et al. (2019) find that Chinese projects in Africa are more likely to benefit the birth regions of the respective leader. Isaksson and Kotsadam (2018a) suggest that Chinese engagement is associated with higher local corruption, which could increase inequality and lower trade union membership (Isaksson and Kotsadam, 2018b). Such effect could decrease the labor share of profits. However, Chinese infrastructure projects are particularly found to lead to an equal distribution of economic activity (Bluhm et al., 2018). Hence, the theoretical predictions are, to some degree contradictory, leaving this an empirical question.

Finally, traditional Western donors often impose conditions and require specific processes in aid-receiving countries. The WB often uses conditions regarding governance, equality, anti-discrimination, among others. The Bank is also considered to be a global leader in "conflict-sensitive programming" (Van der Windt and Humphreys, 2016; World Bank, 2011). This involves the identification of conflict escalators using a detailed Conflict Analysis Framework (CAF) (Wam, 2006) to help WB staff to understand country-specific sources of conflicts. The WB's Operational Procedures instruct WB staff on how to act within a conflict-affected country (World Bank, 2001; Bannon, 2010).

Officially, Chinese aid has fewer strings attached.[6] Still, even for skeptical observers who assume China is largely interested in securing resources and providing employment for Chinese workers, it is implausible that China would welcome recipient governments engaging

[5] 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 goods, Nunn and Qian (2014) show that US food aid leads to more conflict, as it can be looted. 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 may fight. They instead provide aid in a more discrete manner, such as social programs (Berman et al., 2013; Crost et al., 2014; Imai et al., 2018). We investigate aid in different sectors separately in a robustness test.

[6] Anthony Germain on CBC, "China in Africa: No strings attached," last accessed 31.01.2019.

in unprovoked, avoidable conflicts. This would endanger existing investments and the health not only of African but also a large number of Chinese workers in Africa (officially 227,407 by 2016). Moreover, stability is a crucial part of the Chinese development model; in a speech at the 2008 central party congress Hu Jintao mentioned the word stability alone 21 times (freedom did not appear a single time).[7]

To sum up, while politicians, newspapers and some scholars raise concerns about specific aspects of Chinese aid that could give rise to more conflict than the rule-driven approach of the WB, we argue that the net impact on outright conflict is less straightforward. There are reasons to expect WB aid could be more successful in lowering the average risk of conflict. But based on its self-interest and emphasis on stability, China has incentives to "unofficially" set conditions to avoid instability as well.[8]

Actors and types of conflict: Two-sided conflicts between governments and rebels could be affected differently by aid than one-sided conflicts against civilians. Generally, neither donor should be interested in outright conflict. They can threaten to withhold future aid payments to prevent recipients from engaging in conflicts they deem harmful and unnecessary. Lebovic and Voeten (2009) label this the "cost of shame." We argue that this threat is less likely to matter for two-sided conflicts as it is much easier for both sides to justify their actions as a necessary reaction to the other side. One-sided conflict actions against civilians, in contrast, are harder to justify. If governments use excessive violence against citizens, public pressure in donor countries can stop in particular international organizations like the WB from aid payments (Tir and Karreth, 2018). At the same time, China, as an autocratic one-party state where decision-making is less constrained could be able to threaten to cut aid payments more credibly. Generally, both donors have the incentives and means to exert pressure on recipient governments to avoid unprovoked one-sided conflicts, while their direct influence on rebel groups is limited.[9]

Lower level conflict - Government policies and protests: Besides outright, lethal, conflict, we are also interested in lower-level types of conflict that are not necessarily directly

[7] Anthony Germain on BJ Review, last accessed 31.06.2019.

[8] The Guardian also postulates that "Chinese aid to Africa is going to come with all sorts of strings attached, despite the "no-conditionality" rhetoric (The Guardian: "The west has no right to criticise the China-Africa relationship" last accessed 31.01.2019.)

[9] Donors may also 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 aspect should be of lesser importance.

causing a significant number of casualties. The lower-level conflict has two dimensions. Protest events like strikes, riots or demonstrations can be understood as bottom-up actions by citizens against governments. In contrast, government policies like repression are top-down measures by governments to avoid conflicts and such protests. The latter affects the costs of the former, and empirically, we are only able to observe the equilibrium outcome of both dimensions.

WB and Chinese aid can affect the reasons as well as the costs of protest by fostering state capacity. On the one hand side, infrastructure projects like highways, bridges, railroads, and ports strengthen the capacity of the state by extending the spatial reach of its monopoly. Agents of the state – e.g., police officers, judges, and tax collectors – can use their increased capacity in different ways. If they wield it to enforce the rule of law impartially, 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), conflict reduction (Berman et al., 2011) and less reasons to protest. 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), this can trigger protests.[10]

The WB uses an independent "Inspection Panel" to investigate complaints about human rights abuses or local conflict provoked by the WB (Zvogbo and Graham, 2018). It pursues an approach to actively build trust and social cohesion in post-conflict and conflict-affected countries (Bannon, 2010). This approach includes, for example, projects with a focus on community-driven development, and capacity building with regards to accountability and public service delivery. The Kecamatan Development program in Indonesia, for instance, attempted to reduce protests via transparency through a particularly participatory approach (Gibson and Woolcock, 2005; Barron et al., 2011).[11] 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.[12] Hence, all else equal, Chinese projects could be related to more protests.

However, the equilibrium impact of both donors is more complex. Citizens deciding whether to engage in protests also weigh the costs against the benefits of these actions. WB

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

[11] This community-driven development approach inspired the National Solidarity Program - a large scale development program, which was evaluated to increase governmental support in conflict-ridden Afghanistan (Beath et al., 2016).

[12] 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.

policies that foster democratic participation and transparency may be linked, all else equal, to a higher likelihood to protest. Better informed citizens may be more willing to politically engage in more democratic states where the political costs of opposing and the fears of its consequences are lower.

At the same time, Chinese aid could increase the costs of organizing protests, as it decreases trade union membership (Isaksson and Kotsadam, 2018b). Moreover, the enhancement of state capacity also affects the ability to handle protests. China emphasizes social stability as part of its growth model domestically, including the use of force to constrain opposition forces or protesters. Such repression can incite anger and unrest, but also enhance stability via a deterrence effect. An article, for instance, describes how "Chinese officials use advances in facial recognition technology and big data to identify potential troublemakers and reduce the risk of large-scale public demonstrations."[13]

The country is also accused of financially supporting repressive governments in Africa and exporting such repression to recipient countries (Kishi and Raleigh, 2016). For example, Uganda could turn to China after Western donors protested against strict "anti-gay" laws in the country.[14] Several reports describe how China exports its approaches regarding surveillance and censorship. One describes how China "propagate its model abroad by conducting large-scale training of foreign officials" of 36 mostly developing countries.[15] Many of those like Angola, Ethiopia, The Gambia, Kenya, Libya, Morocco, Nigeria, Rwanda, South Africa, Sudan, Zambia, Zimbabwe are in Africa. Another article describes how Uganda and Tanzania introduced cybersecurity laws that are similar to Chinese law after attending training sessions.[16] Freedom house emphasizes how Chinese support helps governments in Sub-Saharan Africa to censor the internet and social media.[17]

China's projects may thus provide more reasons to protest, but repressive policies raise the cost of protests. WB policies may provoke fewer protests due to the implemented safeguards, but stronger democratic standards and less fear of expressing opinions in public make protests more likely. Hence, we expect an increase in repressive government policies related to Chinese aid, but the equilibrium impact of both donors regarding protests remains

[13] See Nikkei.com, last accessed 31.04.2019.

[14] Washington Post, "When China gives aid to African governments, they become more violent,", last accessed 31.01.2019.

[15] See US News, last accessed 31.04.2019.

[16] See Nextgov.com, last accessed 31.04.2019.

[17] See Freedom House, accessed 31.04.2019. In addition to training, China reportedly exports surveillance technology like cameras but also advanced artificial intelligence technology. For instance, China signed an agreement with Zimbabwe, Angola, and Ethiopia to deploy a new facial recognition software to monitor its population.

an empirical question.

Attitudes: The Chinese government regards stability as central for development, and portrays itself as a "rock of stability." [18] However, it does not regard democracy, democratic participation, or equal democratic rights as necessary to achieve stability, or sometimes even sees them as an obstacle to that. Dagong, a Chinese rating agency, writes that "centralized political power enabled [East-Asian countries] to concentrate on solving the most urgent issues in the economic reform step by step," while "countries copying the western system encountered many political obstacles in maintaining stability."[19] A Chinese scholar describes the common perception that developing countries experiencing "chaotic" democratization "inevitably plunge into a chaotic situation marked by soaring prices, shortage of essential supplies, frequent violent conflicts and a precarious state of life and property." This also entails that "the ability to establish and maintain an effective internal order [...] is the most important of all national capacities", with higher priority than "democratic accountability in a country's political development process."[20]

China is keen on spreading its development model and emphasizing its advantages. In exchange for financial support, Chinese development projects sometimes require that partners broadcast Chinese radio or TV to win "African hearts and minds."[21] For instance, a radio station set up in Kenya reserves a specified amount of hours to promote Chinese culture and values, China supplies text books for schools in Liberia, Ghana and Tanzania, and organizes cultural events in South Africa. Cultural centers aim at spreading Chinese culture and values. Note that this is not good or bad per se; Western donors and the WB are engaging in the same efforts to spread the values and norms they want to propagate. The motivation to do so may be mere self-interest or the honest conviction that the respective development model is the best to raise developing countries out of poverty. Empirically, we are interested whether WB projects are related to more positive perceptions of democracy and governance, and if citizens in regions receiving Chinese aid are more likely to accept autocratic, strong states and strict rules to achieve prosperity.

[18] The Economist, last accessed 31.01.2019.
[19] QZ.com, last accessed 31.01.2019.
[20] CGTN, last accessed 31.01.2019.
[21] See LA Times, last accessed 30.07.2019.

3 Data

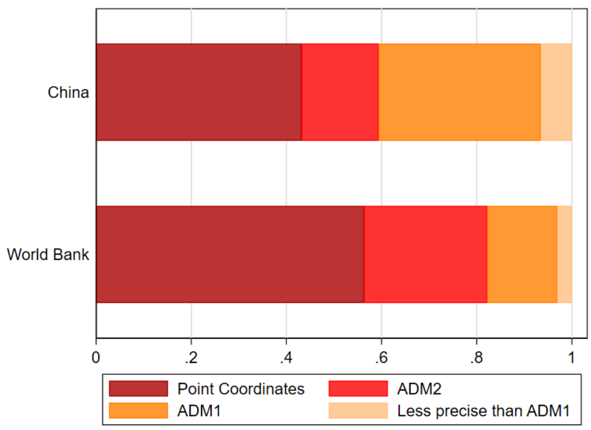
3.1 Aid Data: World Bank and China

We consider all African countries with more than one million inhabitants on the OECD's DAC recipient list in 1995, the initial year of our sample period. We focus on disbursements by IDA, the WB's arm for development aid. For China, we use the media-based data set on Chinese ODA-like commitments from (Dreher et al., 2019), geo-referenced by Strange et al. (2017). All financial flows are thus considered that qualify as aid by having a significant concessionary component.[22]

Our unit of observation is the country-region-year, with regions as the unit of analysis referring to the first level 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).[23] Moreover, this administrative level is also highly relevant for aid allocation. 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 geo-referenced projects, as well as projects where we possess information about the first and second-order

Figure 1: Disbursement/Commitment Amounts by Precision Codes



[22] Other official finance (OOF) flows in China's finance portfolio has less of a development focus. The WB's International Bank for Reconstruction and Development (IBRD) also provides development finance in the form of loans with interest rates closer to market rates.

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

subnational level, 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. This procedure ignores projects with lower precision, mostly direct support for governments, but their average effect would be captured by country-year fixed effects. The data appendix provides more details.[24]

Table 1 compares aid projects by the two donors that we can assign to the ADM1 level. WB disbursements sum up to USD 29.4 billion, distributed over 1,472 projects in 25,041 locations in Africa. Since graduating from IDA eligibility in 1999 (Galiani et al., 2017), China's overseas portfolio of grants, loans, and export credits has also rapidly expanded as part of its 'Going Out' strategy. In Africa, Chinese aid amounts to USD 13.2 bn, from 333 projects in 1,308 locations. Hence, the WB finances a larger number of projects than China, and these projects are present in more places across countries. China finances fewer projects, but China spends almost twice as much per project, and nearly ten times as much per project location.

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.

[24] 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 57 and 58 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 $Aid_{pijt} = \frac{Aid_{pit}}{\int Population_{pi}} * Population_{pj}$. Population data are from the gridded population data provided by the Center for International Earth Science Information Network (CIESIN) Columbia University (2016). As a robustness test, we show results using the ADM2 regions and assign project locations with less precise location information than ADM1 to the capital region.

3.2 Stability Measures

To measure outright conflict, we follow the literature and create a binary *conflict incidence* measure based on the number of battle-related deaths (BRD). The data is taken from the Uppsala Conflict Data Program's (UCDP) geo-referenced Event Dataset (GED) (Croicu and Sundberg, 2015). GED provides a reliable and comprehensive source of geo-referenced conflict events based on media and NGO reports, as well as secondary sources like field reports and books. The database also includes information about the type of conflict and the groups that were involved.[25] Table 2 shows descriptive statistics for all stability measures, with the incidence measures scaled as either 0 or 100. Figure 2b shows a map with all conflict events in our sample period, distinguishing between conflict with less than 5 BRD, with between 5 and 25 BRD, and more than 25 BRD. Studies at the country level usually use thresholds of 25 or 100 to define a conflict. As our research is at the smaller first-order sub-national level, we choose 5 BRD per country-region-year as the threshold in our main specification. For robustness tests, we also use 25 BRD, as well as the log of BRD as a continuous conflict intensity indicator. We also use GED to code whether an outright conflict was a two-sided fight between government-related groups and non-state actors (rebels), or a one-sided action by either of those sides against civilians.

To examine protests and repression, we make use of the Social Conflict Analysis Database (SCAD, (Salehyan et al., 2012)), which provides reliable and detailed geo-referenced information for Africa. We also define a binary *protests incidence* indicator. It takes the value one if there was at least one event in either of the categories demonstrations, strikes or riots, as well as an indicator for *government repression.* [26] Government repression includes, for instance, increased surveillance activities like in Niger, where "after conducting one month of surveillance, the government arrested 9 military officers said to be planning a coup." Figure A10 illustrates the spatial distribution of protests and repression across Africa. Finally, we use selected questions from the Afrobarometer survey waves overlapping with our

[25] Alternatives are the ACLED and PRIO 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 may 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).

[26] SCAD defines government repression as a "Distinct violent event waged primarily by government authorities, or by groups acting in explicit support of government authority, targeting individual, or "collective individual," members of an alleged opposition group or movement." (Salehyan et al., 2012). The coded events include, for instance, "Police arrested a prominent opposition lawyer," "Police arrested four members of comedy group who make videos making fun of the government" or "Militant youths allied with Malawi's ruling party to attack a newspaper photographer" (Salehyan et al., 2012). Repression is distinguished from government conflict against civilians by being associated with less than 5 BRD.

sample period grouped in the categories security, democratic norms and attitudes, as well as government responsiveness and repression.

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 matters for aid allocation. To scale the potential for conflict for regions of different size (Hegre and Sambanis, 2006). Population calculation is based on the *Gridded Population of the World* dataset (Center for International Earth Science Information Network (CIESIN) Columbia University, 2016). 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). 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. Robustness tests use data from Cederman et al. (2014) and Wucherpfennig et al. (2011) about the distribution of ethnic groups. Table A10 in the data appendix provides a more detailed overview of all variables used at any part of the paper.

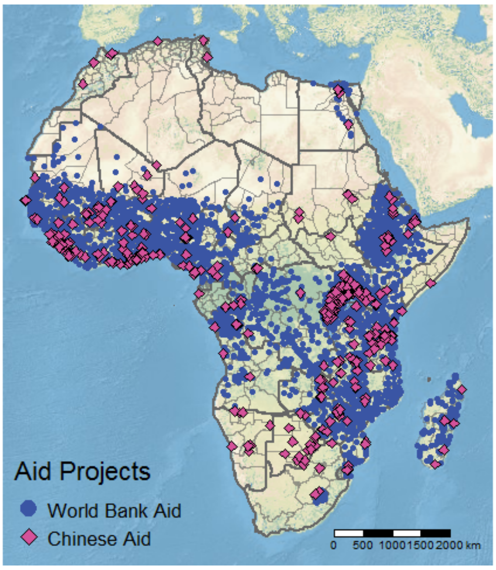
Table 2 provides summary statistics. The final sample comprises 728 ADM1 regions in 45 countries. WB aid is, on average, higher per region-year than Chinese aid: USD 2.2 million versus USD 1.4 million, respectively. Figure 2a illustrates that both donors are active in a large number of countries and regions. Figure 2b reveals sufficient cross-sectional variation in conflict events across as well as within countries to estimate a demanding FE model.

While the information for aid disbursements by the WB's IDA is available from 1995 to 2012, information on Chinese aid commitments in Africa is constrained to the years 2000 to 2012. Both the WB and China are active in most African countries – the WB in 35 countries, and China in 41 countries. There is a significant overlap in their presence between countries, but prior research found no evidence of one donor systematically affecting the allocation choices of the other (Humphrey and Michaelowa, 2018). Hence, we can run our regressions separately for each donor to exploit the full sample period for which we have WB data, without fearing a strong systematic bias in results.

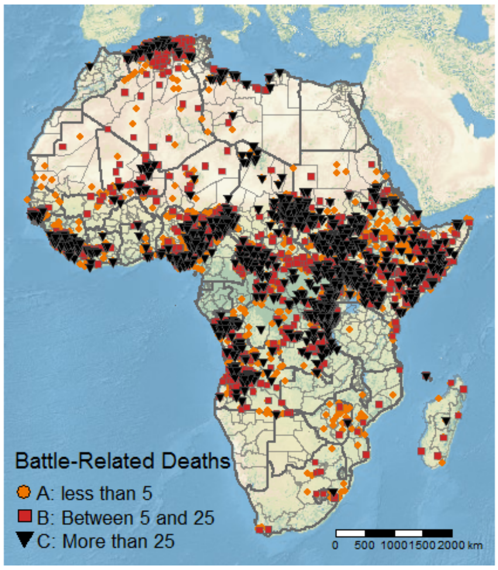
Table 2: Descriptive statistics - ADM1 Region

	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
Riots, Strikes, Demonstrations in Perc.	14	34	0	100
Repression Incidence in Perc.	1	11	0	100
Conflict Incidence in Perc.	12	32	0	100

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



(a)



(b)

Figure 2a Chinese (2000-2012) and WB (1995-2012) development aid. Authors' depiction based on AidData (2017) and Dreher et al. (2019).
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).

4 Empirical Strategy

Of course, the aid projects shown on the map above are not randomly allocated. Donors may 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 may also cause problems if regions formerly plagued by conflict receive more aid afterward. Considering Figures 2a and 2b helps to understand our two different approaches to identification. The first approach utilizes the sub-national data and condition step-by-step on more and more observables and unobservables through various fixed effects, time trends, and controls.

First, precise coding helps to precisely link aid and stability. Angola, for instance, receives more aid projects in regions that also experience more conflict. In contrast, the regions in Sudan that often receive aid are not the ones 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. They 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, like a change in political regimes. One recently emphasized problem in economics is that very restrictive specifications may eliminate too much variation in the data. Thus, in our case, falsely conclude that there is no conflict-fueling effect. For that reason, our first table eliminates variation step-by-step to transparently show how the relationship between aid and conflict changes when reducing further variation. Of course, this does not entirely eliminate concerns about endogenous selection. We will, in the following sections, assess the direction of bias and propose an IV strategy for each donor.

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

Our baseline empirical specifications are

$$C_{i,c,t} = \beta_1 A_{i,c,t-1/t-2} + \delta_i + \tau_t + \Delta_i T + X'^{Ex}_{i,c,t}\beta_2 + \epsilon_{i,c,t}, \tag{1}$$

$$C_{i,c,t} = \beta_1 A_{i,c,t-1/t-2} + \delta_i + \tau_t + \Delta_i T + X'^{Ex}_{i,c,t}\beta_2 + \kappa_{c,t} + \epsilon_{i,c,t}, \tag{2}$$

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. We lag WB aid disbursements by one year, and follow the literature (Dreher et al., 2019, 2017b) in taking a two year lag for Chinese aid commitments, given that disbursements occur on average one year after the commitment.[27]

Our specifications includes time, and region fixed effects, δ_i and τ_t. Furthermore, we add regional linear time trends $\delta_i T$ to control for any differing linear conflict trends across regions. Including country-year fixed effects $\kappa_{c,t}$ asks a subtly different question: conditional on whether the whole country is involved in a conflict or not in a particular year, how did previous aid receipts affect the conditional likelihood of a particular region to also be in conflict? For that reason, the following sections always consider one specification without (eq. 1) and one with country-year fixed effects (eq. 2).

We distinguish between three types of control variables. First, exogenous controls such as climatic shocks. 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, $X^{End}_{i,c,t-2}$, which can be affected directly by aid projects. Using "pre-determined" values solves the bad control issue only if we assume sequential exogeneity. For that reason, those variables are tested but not part of our preferred specifications. 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 A53 and A54 show that the results are similar for other clustering options.

4.2 Instrumental Variable approach

Our IV strategies exploit the heterogeneous impact of a plausibly exogenous time-series, which affects the amount of aid allocated, depending on a pre-determined cross-sectional difference in the probability to receive aid (cf. Nunn and Qian, 2014).[28] The identifying

[27] AidData cannot distinguish exactly how much money from the Chinese commitments is disbursed in a particular year for all projects, but where the information exists one year fits the data best (see also Dreher et al., 2017b). An examination of further lags in Table A13 suggests that this timing is not driving the subsequently reported results.

[28] Nunn and Qian exploit temporal variation in US wheat production, interacted with the aid recipient's probability to receive US food aid. 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 those where cross-sectional units vary in many dimensions, the units in our approach differ only in the pre-determined probability to receive aid.

assumption is that, in the absence of a change in the time series, there would be common trends in aid allocation in low and high aid probability recipient regions. As in any Difference-in-Difference (DiD) setup, both regression stages control for the main constituting terms forming the interaction; only the interaction term is used as the conditionally exogenous instrument in the first stage. We use a cumulative, pre-determined, probability, computed by dividing the number of years a region i has received aid by the number of years passed until year $t-1$.[29] The IV for WB aid and Chinese aid, hence, differs in the donor-specific probability and in the time-varying factor T_t that induces variation over time.

4.2.1 Application to WB aid

Based on discussions with WB staff, as well as recipient country personnel, the mechanism we exploit and document for identification is the following. We exploit the heterogeneous effect of yearly variation in the availability of additional "free" IDA resources on regions with an initially lower or higher likelihood of receiving aid.[30] If there are more funds available, the Bank has the interest to exhaust the funds and allocate them to recipient countries. Countries and regions which were already involved in projects receive a larger share of the additional funds, partly because the costs of information screening and other preparation cost are lower.[31]

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. It should thus be exogenous to stability in any individual sub-national African region, in particular, conditional on country

[29] If our sample begins in 1995, and a region received aid in three out of five years, the value of the probability in 1999 would be 0.6. If aid receipts stop in 1999, the probability would decline to 0.5 in 2000 as the country would have received aid in three out of six years. The constant probability used in Nunn and Qian (2014) or Bluhm et al. (2018) relies on all observed treatment values per unit, i.e., the term for region i in year t also depends on the values in $t+1, t+2, \ldots$. These future values can be a function of conflict by themselves. 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.

[30] 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.

[31] Galiani et al. (2017) use Gross National Income (GNI) as a threshold for IDA eligibility. We prefer the liquidity over graduation for three distinct reasons. First, the continuous liquidity treatment covers a less specific LATE. Few countries only graduate and experience reductions in WB aid afterward. Second, Kerner et al. (2017) suggest that countries have leeway to postpone graduation by reporting lower GNI estimates. In our sample, we find that the threshold does not always imply a strict reduction in IDA allocations.

or even country-year fixed effects.[32]

From 1995 to 2007, we rely on the reconstructed time series by Dreher et al. (2017b); starting in 2008, we use the measure publicly disclosed in the annual financial reports.[33] This is interacted with the pre-determined probability of a region to receive aid, $p_{i,c,t-2}$, to capture that higher probability regions should profit more from higher funding positions. For simplicity, we do not display fixed effects, time trends, and control variables here, so that the equation becomes

$$Aid_{i,c,t-1} = \alpha_1 p_{i,c,t-2} + \alpha_2 IDA_{t-1} + \alpha_3 p_{i,c,t-2} IDA_{t-1} + \epsilon_{i,c,t-1} \tag{3}$$

One potential problem associated with approaches like this is that, even if the temporal variation is plausibly exogenous, trends in the time series may 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 systematic differences in the long term conflict trends between low and high probability regions could bias estimates. The right-hand side figure then shows that the relevant residual variation in outright conflict, net of fixed effects and time trends, exhibits no such trends. Despite a general decline in the funding position, there is sufficient year-on-year variation. [34]

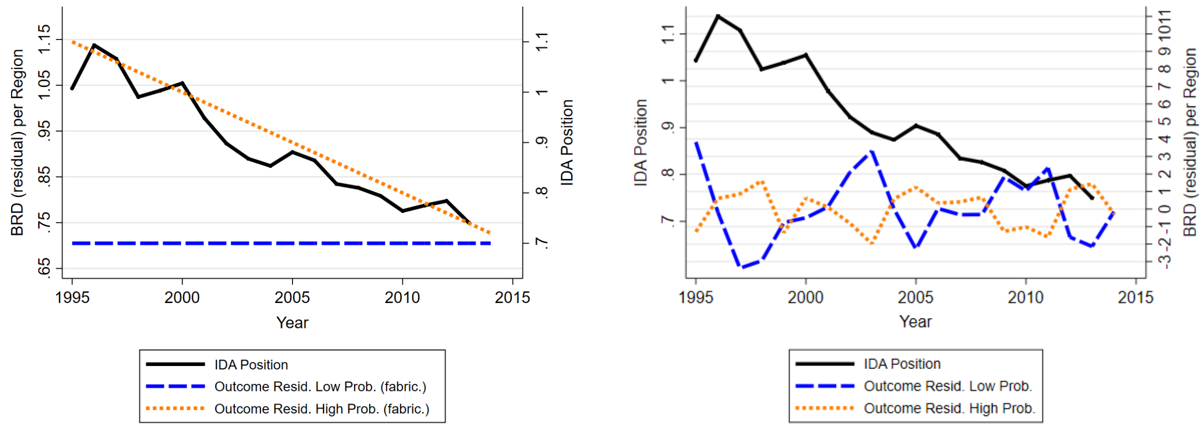
4.2.2 Application to China

Regarding China, we make use of the fact that the economic structure and political incentives frequently lead to excess domestic commodity production. To clear markets and protect domestic companies from potential losses, China commits to more aid projects abroad (Bluhm et al., 2018; Dreher et al., 2017a). This pattern is not entirely unknown from European agricultural overproduction. These additional projects are often large-scale infrastructure projects that directly use overproduced commodities as inputs (Bräutigam, 2011), but Bluhm et al. (2018) show that commodity (over-)production also induces variation in other sectors like education or health. Chinese "mega-deals" (Strange et al., 2017) cannot easily be dupli-

[32] One worry is a correlation with the global level of conflict At the same time, a stronger correlation with conflict in high than in low probability regions. Controlling for global conflict levels interacted with the probability in Tables A25 and A26 does not affect the first or second stage results.

[33] 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 A19. Using both fiscal years t and t-1 to compute the funding position appears more coherent and is applied subsequently.

[34] Figure A?? depicts the time series of logged WB and Chinese aid for high and low probability regions.



(a) Problematic trends (fabricated) in outcomes

(b) Actual trends in outcomes

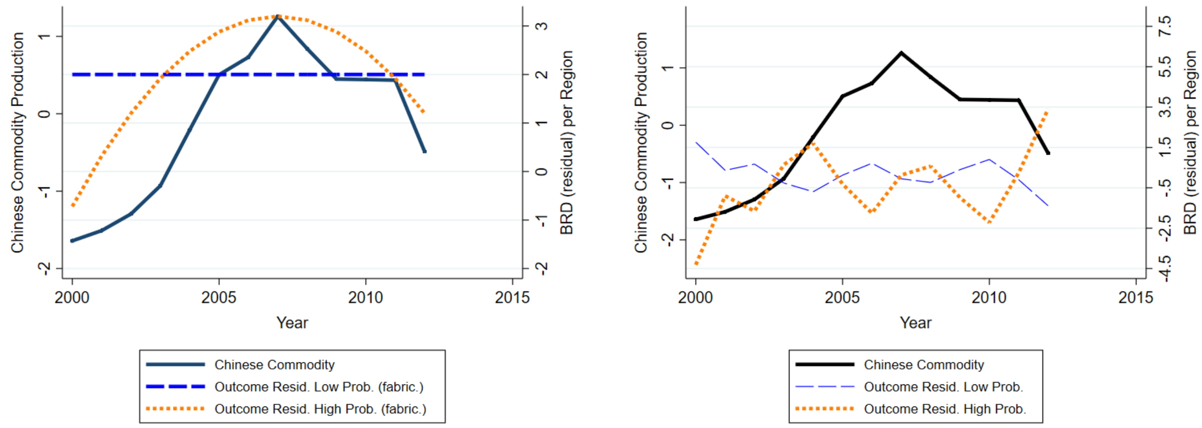
Figure 2: WB- IDA funding position and conflict outcomes for low and high probability regions.

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.

cated or scaled within regions, and the country tries tp strongly expand its influence during our sample period. Thus, additional projects are more often implemented in low probability regions that had initially no or very few projects.

We follow Bluhm et al. (2018) and use principal component analysis to construct a time series on Chinese domestic commodity over-production, $T_{i,c,t}$. The time-varying variable is interacted with the region's pre-determined probability to receive aid, $p_{i,c,t-3}$. This captures that lower probability regions should profit more from Chinese commodity overproduction. The first stage equation is

$$Aid_{i,c,t-2} = \alpha_1 p_{i,c,t-3} + \alpha_2 Commodity_{t-3} + \alpha_3 p_{i,c,t-3} Commodity_{t-3} + X^{Ex}_{i,c,t}\alpha_4 + \epsilon_{i,c,t-2} \quad (4)$$



(a) Problematic trends (fabricated) in outcomes

(b) Actual trends in outcomes

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

Notes: Figure (a) displays the temporal variation we use in our interacted instrument, the Chinese Commodity 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 fabricated trends illustrate potentially problematic trend differences that could induce a spurious correlation. Figure (b) displays the Chinese commodity (over-)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.

The left-hand side of Figure 3 illustrates differing long-term conflict trends in low and high probability regions, which would lead to biased estimates. The commodity time series variable is inverse U-shaped; The IV results may be spurious if conflict trends in either low or high probability regions would, for other reasons, also follow such a pattern. The right-hand side graph, however, assures us that this is not the case.

5 Results

5.1 Outright conflict – 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. We then add fixed effects, time trends, and different categories of control variables step-by-step. 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 whether the country as a whole experience a conflict. Despite the restrictive 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 correlation 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 an economically meaningful and statistically significant conflict-fueling effect. Even if there were substantial changes in Chinese aid, they would not fuel conflict by much compared to the average likelihood of conflict of 12 percent. The following uses our preferred specifications in columns 6 and 8.

5.2 Outright conflict – Instrumental Variables

Table 4 shows the IV results with and without country-year fixed effects. Overall, the first stage works better for the WB (F= 99/86) than for China (F=36/31); all F-statistics, however, are well above the critical value of 10. The interaction term between the prior probability to receive aid with the IDA position, respectively Chinese commodity production, is highly significant in the first stage, and the signs of the coefficients align with our priors. Regions with a higher pre-determined probability profit more from a higher WB liquidity, regions with an initially lower probability profit more from an expansion of the Chinese aid budget. Table A15 and A16 indicate that the WB first stage effect 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. For China, Table A15 reveals that as expected 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.

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 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 $4 \times 0.1886 \approx 0.75$ percentage points.

Table 3: OLS results - Aid and conflict likelihood

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**	-0.1314	-0.1772**	-0.1756**
	(0.0989)	(0.0776)	(0.0683)	(0.0659)	(0.0651)	(0.0717)	(0.0831)	(0.0816)	(0.0894)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.1753**	-0.0233	-0.0026	-0.1090*	-0.0663	-0.0654	-0.0682	-0.0347	-0.0441
	(0.0865)	(0.0705)	(0.0642)	(0.0572)	(0.0644)	(0.0726)	(0.0725)	(0.0883)	(0.0917)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: IV results - Aid and conflict likelihood 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)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
IV First stage: 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	(1)	(2)
IV Second Stage: China		
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.2582	-0.1886
	(0.4282)	(0.5256)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
IV First stage: China		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-14.0193***	-12.6964***
	(2.3180)	(2.2734)
N	7975	7975
Country-Year FE	No	Yes

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

By definition, IV estimates are identified using a particular kind of variation in the variable of interest that is caused by the excluded instrument (local average treatment effect (LATE)). Comparing the IV point estimates with OLS shows no difference with regard to the direction of the effects, but minor variations in size. To check whether the direction of the changes is plausible, Table A13 shows OLS specifications with 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, in line with the IV estimate being very close to the OLS estimate. For China, the lead term is positive, indicating that it is more likely to select into regions that will experience conflict in the future. This suggests an upward bias in China OLS coefficients, which is in line with the IV coefficients for China being more negative.

5.3 Results - Types of Conflict and Actors

Table 5 shows the results using these distinctions with and without country-year FE. The coefficients for two-sided conflict action by government or rebels against each other (column 1 and 2), or between different rebel groups (column 3 and 4) are partly of an economically significant size, but are all far from being statistically significant for both donors. In accordance with our theoretical priors, we find that in a region that receives more WB or Chinese aid, there are, however, significantly less conflicts with at least five battle-related deaths (BRD) by the government against civilians (column 5 and 6). A one standard deviation change in log WB aid decreases the likelihood of violence against civilians with at least 5 BRD by $9 \times 0.2939 \approx 2.61$ percentage points. This is plausible as the WB is known to punish human rights violations by governments. For instance, suspending aid payments in Indonesia to push the government towards finding peaceful bargaining solutions in Timor (Tir and Karreth, 2018).

Although Tir and Karreth (2018) focus their arguments on international organizations like the WB, which impose strong conditionality. The fact that we also find the same significant effect, even larger in size, for China, validates our prior that China also informally has the incentives and ability to stop recipient governments from engaging in conflicts that may be deemed undesirable from the donors perspective. Changing log Chinese aid by one standard deviation decreases the likelihood of this type of conflict substantially by $4 \times 0.5673 \approx 2.27$ percentage points. The value China attributes to social stability, business interests and the widespread presence of Chinese workers may be reasons to convince recipient governments to abstain from engaging in actions that cause civilian casualties and endanger stability. Tir and Karreth (2018) argue that the prospect of gaining access to aid could also constrain rebels. But we find no equivalent significant reduction in rebel violence against civilians (column 7 and 8).

Table 5: Aid and conflict types by actors

Panel A: World Bank Aid - IV	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	State vs. N-State		N-State vs. N-State		State vs. Civilians		N-State vs. Civilians	
IV: IDA Position - Actors 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								
	State vs. N-State		N-State vs. N-State		State vs. Civilians		N-State vs. Civilians	
IV: Chinese Commodity - Actors ln($Chinese\,Aid_{\text{t-2}}$)	0.2749	0.2200	0.2462	0.4178	-0.5336**	-0.5673**	-0.3273	-0.3553
	(0.2104)	(0.2280)	(0.1924)	(0.2637)	(0.2300)	(0.2877)	(0.2520)	(0.3066)
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	36.578	31.190	36.578	31.190	36.578	31.190	36.578	31.190
Country-Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD$\geq$5, 0 if BRD$<$5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Table A37 depicts corresponding OLS results.

5.4 Results - Protest and government repression

Panel A of table 6 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.[35] For the WB, both specifications yield a negative coefficient but remain statistically insignificant. Regarding China, we observe negative coefficients, which are of modest size (100% more aid increase the likelihood of riots by 0.07%) and remain statistically insignificant. Accordingly, despite reports indicating increasing protests against the presence of Chinese business (Wegenast et al., 2017), we find no clear relationship between Chinese aid and citizen protests over our sample period.[36]

Recipient governments may achieve this absence of protests and outright conflict by intensifying non-lethal repression. Panel B of table 6 tests whether aid is related to more reports of non-lethal government repression. In the underlying SCAD data events range from the repression of opposition lawyers to constraining anti-government artists in Egypt and media restrictions in Malawi (Salehyan et al., 2012). [37] The results indicate neither a positive nor significantly negative relationship for the WB. The results for China contrast our previous findings and establish that repression intensifies in regions where China is present. A 100% increase in Chinese aid increases the likelihood of experiencing repression by about 0.77%, which is significant, considering an average of 2.26%.

[35] Table A39 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.

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

[37] 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.

Table 6: Protests and non-lethal government repression [SCAD]

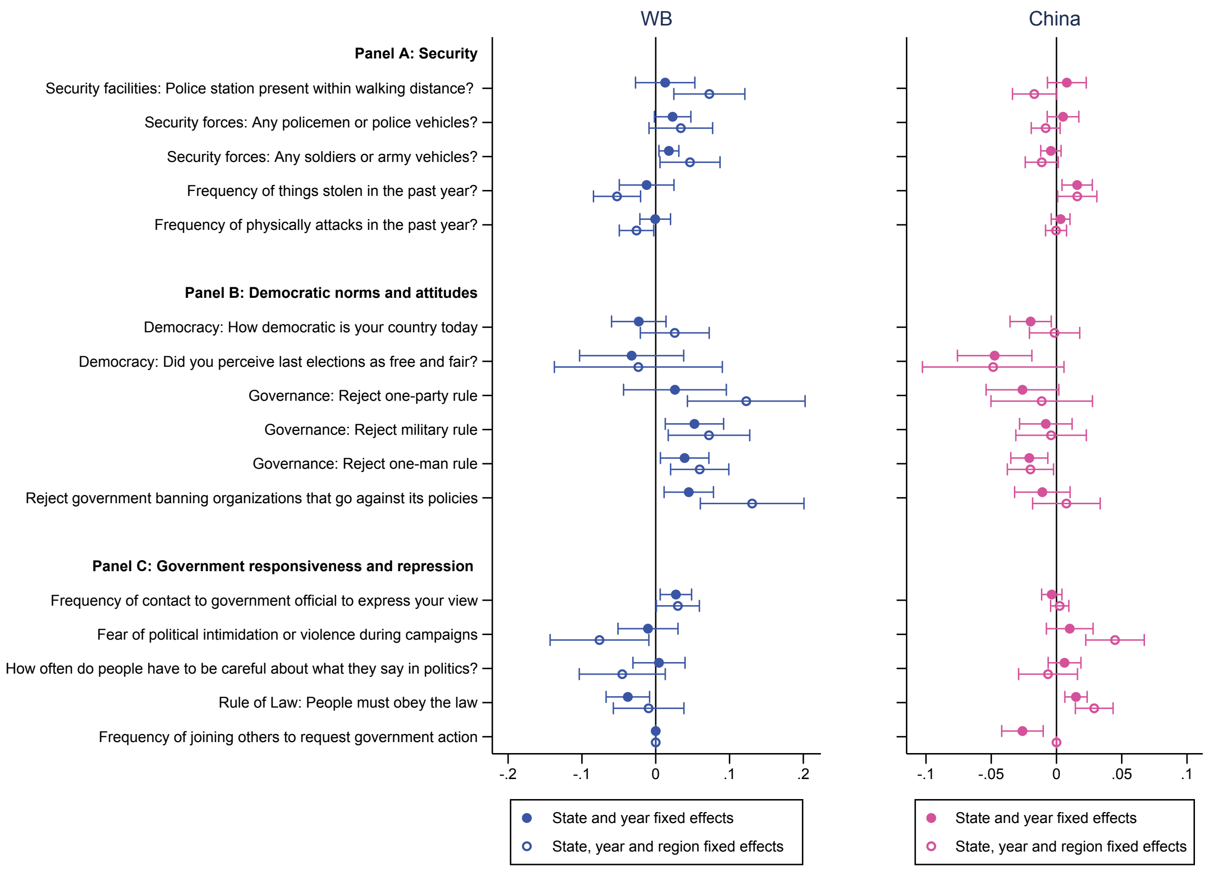
Panel A: Riots, demonstrations or strikes	(1)	(2)
IV Second Stage: World Bank		
ln($World\,Bank\,Aid_{\text{t-1}}$)	-0.3854	-0.2032
	(0.3092)	(0.3362)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
IV Second Stage: China		
ln($Chinese\,Aid_{\text{t-2}}$)	-0.1599	-0.0742
	(0.3964)	(0.4452)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
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($Chinese\,Aid_{\text{t-2}}$)	0.6103**	0.7696**
	(0.2873)	(0.3439)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
Country-Year FE	No	Yes

Notes: The dependent variables are binary protest and government repression incidence indicators, taking on the value 1 if there was at least one event in the respective category. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level.Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.5 Results - Attitudes

Examining the associated mechanisms for all effects is beyond the scope of this paper. Still, we can present some correlational evidence using geo-referenced 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. 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 A49 provides the full regression results. Afrobarometer surveys were 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 into 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 may select into regions more likely to experience conflict and a deterioration in state capacity.

Panel B examines democratic norms and attitudes. The results are not necessarily causal, but differences stand out that reflect the differential approaches of both donors. There are indications that the perception of democracy, and the fairness of elections, deteriorate in regions with Chinese aid projects. The WB seems to have a consistently positive impact on democratic norms and a neutral to a positive effect on stability. 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. In a more detailed examination, Isaksson and Kotsadam (2018a) also find 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 contact their government officials and express their views frequently. 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 apparent 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. These correlations correspond to the different norms and conditions of the WB and China that we described above.

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. It is important to reconsider that aid by both donors is, if anything, leading to less conflict. The results on mechanisms suggest that, WB aid goes with improved 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 of stability seems to come at the cost of increased government repression in addition to a weakening of democratic processes.

5.6 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.[38]

In Table A45 (A46), 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. All coefficients are insignificant, and the majority are negative, especially, when conditioning on more restrictive fixed effects. 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 take the concern serious that our instrumental variable may intersect with a spurious trend as suggested by Christian and Barrett (2017). In this regard, when taking non-stationarity (Table A20) of the time series into account by taking first differences of conflict, aid and our liquidity indicator. The second stage results in Table A21 remain clearly indistinguishable from zero. While it is arguably unlikely that conflict

[38] Point estimates for the less precisely coded aid can be found in Table A48. Although the coefficient for non-geocoded WB aid at the country level turns positive it remains small and insignificant. This supports that there is also a null effect at the country level. OLS and IV point estimates for geo-coded aid aggregated at the country level are shown in Table A47. The coefficients remain small and insignificant, as well.

in a specific sub-national region determines our global liquidity indicators, we also assess the robustness of the instrumental variables by controlling for global conflict levels in Tables A25 and A26. The strength of the instruments remains virtually unaffected and the point estimates remain negative and statistically insignificant.

The second component of the IV, the probability term, may be computed in different ways. We test various plausible options. 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 corresponding panel (starting at 1998 for the WB's IDA, and 2003 for Chinese Commodity Production). Thus, the first probability is based on at least two observations. Table A23 uses a constant probability from the third year of the respective sample onwards. Table A24 drops the 10 highest leverage region-year observations. Figures A11 and A12 display the IV estimates dropping country-by-country, 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 A18 reports reduced-form estimates. Table A14 uses a lead of aid as a placebo treatment in the first stage, which always shows up as statistically insignificantly. Table A17 reports the first stage, including the coefficient for the probability.

Political Systems: Development aid may have differential impacts across political systems due to different allocation decisions and distributional aspects. As a further sensitivity exercise, we consider heterogenous effects across democratic and autocratic systems based on the distinction due to the Polity IV data (Marshall et al., 2014). The WB disburses 20% of its aid to democratic countries, where 38% of Chinese commitments go to regions of democratic states.[39] Considering the results in Tables A43 and A44 , we find that effects across democratic and autocratic subsamples are similar in sign and statistical significance as average effects. While the effects for the WB are insignificant, repression significantly increases in regions that receive Chinese aid both in autocracies and democracies. Thus, we do not find evidence for heterogenous effects across regimes.[40]

[39] On a first view this allocation patterns may seem surprising. Yet, a selection mechanism may prevail, where both donors give more to the opposed political system, e.g., to foster regime change (Aidt et al., 2018).

[40] We also try to capture changes in the aid approach by traditional donors like the WB by splitting the sample in two periods. The results in Table A55 support the main finding that aid on average does not effect outright conflict in either sample.

Both donors in same specification: One trade-off was whether to show both donors over the same period and in the same equation. This should not be decisive, as China is only active in 6% of the region-years that also feature WB projects. Moreover, Humphrey and Michaelowa (2018) find no systematic relationship between the selection of locations by the two donors at the country-level. Still, accounting for aid from one donor as a potential omitted variable in the other donor's equation is a potential issue. Table A59 (Table A60) shows that the OLS (IV) results also suggest no conflict-fueling effects when including both donors jointly. In joint IV specifications for both donors, the K-P F-statistics for the WB becomes smaller than 10 (Table A60), giving rise to concerns about a weak IV. Still, the table shows that both instruments capture distinct variation: the interaction instrument for the WB is still significant in explaining variation in WB aid, and the IV for China is still significant in explaining variation in Chinese aid. With the caveat of a weak IV in mind, the table still indicates no conflict-fueling effects for both donors.

Non-linear estimators: In line with Berman et al. (2017), we also run a Poisson Pseudo Maximum Likelihood estimation in Table A50, which is suitable for binary outcomes with a large fraction of zeros. Moreover, we implement a conditional logit estimation in Table 51. The results are generally in line with the main findings in terms of coefficient signs. However, note that the models only converge when restricting us to the use of year fixed effects.

Temporal dependence: As conflict may be highly persistent over time, we include a lagged dependent variable in Table A52. The results are very similar, with mostly negative and partly significant coefficients for the WB and China.

6 Conclusion

China constantly increases its range of development projects in Africa. This raises both hopes and rejections among political and academic observers. The big question is whether African countries will benefit or suffer from this foreign engagement? To answer this question, we compare the effect of Chinese aid on state stability to a donor that represents a strongly contrasting approach to development -- the World Bank (WB). China is the major emerging donor, emphasizing mutual economic benefits without official economic or political conditions for recipient governments and has no specific guidelines to manage potential conflict risks (Asmus et al., 2017; Hernandez, 2017). In contrast, the WB is a traditional, multilateral donor that emphasizes human right conditions, expert knowledge, and engages explicitly in conflict-sensitive programming. Without taking a normative stance, we compare the effects of those different development approaches on a comprehensive set of stability measures. Our paper contributes to the literature by providing, as we hope, the most comprehensive analysis of the causal effect of development aid projects on a comprehensive set of stability measures in a multi-country analysis at the sub-national level this far.

Our results using aid projects and outright conflict in the same region show no signs of a conflict-fueling effect. The WB tends to have a conflict-reducing effect in some fixed effects specifications, but when using instrumental variable strategies, estimates for both donors are negative and insignificant, on average. Looking at heterogeneity with regard to actors and types of conflict, we find that the threat of losing out on future aid payments leads to a reduction in lethal violence by governments against civilians related to both Chinese and WB projects.

In contrast to a substantial amount of media reports, we also find no net effect of Chinese aid projects on civilian unrest and protests in Africa. At the same time, we do, however, observe that in regions in which China is engaged the likelihood of government repression against targeted individuals or groups increases. Thus we cannot say with certainty whether the non-significant result on protest reflects the higher costs of protesting due to repression or that there is no reason to protest. WB aid has neither a significant net effect on protests or government repression.

Nonetheless, when considering attitudes from Afrobarometer surveys, our results suggest that WB aid has positive effects on perceived safety, democratic norms, and democratic values. Chinese aid is associated with attitudes related to stability like a higher adherence to the rule of law, but also with a higher acceptance of autocratic approaches. The results suggest a rationale where China is eager to export stability and avoid violent conflict that endangers its workers and investment. China may also be more supportive of repression and autocratic rule than traditional Western-influenced donors like the WB.

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Appendix

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A Data Appendix

A.1 Sources

Table 7 lists descriptions and sources of our independent, dependent and control variables.

Table 7: Data Sources

Variable Name	*Variable Description*	Time Period	*Variable Source*
WB Aid	log of WB Aid disbursements per region-year	1995-2012	Strandow et al. (2011)
Chinese Aid	log of Chinese Aid commitments per region-year	2000-2012	Dreher et al. (2017b)
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 (2015)
Population	Continuous indicator of regional population	1995-2014	(CIESIN 2016)
Drought (end of rainseason)	SPI value of drought severity of the region's rainy season	1995-2014	Tollefsen et al. (2012); 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); Guttman (1999)
Temperature	Mean temperature (in degrees Celsius) per region-year	1995-2014	Tollefsen et al. (2012); Fan and Van den Dool (2008)
Precipitation	Total amount of precipitation (in millimeter) per region-year	1995-2014	Tollefsen et al. (2012); Schneider et al. (2015)
Chinese Commodity	Chinese Commodity production (factor, standardized)	1999-2013	Bluhm et al. (2018); Dreher et al. (2017a)
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. (2017b)
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 ADM1 region	Constant	Natural Earth, from 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); Uchida and Nelson (2009)
Borders	Binary indicator if an 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

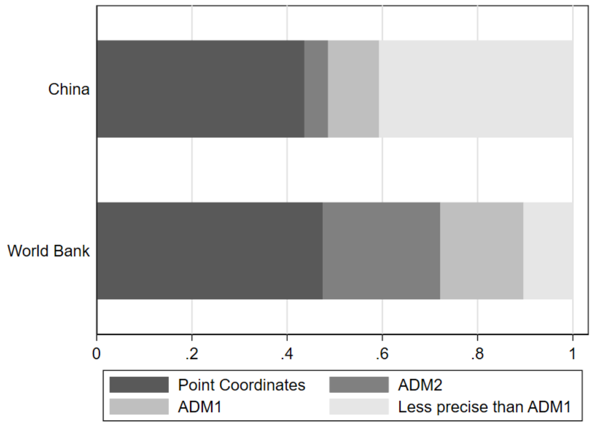
For our analysis, we draw on the "WB IBRD-IDA, Level 1, Version 1.4.1" provided by the AidData consortium, which covers approved loans under the IBRD-IDA lending line between 1995 and 2014.[41] These data correspond to project aid disbursed from 5,684 projects in 61,243 locations. The data builds on the information provided by the WB, including the disbursement dates, project sectors, and disbursed values. These values are 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. Some projects include exact locations on latitude and longitude. 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). To include as many disbursements as possible, but to be also able to grasp the advantages of geo-referenced data, we focus our analysis on these administrative levels. For our administrative boundaries, we build on the GADM dataset constructed by Hijmans et al. (2010). One difficulty with this 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 these 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).

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.

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



(a)

Figure 5: No. of Project Locations by Precision Codes

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 classify as Official Development Assistance. For this purpose, disbursements are 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.[42] 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, further analysis focuses on the remaining 70% of development aid. Second, we then allocate all aid with precision codes 1-3 to the corresponding ADM2 regions. This is done by taking the location share (either by equal or population weights) of the transaction amount per location. A certain ADM2 region may 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 region may have several locations per project or even several projects, we collapse our data by ADM1 region. To allow for inference on the ADM2 level, we assume 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 9: 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

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

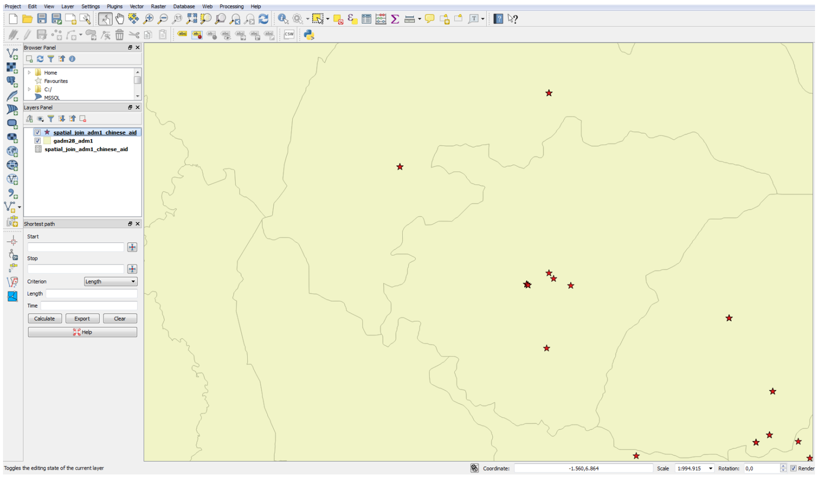
Population weighting

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 to be able to distribute those aid disbursements. We then consequently attribute the population of an 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 may 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 may 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)

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.

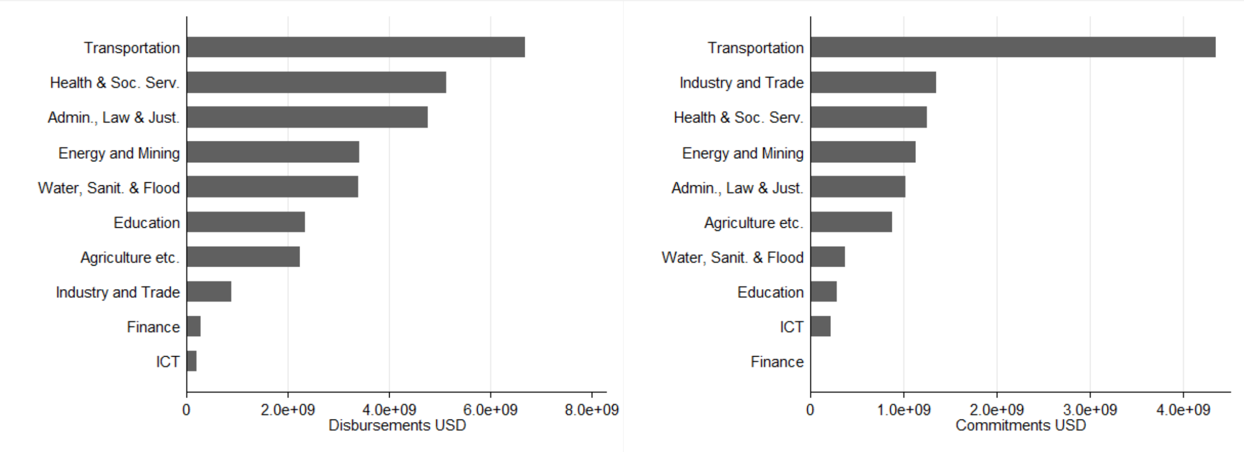
Figure 6: Chinese Aid ADM1 Spatial Join

To create our data, we first load our ADM2 data into Stata and drop the ADM0 and ADM1 identifiers 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 "aid-data_china_1_1_1.xlsx" by (Dreher et al., 2019) 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 somewhat 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 compare 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 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. The Chinese aid commitments are coded like WB disbursements with different precision (e.g., some are coded only for geographic features. Such aid 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 sub-regional levels 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, projects may 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 10 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 10: 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 (Croicu and Sundberg, 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.

A useful feature of the UCDP data is the possibility to discern three different types of violence. Those are 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).[43] UCDP data can be considered as comprehensive for our 1995 to 2012 sample. Hence, all missing values are treated as zeros. For Syria, information on battle-related deaths are not reported and is not part of our analysis.

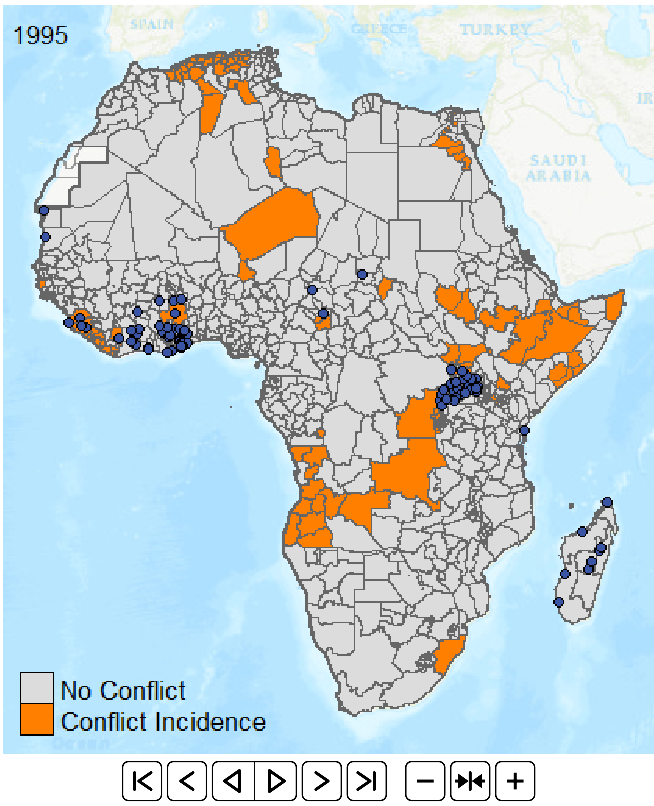


Figure 8: WB Aid and Conflict - By Year

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

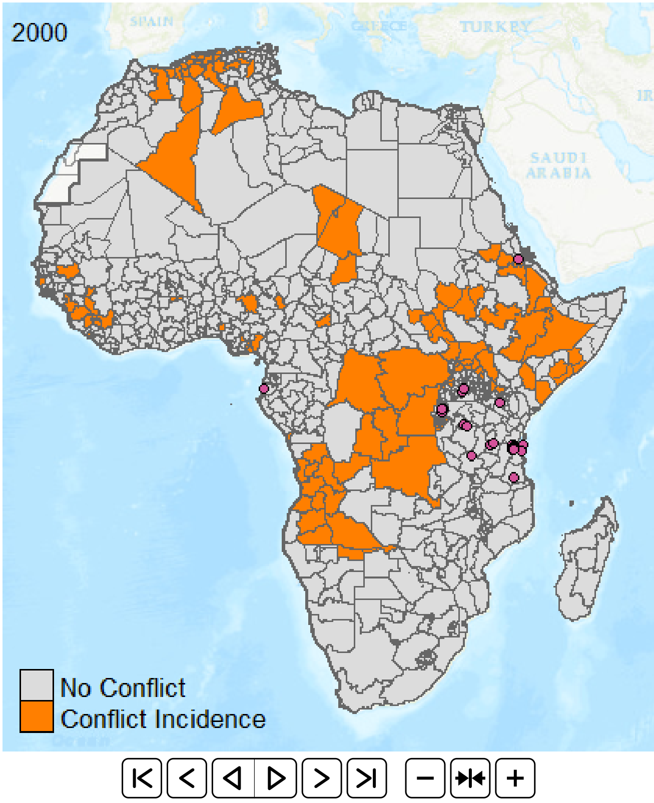


Figure 9: Chinese Aid and Conflict - By Year

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.[44] 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 geo-referenced 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 similarly.

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

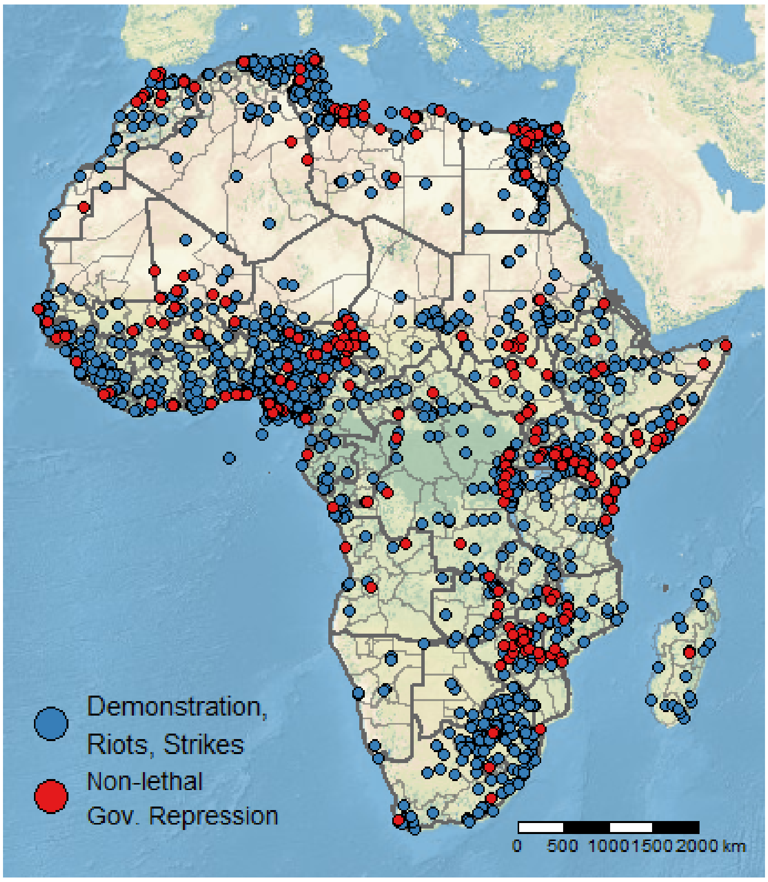


Figure 10: SCAD Data for precision codes 1-4

Matching EPR to GREG

To measure ethnic homelands, we use the GREG dataset (Weidmann et al., 2010). It is a geo-referenced 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. 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 World Bank Aid in the Financial Sector

A more profound 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 disbursements are 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 11 shows that 50% of all aid projects that are significantly targeted at the financial sector are aimed at sectoral reforms. Projects in this category support existing government efforts for sectoral reforms and development but mainly include new projects that are launched outside the initiative of the recipient government.

A.5 Afrobarometer

Measures on people's norms about democracy are taken from Afrobarometer Data (2018). The geo-coded individual responses are matched with the administrative region and the response values to the respective questions are averaged on the first administrative level. Such an approach allows the matching of individual responses with regional aid flows for the subsequent analysis.

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 11: World Bank Aid in the Financial Sector

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

B Analytical Appendix

B.1 Instrumental Variable

B.1.1 Motivation of Instrumental Variable

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 13 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. This correlation may also correspond to a geographically more selective allocation of Chinese funds as described in Figure 2a. 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 14. The instrumental variable approach is, thus, warranted to reduce selection bias.

Figure **??** 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 15 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 16, in turn, indicates that for the WB the intensive margin matters as well (e.g., provided that at least one active aid project, how much funds does a region receive?).

Table 18 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.[45] For transparency, Table 17 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).

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

Table 13: 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
	(0.1236)	(0.1124)
ln($World\,Bank\,Aid_{\text{t}}$)	-0.1089	-0.2128**
	(0.1047)	(0.0984)
ln($World\,Bank\,Aid_{\text{t-1}}$)	0.0214	-0.0933
	(0.0893)	(0.0900)
ln($World\,Bank\,Aid_{\text{t-2}}$)	0.0516	0.1424
	(0.0876)	(0.1015)
ln($World\,Bank\,Aid_{\text{t-3}}$)	-0.0811	-0.0535
	(0.0878)	(0.1000)
N	10150	10150
Panel B: Chinese Aid		
Lead and Lag: China		
ln($Chinese\,Aid_{\text{t+1}}$)	0.1681	0.2083*
	(0.1239)	(0.1239)
ln($Chinese\,Aid_{\text{t}}$)	-0.0127	0.0231
	(0.1263)	(0.1367)
ln($Chinese\,Aid_{\text{t-1}}$)	-0.0086	-0.0481
	(0.1518)	(0.1562)
ln($Chinese\,Aid_{\text{t-2}}$)	0.0121	-0.0506
	(0.1156)	(0.1285)
ln($Chinese\,Aid_{\text{t-3}}$)	0.0572	-0.0308
	(0.0978)	(0.1117)
N	6525	6525
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country- × Year	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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.
Interpretation: The lead terms of the table indicate that World Bank aid does not exhibit a selection effect, while China seem to select into regions more likely to experience conflict in the future. Table 14 indicates that our instrumental variable approach succeeds in reducing this selection bias.

Table 14: ADM1 - Absence of Pre-Trends with IV. Regression with Instrumented Lead of Aid

	(1)	(2)
Panel A: WB Aid		
Placebo (Lead): World Bank		
$\ln(World\,Bank\,Aid_{\mathrm{t+1}})$	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		
$\ln(Chinese\,Aid_{\mathrm{t+1}})$	0.0396	-0.3753
	(0.2888)	(0.3351)
N	8700	8700
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	34.263	29.941
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country $\times$ Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD$\geq$5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.

Interpretation: The lead terms indicate that our instrumental variable method succeeds in addressing the identified selection bias of Table 13.

Table 15: ADM1 IV (First Stage - Extensive Margin (Likelihood of at least one active project))

	(1)	(2)
Panel A: WB Aid		
IV FS Extensive Margin: IDA Position		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	4.0782***	4.8249***
	(0.4140)	(0.5238)
N	12325	12325
Panel B: Chinese Aid		
IV FS Extensive Margin: Chinese Commodity		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-0.7267***	-0.6591***
	(0.1205)	(0.1163)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The table displays regression coefficients the first stage of the IV regression, when instead of the aid amount a binary indicator of aid receipts is used. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 4.2.1.
Interpretation: The table shows differences in how both donor allocate aid to regions. An increase in the IDA position increases a region's probability to receive more aid projects if the region already received had a WB project in the past. On the contrary, an increase in Chinese overall aid linked to commodity (over-)production increases the region's probability to receive aid more for regions that did not receive aid in the past. This is in line with China's strategic aim of expanding to new regions.

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

	(1)	(2)
Panel A: WB Aid		
IV FS Intensive Margin: IDA Position		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	4.4155	8.5243**
	(3.3348)	(3.7926)
N	7091	7081
Country-Year FE	No	Yes
Regional Time Trend	Yes	Yes
Country Time Trend:	Yes	Yes
$CountryTimeTrend^2$:	Yes	Yes
Panel B: Chinese Aid: IV FS Intensive Margin: Chinese Commodity		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-0.6974	0.0592
	(1.5012)	(2.3391)
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. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 4.2.1.

Interpretation: For the World Bank, the first stage effect seems partly also related to the intensive margin, i.e. the expansion of existing projects. That is, regions that already received aid in the past are likely to larger amounts of aid if more additional funds are available. For China, there is no evidence in favor of a change at the intensive margin. The first stage effect seems to be driven by extensive margin changes.

Table 17: 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		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-14.0193***	-12.6964***
	(2.3180)	(2.2734)
$Cum.\,Prob_{\text{t-3}}$	-43.8804***	-39.5225***
	(4.7041)	(4.4175)
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, displaying additionally the constituent term of the probability, which was not shown in Table 4. This table display the constituent term for completeness. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.

Table 18: ADM1 Reduced Form

	(1)	(2)
Panel A: WB Aid		
Reduced Form: IDA Position		
$Cum.\,Prob_{\text{t-2}}$	10.8281	19.2994
	(27.3795)	(33.4583)
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	-7.1921	-18.2132
	(26.5498)	(33.5818)
N	12325	12325
Panel B: Chinese Aid		
Reduced Form: Chinese Commodity		
$Cum.\,Prob_{\text{t-3}}$	-8.1658	-14.3840
	(9.7637)	(10.2361)
$Commodity,_{\text{factor1}} \times \text{Cum. Prob}_{\text{t-3}}$	6.6166	5.1407
	(6.6138)	(7.1640)
N	7250	7250
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country × Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.
Interpretation: Both interacted instruments are not significantly correlated with the conflict outcome and are in line with the main results in Table 4.

B.1.2 Robustness of Instrumental Variable

The main specification uses 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 19 depicts instrumental variable results using only the variation in $t-1$. The results are largely unchanged.

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 (1995 to 1997 for the WB's IDA; 2000 to 2002 for Chinese Commodities) in Table 23 or if dropping the first year of the respective panel (starting at 1998 for the WB's IDA, and 2003 for Chinese Commodity Production) Table 22.

Finally, first stage results may be susceptible to a small share of very influential observations. Table 24 indicates that results are qualitatively unchanged if we exclude the ten high leverage region-years from the sample. Figures 11 and 12 display the first stage relationship leaving out single countries, suggesting that there are no individual states driving the relationship.

Table 20: Test for (Trend) Stationarity - Hadri type

	(1)	(2)
ln(World Bank Aid $_{\mathrm{t}}$)	125.8488***	89.4980***
	(0.0000)	(0.0000)
ln(Chinese Aid $_{\mathrm{t}}$)	2.9868***	1.1684
	(0.0014)	(0.1213)
IDA Position $_{\mathrm{t-1}}$ $\times$ Cum. Prob $_{\mathrm{t-2}}$	145.3093***	121.1980***
	(0.0000)	(0.0000)
Chinese Commodity $_{\mathrm{t-3}}$ $\times$ Cum. Prob $_{\mathrm{t-3}}$	98.1532***	65.5592***
	(0.0000)	(0.0000)
Conflict	56.8260***	23.5170***
	(0.0000)	(0.0000)
Linear Trend	No	Yes

Notes: Conflict refers to category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD$<$5). Hadri type test coefficient estimates for the five variables indicated in rows. p-values in columns refer to the null hypothesis "All panels are (trend) stationary." * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.6.
Interpretation: The test shows that (trend) stationarity is rejected, hence robustness tests under a weak dependence assumption is conducted in Table 21.

A (non-)linear trend in our outcome, treatment and instrumental variable may render

Table 19: 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: IDA Position (t-1)		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	51.3655***	65.1984***
	(5.6627)	(6.9103)
N	12325	12325
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 4.2.1.
Interpretation: The instrumental variable is nearly unaltered even if changing the sample: Here, probabilities are not based on a rolling average but based on the last year's IDA position, $t - 1$.

the panels non-stationary and lead to spurious findings. The Hadri test assesses the null hypothesis "All Panels are (trend) stationary". Table 20 indicates that there are at least some panels being non-stationary and may include a trend. For this reason, we correct for the non-stationarity and take first differences of outcome, treatment and instrumental variables. Results in Table 21 remain robust and support the main findings.

Table 21: ADM1 IV (First Difference WB & Chinese aid)

	(1)	(2)
Panel A: WB Aid		
IV Second Stage: World Bank		
L.d1lnaid	0.7606	0.2460
	(1.1439)	(1.2420)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	64.200	35.064
IV First stage: World Bank		
$IDA\,Position_{\text{(t-1)-(t-2)}} \times \text{Cum. Prob}_{\text{t-2}}$	18.7864***	29.3949***
	(2.3424)	(4.9589)
Panel B: Chinese Aid		
IV First stage: China		
L2.d1lnaid_c	-0.3690	-0.5025
	(0.4856)	(0.6253)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	20.972	13.774
First Stage: Chinese Commodity		
$Commodity,_{\text{(t-3)-(t-4)}} \times \text{Cum. Prob}_{\text{t-3}}$	-13.5621***	-10.5846***
	(2.9568)	(2.8471)
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD$\geq$5, 0 if BRD$<$5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 or section 5.6.
Interpretation: The Hadri test in Table 20 shows that despite a certain degree of time persistence, the results of the first stages using first differences are nearly unchanged under the assumption of weakly dependent time series.

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($Chinese\,Aid_{\text{t-2}}$)	-0.5634	-0.5104
	(0.5786)	(0.7241)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.620	16.927
IV First stage: China		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-11.7436***	-10.0728***
	(2.4692)	(2.4483)
N	7250	7250
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.
Interpretation: The instrumental variable is nearly unchanged when dropping the first year. This accounts for a potentially overly high leverage of the first year in influencing the cross-sectional probability terms.

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***
	(8.3419)	(11.9769)
N	11600	11600
Panel B: Chinese Aid		
IV Second Stage: China		
$\ln(Chinese\,Aid_{\text{t-2}})$	-1.4689	-1.2846
	(1.3446)	(1.4723)
Kleibergen-Paap underidentification test p-value	0.001	0.002
Kleibergen-Paap weak identification F-statistic	13.035	9.925
IV First stage: China		
$Chinese\,Commodity_{\text{t-3}} \times \text{Con. Prob}_{03}$	-5.8046***	-5.7207***
	(1.6061)	(1.8130)
N	7250	7250
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

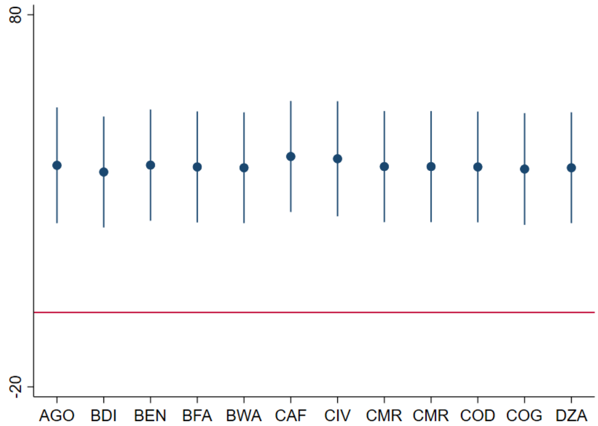
Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 Commodities) and held thereafter constant. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.6.
Interpretation: An alternative to our cumulative, updated probability is a constant probability. Computing this over the whole sample period is potentially problematic, but we can exclude the first third of the sample to compute a constant, but pre-determined probability. When doing this, the signs of the instrumental variable in the first stage remain unchanged, they are only smaller in magnitude.

Table 24: ADM1 IV (Without high leverage region)

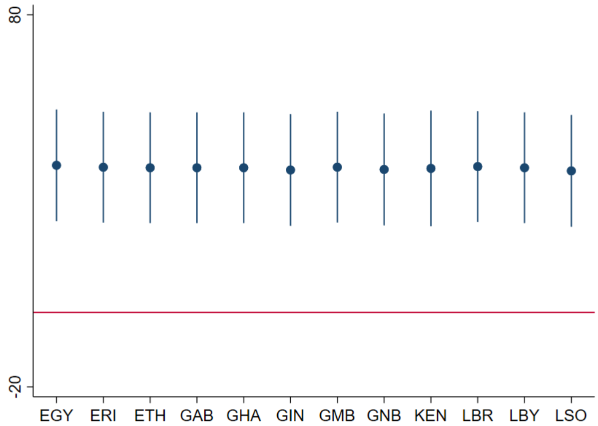
	(1)	(2)
Panel A: WB Aid		
IV Second Stage: World Bank		
ln($World\,Bank\,Aid_{\text{t-1}}$)	-0.0990	-0.2268
	(0.3761)	(0.4197)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.363	86.752
IV First stage: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	70.8414***	80.8936***
	(7.1068)	(8.6851)
N	12317	12291
Panel B: Chinese Aid		
IV Second Stage: China		
ln($Chinese\,Aid_{\text{t-2}}$)	-0.2592	-0.1934
	(0.4281)	(0.5251)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.571	31.181
IV First stage: China		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-14.0197***	-12.6973***
	(2.3183)	(2.2739)
N	7974	7974
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.

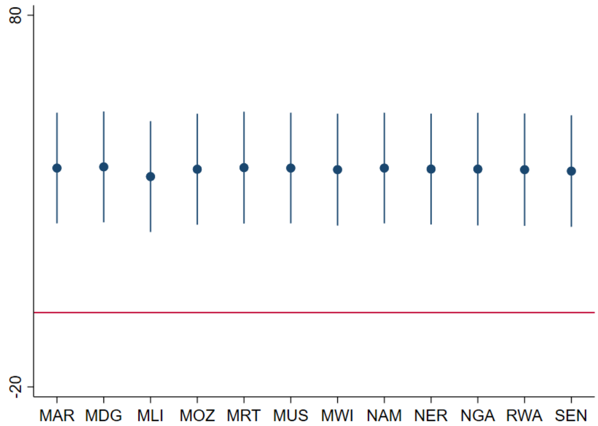
Interpretation: One concern is that the predictive power of the instrumental variables is driven by a few regions that received a lot of aid in the past. The table shows that when dropping the 10 region-year observations receiving most aid our results still hold.



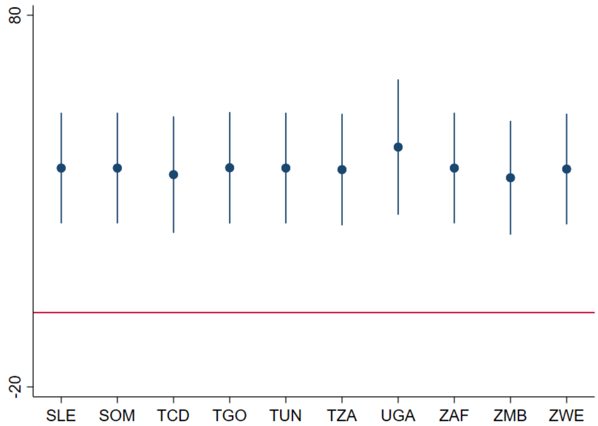
(a) Leave one out (i)



(b) Leave one out (ii)



(c) Leave one out (iii)

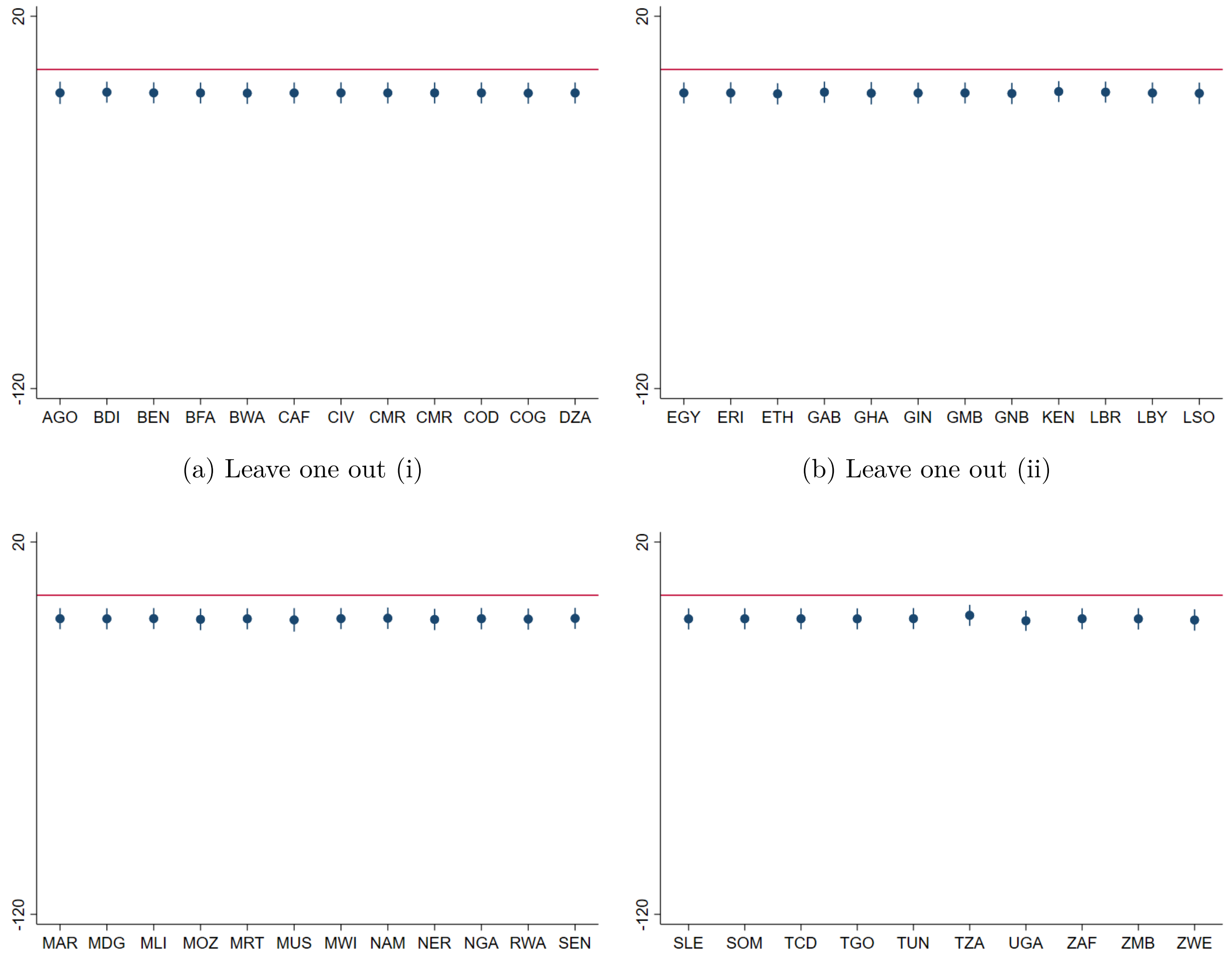


(d) Leave one out (iv)

Figure 11: 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 5.6.

Interpretation: To rule out that one particular country drives the results, we run a series of regressions, each leaving out one country. The graph shows that the results are not affected when doing that for any particular country.



(a) Leave one out (i)

(b) Leave one out (ii)

(c) Leave one out (iii)

(d) Leave one out (iv)

Figure 12: Robustness of first stage for Chinese Aid - Leaving one country out

Note: Results depict coefficients of the instrumental variable $probability_{i,c,t-3} \times ln(Chinese\,Commodity_{t-3})$ 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 5.6.

Interpretation: To rule out that one particular country drives the results, we run a series of regressions, each leaving out one country. The graph shows that the results are not affected when doing that for any particular country.

Table 25: ADM1 IV (WB - Global Time Series)

	(1)	(2)
Panel A: WB Second Stage		
IV Second Stage: World Bank		
	Glob. Conflict	Glob. Conflict
$\ln(\text{World Bank Aid}_{\text{t-1}})$	-0.1484	-0.0605
	(0.3637)	(0.3788)
N	12325	12325
Kleibergen-Paap under-ID p-val.	0.000	0.000
Kleibergen-Paap weak ID F-stat	99.771	99.659
Panel B: WB First Stage		
IV First stage: World Bank		
$\text{IDA Position}_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	76.5677***	95.7504***
	(7.6586)	(9.5846)
$\ln(\text{Global BRD}_{\text{t-1}}) \times \text{Cum. Prob}_{\text{t-2}}$	-0.9489	-2.9929***
	(0.5929)	(1.0281)
N	12325	12325
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. All regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. Click here to go back to section 5.6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interpretation: One potential concern is that the time-varying WB liquidity and overall amount of WB aid react to overall global conflicts in a way that affects low and high probability regions differently. The table shows that controling for an interaction of global battle-related deaths with the probability to receive aid neither changes the first nor second stage coefficients to a noticeable degree.

Table 26: ADM1 IV (China - Global Time Series)

	(1)	(2)
Panel A: China Second Stage		
IV Second Stage: China		
	Glob. Conflict	Glob. Conflict
$\ln(\text{Chinese Commodity}_{\text{t-2}})$	-0.2070	-0.1037
	(0.4766)	(0.5948)
N	7975	7975
Kleibergen-Paap under-ID p-val.	0.000	0.000
Kleibergen-Paap weak ID F-stat	31.432	26.756
Panel B: China First Stage		
IV First stage: China		
$\text{Chinese Commodity}_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-13.0574***	-11.8020***
	(2.3254)	(2.2784)
$\ln(\text{Global BRD}_{\text{t-3}}) \times \text{Cum. Prob}_{\text{t-3}}$	2.6516	2.1932
	(2.3520)	(2.3782)
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 dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. All regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. Click here to go back to section 5.6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interpretation: One potential concern is that the time-varying commodity (over-)production and overall amount of Chinese aid react to overall global conflicts in a way that affects low and high probability regions differently. The table shows that controling for an interaction of global battle-related deaths with the probability to receive aid neither changes the first nor second stage coefficients to a noticeable degree.

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. While the IV specifications indicate medium-sized negative for the WB and small positive coefficients for China, both stay insignificant. 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 seriously by disentangling the results from Table 6 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 significant 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 the 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**	-0.1156*	-0.1386**	-0.1513**
	(0.0659)	(0.0551)	(0.0536)	(0.0528)	(0.0532)	(0.0596)	(0.0656)	(0.0673)	(0.0708)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
ln($Chinese\,Aid_{\text{t-2}}$)	-0.0917	-0.0209	0.0184	-0.0285	-0.0140	0.0059	-0.0021	-0.0022	-0.0096
	(0.0614)	(0.0504)	(0.0378)	(0.0446)	(0.0510)	(0.0521)	(0.0531)	(0.0566)	(0.0605)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 dependent variable is a binary conflict incidence indicator (100 if BRD≥25, 0 if BRD<25). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.
Interpretation: To address concerns that the results hold only for a conflict measure of at least 5 battle-related deaths, the table shows that the results are nearly unchanged compared to Table 3 if considering a conflict threshold of at least 25 battle-related deaths. In addition, the coefficients for our preferred specification (8) becomes insignificant in the IV setting of Table 28.

Table 28: 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		
$\ln(Chinese\,Aid_{\text{t-2}})$	0.1289	0.1652
	(0.2757)	(0.3140)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
IV First stage: China		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-14.0193***	-12.6964***
	(2.3180)	(2.2734)
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 dependent variable is a binary conflict incidence indicator (100 if BRD≥25, 0 if BRD<25). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.
Interpretation: To address concerns that the results hold only for a conflict measure of at least 5 battle-related deaths, the table shows that the results are nearly unchanged compared to Table 4 if considering a conflict threshold of at least 25 battle-related deaths.

Table 29: 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**	-0.0106	-0.0142*	-0.0131
	(0.0092)	(0.0071)	(0.0065)	(0.0060)	(0.0059)	(0.0065)	(0.0077)	(0.0074)	(0.0082)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
ln($Chinese\,Aid_{\text{t-2}}$)	-0.0119	0.0034	0.0068	-0.0055	-0.0008	0.0004	0.0001	0.0034	0.0025
	(0.0087)	(0.0065)	(0.0054)	(0.0048)	(0.0055)	(0.0057)	(0.0057)	(0.0063)	(0.0064)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 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 5.6.

Interpretation: To address concerns that the results hold only for a dichotomous conflict measure, the table shows that the results are nearly unchanged compared to Table 3 if considering log of battle-related deaths as the dependent variable. In addition, the coefficients for our preferred specification (8) become insignificant in the IV setting of Table 30.

Table 30: 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)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
IV First stage: 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		
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.0312	-0.0180
	(0.0337)	(0.0419)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
IV First stage: China		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-14.0193***	-12.6964***
	(2.3180)	(2.2734)
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 for the log of battle-related deaths +0.01 as dependent variable (category 3). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.

Interpretation: To address concerns that the results hold only for a dichotomous conflict measure, the table shows that the results are nearly unchanged compared to Table 4 if considering log of battle-related deaths as the dependent variable.

Table 31: 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	0.0272	0.0390	0.0260
	(0.0684)	(0.0708)	(0.0705)	(0.0472)	(0.0454)	(0.0569)	(0.0640)	(0.0633)	(0.0700)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
$\ln(Chinese\,Aid_{\text{t-2}})$	0.7830***	0.8995***	0.9203***	-0.1090	-0.0865	-0.0781	-0.0711	-0.1094	-0.0955
	(0.1899)	(0.1649)	(0.1700)	(0.0766)	(0.0864)	(0.0964)	(0.0983)	(0.1188)	(0.1213)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 a binary indicator for demonstrations as dependent variable. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.4.

Interpretation: To address concerns that our non-finding for the OLS results on protests in Table 39 is driven by the aggregation of riots, demonstrations, and strikes, we consider each protest type by itself. The table shows that our preferred specifications (6) and (8) still exhibit no statistically significant relationship between demonstrations and aid.

Table 32: 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	-0.0203	-0.0853	-0.0864
	(0.0620)	(0.0856)	(0.0617)	(0.0533)	(0.0510)	(0.0584)	(0.0635)	(0.0710)	(0.0771)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
ln($Chinese\,Aid_{\text{t-2}}$)	0.4258***	0.5248***	0.5289***	0.0006	0.0399	0.0316	0.0411	0.0424	0.0524
	(0.1482)	(0.1261)	(0.1292)	(0.0814)	(0.0933)	(0.0985)	(0.0995)	(0.1175)	(0.1195)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 a binary indicator for riots as dependent variable. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.4.

Interpretation: To address concerns that our non-finding for the OLS results on protests in Table 39 is driven by the aggregation of riots, demonstrations, and strikes, we consider each protest type by itself. The table shows that our preferred specifications (6) and (8) still exhibit no statistically significant relationship between riots and aid.

Table 33: 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	-0.0374	-0.0717	-0.0704
	(0.0310)	(0.0391)	(0.0377)	(0.0309)	(0.0333)	(0.0415)	(0.0454)	(0.0503)	(0.0555)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
ln($Chinese\,Aid_{\text{t-2}}$)	0.1611*	0.1832**	0.1931**	-0.1785**	-0.2042**	-0.1845**	-0.1817*	-0.1620	-0.1654
	(0.0847)	(0.0810)	(0.0846)	(0.0712)	(0.0804)	(0.0938)	(0.0959)	(0.1046)	(0.1114)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 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 5.4.
Interpretation: To address concerns that our non-finding for the OLS results on protests in Table 39 is driven by the aggregation of riots, demonstrations, and strikes, we consider each protest type by itself. The table shows that our preferred specifications (6) and (8) still exhibit no statistically significant relationship between strikes and aid. This is not the case for specification (6), which is addressed in table 34.

Table 34: 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
$\ln(Chinese\,Aid_{\text{t-2}})$	0.0498	0.0686	-0.0629	0.0424	-0.1489	-0.0776
	(0.4018)	(0.4707)	(0.3622)	(0.4312)	(0.4183)	(0.5076)
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	36.578	31.190	36.578	31.190	36.578	31.190
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. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Click here to go back to section 5.4

Interpretation: The table shows the intrumental variables results for specification (6) and (8) of Tables 31, 32, and 33. There is no evidence that aid by either donor is statistically significantly affecting demonstrations, riots, and strikes individually in Africa during our sample period.

Table 35: ADM1 IV (Repression (non-lethal) - Regions with UCDP violence against civilians coded as zero)

	(1)	(2)
Panel A: WB Aid		
IV: IDA Position - Actors		
$\ln(World\ Bank\ Aid_{\text{t-1}})$	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: Chinese Commodity - Actors		
$\ln(Chinese\ Aid_{\text{t-2}})$	0.6103^{**}	0.7696^{**}
	(0.2873)	(0.3439)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
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 for a binary pro-governmental violence indicator as dependent variable. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.4.

Interpretation: One concern is that our findings in Table 6, based on the SCAD repression data are somehow affected by repression overlapping with lethal conflicts recorded in the UCDP-GED data. To test the robustness of the repression results, this table shows that theynearly unchanged even if the repression indicator ignores cases that also feature recorded UCDP violence against civilians. Repression is thus distinct from large scale conflict against civilians events.

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		
$\ln(Chinese\,Aid_{\text{t-2}})$	0.0072**	0.0092**
	(0.0032)	(0.0045)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
Country-Year FE	No	Yes

Notes: The table displays regression coefficients for a continuous measure of non-lethal pro-government violence as dependent variable. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.4.
Interpretation: The table addresses the concern that the results of Table 6 only hold for the binary dependent variable of non-lethal government repression. The relationship of Chinese aid on non-lethal government repression remains positive and statistically significant.

Comparison with OLS estimates

To test if results substantially change when using OLS, we consider the results corresponding to the IV estimates on actors (Table 5) and the aggregated outcome for riots, demonstrations, and strikes (Table 6). Table 37 suggests mostly neutral effects, while significantly negatively coefficients of WB aid occur for state-based and non-state violence. Regarding riots, demonstrations, and strikes, Table 39 shows that the different actors' results become insignificant once we condition on regional level fixed effects.

Table 37: Actors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: WB Aid - OLS								
	State vs. N-State		N-State vs. N-State		State vs. Civilans		N-State vs. Civilians	
OLS: WB - Actors $\ln(World\,Bank\,Aid_{\text{t-1}})$	-0.1229**	-0.1365**	-0.0348	-0.0784	-0.0596	-0.0372	-0.1040**	-0.0979**
	(0.0580)	(0.0615)	(0.0417)	(0.0526)	(0.0373)	(0.0384)	(0.0427)	(0.0473)
N	13050	13050	13050	13050	13050	13050	13050	13050
Panel B: Chinese Aid - OLS								
	State vs. N-State		N-State vs. N-State		State vs. Civilans		N-State vs. Civilians	
OLS: China - Actors $\ln(Chinese\,Aid_{\text{t-2}})$	-0.0009	0.0122	-0.0162	0.0016	-0.0702	-0.0625	-0.0338	-0.0334
	(0.0491)	(0.0591)	(0.0529)	(0.0659)	(0.0427)	(0.0454)	(0.0292)	(0.0373)
N	8700	8700	8700	8700	8700	8700	8700	8700
Country-Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD$\geq$5, 0 if BRD$<$5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.

Interpretation: For state-based violence against civilians, the coefficients are negative and statistically insignificant, while the IV coeficients in Table 5 were also statistically significant.

Table 38: OLS results (Protests: 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	-0.0443	-0.0092	-0.0270
	(0.0912)	(0.1028)	(0.0885)	(0.0641)	(0.0635)	(0.0779)	(0.0845)	(0.0897)	(0.0993)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
$\ln(Chinese\,Aid_{\text{t-2}})$	0.8761***	1.0301***	1.0445***	-0.1026	-0.0468	-0.0182	-0.0041	0.0141	0.0330
	(0.2247)	(0.1888)	(0.1939)	(0.0880)	(0.0973)	(0.1005)	(0.1022)	(0.1265)	(0.1296)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 a binary indicator for any violence of these three types as dependent variable. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.4.
Interpretation: The table display the corresponding OLS results of Table 6. The results are in line with the instrumental variable estimates since they are mostly negative, but statistically insignificant.

Table 39: OLS results (Non-lethal Government Repression)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln($World\,Bank\,Aid_{\text{t-1}}$)	0.0406**	0.0645***	0.0955***	0.0474**	0.0301	0.0327	0.0200	0.0139	-0.0022
	(0.0177)	(0.0217)	(0.0231)	(0.0193)	(0.0191)	(0.0209)	(0.0232)	(0.0289)	(0.0287)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
ln($Chinese\,Aid_{\text{t-2}}$)	0.2144***	0.2116***	0.2248***	0.0279	0.0185	0.0126	0.0151	0.0079	0.0116
	(0.0814)	(0.0702)	(0.0712)	(0.0476)	(0.0521)	(0.0552)	(0.0564)	(0.0660)	(0.0674)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 non-lethal government repression as dependent variable. The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.4.
Interpretation: The table display the corresponding OLS results of Table 6. The results are in line with the IV estimates in Table 6. The estimate for China is positive and significant.

B.3 Channels - Aid Sectors

Aid in different sectors could be more or less likely to fuel or calm down a conflict. We examine aid projects in eight subcategories with and without country-year FE. 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. Thus, we show results for China using OLS only.

Interesting differences across sectors emerge, suggesting that aid in different sectors has different effects on subsequent conflict. Table 40 shows that there are positive coefficients of WB (Chinese) aid in a few categories, but they never become 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). A 100% increase in WB finance aid leads to a 1.59 percentage point reduction in the conflict likelihood – 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.[46] 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, as well as technical assistance to enhance transparency and regulation.

Regarding the transportation sector, a 100% increase in WB (Chinese) aid leads to a 6.7 (3.4) percentage points reduction in the conflict likelihood. This sector comprises many large-scale infrastructure projects, as well as large disbursements in dollar terms. The negative effect suggests that high transportation costs were significant obstacles for exchange, consumption, public goods 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.[47]

[46] Out of 40 projects, 26 were in one of those categories. Appendix section A.4 documents how we retrieve detailed information on World Bank aid in the finance sector.

[47] Improvements in transportation infrastructure are likely linked to higher accessibility for the media and correlate with mobile phone coverage. This would induce an upward bias to our estimates (Weidmann, 2016; Von Borzyskowski and Wahman, 2019).

Overall, the heterogeneities across aid categories 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 neither donor. The overall negative relationship does not seem to mask strong conflict-fueling effects in certain sectors.[48]

[48] Table A56 presents the regressions for the WB using OLS and for China using IV. The results are slightly different, but there is no significant positive effect on any sector. One caveat of these regressions is that high collinearity and insufficient power make regressions infeasible where all individual sectoral aid variables are jointly included.

Table 40: Aid sectors and conflict

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		-0.0168	0.3516	-0.2780*	-0.2974	0.8388
	(0.2001)	(0.1446)	(0.1321)	(0.1584)		(0.1604)	(0.2681)	(0.1633)	(0.1842)	(0.8914)
Panel D:Country-Year FE										
ln($Chinese\,Aid_{\text{t-2}}$)	-0.1946	-0.1881	0.1281	-0.0484		0.0287	0.3241	-0.3378*	0.0377	0.7787
	(0.2307)	(0.1405)	(0.1252)	(0.1635)		(0.1533)	(0.2792)	(0.1946)	(0.2148)	(0.7926)
N	8700	8700	8700	8700	8700	8700	8700	8700	8700	8700

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interpretation: One may be concerned about the existence of a certain conflict-increasing type of aid that is masked in our overall aid measure. To address this concern, we find that aid in any sectors is, if anything, significantly negatively related to conflict. However, there is a fair bit of heterogeneity. This also highlights that some types of aid may have a different effect in the short and in the long run. Generally, this suggests ample room for future research to explore these results in more detail.

B.4 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). This dataset is a geo-referenced 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.

The first important question is whether the effect of aid projects differs between more and less ethnically fractionalized regions. Theoretically, one may 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 42 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. [49]

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 eight different power statuses to groups. The difference is 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

[49] 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.

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 may be hidden in the averages. For instance, it may be that there is no conflict-inducing effect on average. However, assuming that aid project benefit governing groups more often, existing tensions and conflict may be fueled especially in mixed districts where other 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 41. 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, both coefficients for mixed regions are positive. However, all coefficients are statistically insignificant. Even when considering governing coalition structures, on average Chinese aid does not increase conflicts with at least 5 BRDs.[50] 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. 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 42. 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.

[50] 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.

Table 41: 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- IV:						
Conflict in region belonging to ...	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
ln($Chinese\ Aid_{\text{t-2}}$)	-0.6513	0.7011	-0.7345	-1.2272	0.6919	1.1403
	(1.0808)	(3.4968)	(0.5935)	(0.7612)	(0.6681)	(0.9162)
N	1335	1285	2487	2420	2944	2924
Kleibergen-Paap underidentification test p-value	0.033	0.055	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	15.575	3.709	59.921	46.322	22.702	19.653
Country $\times$ Year FE	No	Yes	No	Yes	No	Yes
Control for Fractionalization	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD$\geq$5, 0 if BRD$<$5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interpretation: The table addresses concerns that our analysis masked a conflict-increasing effect of aid flowing to regions with different levels of political power. There is no evidence of such an effect of aid.

Table 42: 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:				
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.4831	-0.5251	0.0510	0.7714
	(0.5695)	(0.7265)	(0.6113)	(0.7163)
N	3542	3542	3234	3234
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	51.569	38.166	23.501	20.763
Country $\times$ Year FE	No	Yes	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interpretation: Does aid increase the conflict likelihood if a region is highly fractionalized due to ethnic tensions? The table shows that there is no evidence for such an effect.

B.5 Regime Types

Development aid may have differential impacts across political systems due to different allocation decisions and distributional aspects. As a further sensitivity check, we consider heterogeneous effects across regime types. Based on the Polity IV data by Marshall et al. (2014), we distinguish democracies (Polity Score *geq* +7) and autocracies (Polity Score <+7). Results are depicted for outright conflict in Table 43 and for repression in Table 44.

Table 43: IV results - Aid and conflict across regime types

Panel A: World Bank Aid	(1)	(2)	(3)	(4)
	Autocracy		Democracy	
$\ln(World\,Bank\,Aid_{\text{t-1}})$	-0.3335	-0.3267	4.0175	1.0187
	(0.4762)	(0.5092)	(5.0638)	(2.0015)
N	10411	10411	1914	1914
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.255	0.103
Kleibergen-Paap weak identification F-statistic	71.845	66.353	1.238	2.867
Panel B: Chinese Aid	(1)	(2)	(3)	(4)
	Autocracy		Democracy	
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.3292	-0.4861	0.1872	0.2647
	(0.6014)	(0.7091)	(0.4943)	(0.9213)
N	6409	5521	1556	1311
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.017	0.044
Kleibergen-Paap weak identification F-statistic	42.309	33.295	3.960	19.005
Country-Year FE	No	Yes	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. Click here to go back to section 5.6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Interpretation: One may be concerned that not differentiating between regime types may have masked an aid-conflict relationship. After all, there is the tendency that accountability principles are weaker and power concentration higher in autocratic countries. The table does not provide evidence that aid in autocratic or democratic countries has a significant relationship with conflict.

Table 44: IV results - Aid and repression across regime types

Panel A: World Bank Aid	(1)	(2)	(3)	(4)
	Autocracy		Democracy	
$\ln(World\,Bank\,Aid_{\text{t-1}})$	0.0936	0.0338	2.1565	0.6255
	(0.1160)	(0.1293)	(2.3762)	(0.6082)
N	10411	10411	1914	1914
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.255	0.103
Kleibergen-Paap weak identification F-statistic	71.845	66.353	1.238	2.867
Panel B: Chinese Aid	(1)	(2)	(3)	(4)
	Autocracy		Democracy	
$\ln(Chinese\,Aid_{\text{t-2}})$	0.6312	0.8240*	0.7814**	1.0828***
	(0.4112)	(0.4851)	(0.3267)	(0.3016)
N	6409	5521	1556	1311
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.017	0.044
Kleibergen-Paap weak identification F-statistic	42.309	33.295	3.960	19.005
Country-Year FE	No	Yes	No	Yes

Notes: The dependent variable is a binary indicator on occurrence of non-lethal repression (pro-government violence). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. Click here to go back to section 5.6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Interpretation: One may be concerned that not differentiating between regime types may have masked a potential relationship between government repression and aid. In line with Table 6, only Chinese Aid does correlate with higher government repression incidences. This result holds for autocratic and democratic countries, although the relationship seems to be stronger in democratic countries.

B.6 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 area 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). This is specifically relevant in the aid-conflict nexus where different political entities may 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 45 (46). 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 may not manifest on the regional level, but spill over to other localities. Also on the country-level Table 47 does provide neither for the WB nor for China any evidence of a significant link between aid and conflict. All OLS and IV estimates in Table 47 are negative and for China even statistically significant using OLS method. Thus, the analysis on the country level is in line with the results on the regional level. The negative and non-significant effects, which are not in line with previous literature on the country level (for instance, Collier and Hoeffler, 2004), may be due to our focus on aid flows, which are geocoded (see Section 3.1). 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 48 indicate significantly negative to neutral effects.[51] Hence, even when accounting for non-geocoded aid the main conclusion holds that there is no evidence that aid is positively related to conflict.

[51] Ideally, we would have liked to consider results in Table 48 also via an instrumental variable approach, which was not possible due to weak IV concerns in the first stage.

Table 45: ADM2 level 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)	(0.0228)	(0.0231)	(0.0256)	(0.0246)	(0.0263)
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)	(0.0388)	(0.0319)	(0.0327)	(0.0438)	(0.0454)
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 × 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 dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes second order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.
Interpretation: One concern may be that the results in Table 3 only hold for the aggregated data at the first sub-national administrative level, but there may be conflict-fueling effects at lower levels. We address this concern by validating the ADM1 results with an alternative lower-level of aggregation, the second-order administrative sub-divisions (ADM2). The table shows that once region fixed effects are included all coefficient signs are unchanged and the magnitude becomes stronger, on average.

Table 46: ADM2-level 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
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	82.851	67.210
IV First stage: World Bank		
$IDA\ Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	62.4924***	69.9580***
	(6.8656)	(8.5333)
N	99367	99367
Panel B: Chinese Aid		
IV Second Stage: China		
$\ln(Chinese\ Aid_{\text{t-2}})$	0.0517	0.0496
	(0.2007)	(0.2748)
N	64285	64285
Kleibergen-Paap underidentification test p-value	0.001	0.001
Kleibergen-Paap weak identification F-statistic	12.896	13.020
IV First stage: China		
$\text{Commodity}_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-14.2846***	-12.8430***
	(3.9779)	(3.5593)
N	64285	64285
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes second order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.

Interpretation: One concern may be that the results in Table 3 only hold for the aggregated data at the first sub-national administrative level, but there may be conflict-fueling effects at lower levels. We address this concern by validating the ADM1 results with an alternative lower-level of aggregation, the second-order administrative sub-divisions (ADM2). The table shows that while the first stage results are nearly identical, the coefficients in the second stage remain small and statistically insignificant. We test the consequences of higher levels of aggregation in Table 47 and 48.

Table 47: Country level aggregation with OLS and IV

Cross-Country Analysis				
$\ln(WB\,Aid_{\text{t-1}})$	-0.2157	-2.4586		
	(0.2638)	(3.9577)		
$\ln(Chinese\,Aid_{\text{t-2}})$			-0.2056*	-1.0947
			(0.1041)	(0.7621)
N	836	792	792	528
Kleibergen-Paap underidentification test p-value		0.101		0.000
Kleibergen-Paap weak identification F-statistic		2.743		22.130
Estimation method:	OLS	IV	OLS	IV

Notes: Dependent variable is a binary conflict indicator (100 if BRD≥25, 0 if BRD<25). 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, as well as a linear country-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 5.6.
Interpretation: To test if a higher levels of data aggregation leads to a different conclusion about the effect of aid on conflict, the estimates refer to the country level, where aid and battle-related deaths were aggregated at the country level. The coefficients are very small and statistically insignificant. Even though the Kleibergen-Paap F-statistic is well below the critical value of 10 for the World Bank estimations, the other results indicate that there is no evidence that aid fuels conflict also when aggregating our date on the country level.

Table 48: Country level aggregation with inclusion of non-geocoded projects

Panel A: WB Aid	Geocoded only	Non-Geocoded aid incld.
(WB Aid $_{\text{t-1}}$)	-0.2157	-0.1491
	(0.2638)	(0.3263)
(WB Aid $_{\text{t-1}}$) non-geocoded		-0.1649
		(0.3675)
R^2	0.757	0.757
N	836	836
Panel B: Chinese Aid		
(Chinese Aid $_{\text{t-2}}$)	-0.2056*	-0.2016*
	(0.1041)	(0.1075)
(Chinese Aid $_{\text{t-2}}$) non-geocoded		-0.0735
		(0.1986)
R^2	0.763	0.763
N	792	792

Notes: Dependent variable: Category 2 binary conflict indicator (100 if BRD≥25, 0 if BRD<25). Estimates refer to the country level, where aid and battle-related deaths were aggregated at the country level. The first column depicts coefficients for geocoded aid aggregated at the country level. The second column controlls 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 1995-2012 (WB) and the 2000-2012 period (China). The regression includes country and year fixed effects, as well as a linear country-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 5.6.
Interpretation: One potential issues is that the aid measures in Table 47 ignore projects that were not geo-coded or at least assigned to an ADM1 regions. This table shows that the main coefficients remain negative and do not change much when controlling for non-geocoded aid at the country level. Hence, omitting non-geocoded aid does not bias our results.

B.7 Mechanisms - Afrobarometer

Table 49: Mechanisms - Afrobarometer

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

Notes: Significance levels: * 0.10 ** 0.05 *** 0.01. Click here to go back to section 5.5.

B.8 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 50. In line with the main findings results are mostly non-significant and have a negative sign if turning statistically significant.[52] 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 52, thus, presents the results including a lagged dependent variable, extending the main model by a lagged conflict indicator:

$$C_{i,c,t} = \beta_1 A_{i,c,t-1/t-2} + \beta_2 C_{i,c,t-1} + \lambda_c + \tau_t + \delta_i + \lambda_c T + \lambda_c T^2 + X^{Ex}_{i,c,t}\beta_2 + \delta_i T + X^{En}_{i,c,t-2}\beta_3 + \kappa_{c,t} + \epsilon_{i,c,t}, \tag{5}$$

None of the coefficients in Table 52 is positive, stressing the robustness of our main findings.

Although less often considered, the choice of standard error clustering can affect results substantially. Tables 53 and 54, 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, the results assure us that the insignificant findings are not driven by our choice of standard error clustering.

[52] 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 50: PPML

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

Notes: Dependent variables- In column (1) a binary conflict indicator (100 if BRD$\geq$5, 0 if BRD$<$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 5.6.

Interpretation: To address concerns that OLS regression is not an optimal method for binary dependent variables and dependent variables with many zeros we verify our results with Poisson pseudo-maximum likelihood estimation (Silva and Tenreyro, 2011). The results are in line with our main specification since the majority of the coefficients are not statistically significant or statistically significant but negative.

Table 51: Conditional Logit

	(1)	(2)
Panel A: WB Aid		
	Intensity 1 (Dummy)	Non-lethal repression (Dummy)
$\ln(World\,Bank\,Aid_{\text{t-1}})$	0.0011	0.0201
	(0.0098)	(0.0182)
R^2		
N	6192	1476
Panel B: Chinese Aid		
	Intensity 1 (Dummy)	Non-lethal repression (Dummy)
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.0201*	0.0026
	(0.0113)	(0.0178)
R^2		
N	3731	962

Notes: Dependent variables- In column (1) a binary conflict indicator (100 if BRD$\geq$5, 0 if BRD$<$5) and in column (2) a binary indicator if any event of non-lethal pro-government violence took place. 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 5.6.

Interpretation: To address concerns that OLS regression is not an optimal method for binary dependent variables, we verify our results with conditional logit and find consistent results.

Table 52: OLS results: Lagged dependent variable

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln($World\ Bank\ Aid_{t\text{-}1}$)	-0.0844	-0.0069	-0.0173	-0.1659***	-0.1575***	-0.1406**	-0.1149	-0.1647**	-0.1652*
	(0.0520)	(0.0551)	(0.0458)	(0.0585)	(0.0586)	(0.0680)	(0.0795)	(0.0780)	(0.0862)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
ln($Chinese\ Aid_{t\text{-}2}$)	-0.0965*	-0.0300	-0.0082	-0.0983*	-0.0634	-0.0661	-0.0686	-0.0345	-0.0437
	(0.0563)	(0.0589)	(0.0588)	(0.0589)	(0.0660)	(0.0725)	(0.0721)	(0.0889)	(0.0925)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 is a 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. 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 5.6.
Interpretation: To address concerns of conflict persistence, these regressions control for the first lag of the binary indicator. The coefficients are nearly unchanged compared to Table 3.

Table 53: 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**	-0.1314*	-0.1772**	-0.1756*
	(0.0709)	(0.0643)	(0.0666)	(0.0611)	(0.0624)	(0.0672)	(0.0771)	(0.0799)	(0.0895)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
ln($Chinese\,Aid_{\text{t-2}}$)	-0.1753**	-0.0233	-0.0026	-0.1090**	-0.0663	-0.0654	-0.0682	-0.0347	-0.0441
	(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	8254	8700	8254
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. 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.

Interpretation: One may be concerned that our null finding is based on too conservative clustering of our standard errors. To address this, the standard errors in parentheses are clustered at the regional level. As expected, the standard errors become slightly smaller which increases the statistical significance of the negative coefficients.

Table 54: 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($Chinese\,Aid_{\text{t-2}}$)	-0.2582	-0.1886
	(0.4169)	(0.5231)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	55.897	41.160
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable is a binary conflict indicator (100 if BRD≥5, 0 if BRD<5). The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. 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.
Interpretation: One may be concerned that our null finding is based on a clustering of our standard errors that is too conservative. To address this, the standard errors in parentheses are clustered at the regional level. The standard errors even become slightly smaller, but the negative coefficients remain statistically insignificant.

Time Contingency

Policy changes over time may affect the conflict implications of foreign aid, e.g., via conditionality or choice of different projects. This could, for instance, be a change in Western or US policy paradigms that also affected WB strategies and decisions. To allow for heterogeneity over time, we split the sample in an early period (for the WB 1995-2003 and for China 2000-2005) and a late period (for the WB 2004-2012 and for China 2006-2012). Coefficients remain insignificant, which provides further evidence that neutral effects on average are not driven by a specific time period.

Table 55: ADM1 IV (WB Aid - Time Split)

Panel A: WB Aid		
$\ln(World\,Bank\,Aid_{\text{t-1}})^{<=2003}$	0.7770	0.2329
	(0.6407)	(0.6338)
$\ln(World\,Bank\,Aid_{\text{t-1}})^{>2003}$	-1.1608	-0.8405
	(0.9499)	(1.0267)
N	12325	12325
Kleibergen-Paap underid. test p-value	0.000	0.000
Kleibergen-Paap weak id. F-statistic	19.628	10.073
Panel B: Chinese Aid		
$\ln(Chinese\,Aid_{\text{t-2}}{}^{<=2005})$	-0.1320	0.0335
	(0.6197)	(0.5777)
$\ln(Chinese\,Aid_{\text{t-2}}{}^{>2005})$	-0.2266	-0.1853
	(0.7862)	(0.9107)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.022	0.026
Kleibergen-Paap weak identification F-statistic	7.204	6.972
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Standard errors in parentheses, two-way clustered at the country-year and regional level. 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 5.6.

Interpretation: Are our results driven by different policy regimes over time? To address this concern, the table splits the sample into different time periods, which does not alter our main conclusion.

Definition of aid (Sectors and weighting scheme)

Table 56 reports the OLS/IV estimates corresponding to sectoral aid in Table 40. Although significance is affected the negative signs in the transport and finance sectors are retained.

Instead of attributing aid to different project locations equally, we assume a weighting scheme by population size. Tables 57 and 58 indicate that results are not driven by this assumption.

Table 56: 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
	(0.0734)	(0.0832)	(0.1526)	(0.0759)	(0.0886)	(0.0688)	(0.0855)	(0.0689)	(0.0816)	(0.0933)
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*
	(0.0872)	(0.0953)	(0.1737)	(0.0990)	(0.1352)	(0.0896)	(0.0935)	(0.0898)	(0.1010)	(0.1067)
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	JX	LX	TX	WX	YX	
ln($Chinese\,Aid_{\text{t-2}}$)	-1.4578**	-2.5352	-0.5066	0.7578	-0.1554	1.0265**	-0.4216	0.1977	-7.0545	
	(0.7314)	(1.6254)	(0.3691)	(0.6847)	(0.3838)	(0.4776)	(0.3463)	(0.5326)	(102.9015)	
Kleibergen-Paap underid. test p-value	0.176	0.015	0.472	0.120	0.062	0.214	0.028	0.554	0.101	
Kleibergen-Paap weak id. F-statistic	1.712	11.768	0.484	3.225	4.727	1.718	6.006	0.318	7.075	
Panel D: Country-Year FE										
ln($Chinese\,Aid_{\text{t-2}}$)	-1.0048	-2.2549	-0.3010	0.8156	0.1259	0.9374*	-0.4798	0.5000	1.3334	
	(0.8080)	(1.8415)	(0.3837)	(0.7330)	(0.4240)	(0.5226)	(0.4277)	(0.6383)	(2.8884)	
N	8700	8700	8700	8700	8700	8700	8700	8700	8700	
Kleibergen-Paap underidentification test p-value	0.232	0.011	0.674	0.095	0.064	0.530	0.043	0.626	0.173	
Kleibergen-Paap weak identification F-statistic	1.107	10.909	0.156	2.936	4.322	0.369	4.282	0.212	2.467	

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD≥5, 0 if BRD<5). The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Regressions account for (time-varying) exogenous controls and time trends. Time Trends include linear and squared country-specific time trends as well as a linear regional trend. AX - "Agriculture, fishing, and forestry" BX - "Public Administration, Law, and Justice" CX - "Information and communications" EX - "Education" FX - "Finance" JX - "Health and other social services" LX - "Energy and mining" TX - "Transportation" WX - "Water, sanitation and flood protection" YX - "Industry and Trade" Standard errors in parentheses, two-way clustered at the country-year and regional level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section B.3.

Interpretation: The table shows the corresponding OLS and IV estimation of Table 40. Despite changes in coefficient size, the two estimation largely agree with one another in coefficient sign.

Table 57: 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**	-0.1357	-0.1867**	-0.1829**
	(0.1005)	(0.0788)	(0.0692)	(0.0667)	(0.0663)	(0.0732)	(0.0840)	(0.0833)	(0.0909)
N	13104	13104	13104	13104	13050	13050	11699	13050	11699
Panel B: Chinese Aid									
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.1776**	-0.0246	-0.0037	-0.1137**	-0.0718	-0.0696	-0.0723	-0.0390	-0.0482
	(0.0865)	(0.0704)	(0.0648)	(0.0576)	(0.0648)	(0.0728)	(0.0726)	(0.0891)	(0.0925)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 is a 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.

Interpretation: To assign aid projects to each ADM1 region we assumed equal aid distribution across project localities in Table 3. This table shows that a weighting scheme based on the region's population size does not alter the coefficient significantly. Thus, the results are not based on specific aid allocation assumptions.

Table 58: 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	100.841	88.424
Panel B: Chinese Aid	(1)	(2)
IV Second Stage: China		
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.2613	-0.1903
	(0.4332)	(0.5305)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.887	31.502
Country-Year FE	No	Yes

Notes: Dependent variable is a 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.
Interpretation: To assign aid projects to each ADM1 region we assumed equal aid distribution across project localities in Table 3. This table shows that a weighting scheme based on the region's population size does not alter the coefficient significantly. Thus, the results are not based on specific aid allocation assumptions.

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 59 (OLS) and 60 (IV), the effects for the WB becomes less negative. Tables 59 (OLS) and 60 (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 60 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 A61 and Table A62 show that the results also hold when restricting the WB results to the same years where data for Chinese aid is available, once for OLS and once for IV.

Table 59: OLS results - Both Donors

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)	(0.0859)	(0.0866)	(0.0887)	(0.0884)	(0.0925)
$\ln(Chinese\,Aid_{\text{t-2}})$	-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)	(0.0644)	(0.0727)	(0.0735)	(0.0884)	(0.0898)
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: The dependent variable is a binary conflict incidence indicator (100 if BRD$\geq$5, 0 if BRD$<$5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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.

Interpretation: The table shows the results when simultaneously including WB aid and Chinese aid in the regression equation. The coefficient for the WB aid remain negative, but are somehow smaller compared to Table 3 and lose statistical significance. The coefficients for Chinese aid remain largely unchanged. Table 61 shows that the change for the WB is mainly driven to reducing the sample period by 5 years.

Table 60: ADM1 IV - Both Donors (Intensity 1)

	(1)	(2)
IV Second Stage: World Bank		
$\ln(World\,Bank\,Aid_{\text{t-1}})$	-0.7029	-2.3839
	(1.0780)	(1.6965)
$\ln(Chinese\,Aid_{\text{t-1}})$	-0.2482	-0.1655
	(0.4319)	(0.5415)
Kleibergen-Paap underidentification test p-value	0.000	0.005
Kleibergen-Paap weak identification F-statistic	11.573	3.489
IV First stage: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	57.3235***	63.8053***
	(12.0425)	(24.1932)
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-0.2181	-0.1051
	(0.6571)	(0.6166)
N	7975	7975
IV First stage: China		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	-17.9057*	-10.1067
	(9.3878)	(13.2890)
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-13.9921***	-12.7060***
	(2.3178)	(2.2742)
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 dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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.

Interpretation: The table shows the results when simultaneously including WB aid and Chinese aid in the regression equation. The coefficient for the WB aid differ in size, but not in sign and significance, compared to Table 4. The coefficients for Chinese aid are largely unchanged. Table 62 shows that the difference for the WB this is mainly due to reducing the sample period by 5 years.

Table 61: OLS results: (WB Aid - Same Years as Chinese Aid)

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln($World\,Bank\,Aid_{\text{t-1}}$)	-0.1505	0.0559	0.0811	-0.0606	-0.0976	0.0657	0.0717	-0.0795	-0.1004
	(0.1197)	(0.0949)	(0.0910)	(0.0864)	(0.0859)	(0.0865)	(0.0886)	(0.0884)	(0.0944)
N	8736	8736	8736	8736	8700	8700	8254	8700	8254
Panel B: Chinese Aid									
ln($Chinese\,Aid_{\text{t-2}}$)	-0.1753**	-0.0233	-0.0026	-0.1090*	-0.0663	-0.0654	-0.0682	-0.0347	-0.0441
	(0.0865)	(0.0705)	(0.0642)	(0.0572)	(0.0644)	(0.0726)	(0.0725)	(0.0883)	(0.0917)
N	9464	9464	9464	9464	8700	8700	8254	8700	8254
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 dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interpretation: The table shows the results when restricting our estimations for WB aid to the years with available information for Chinese aid, which reduces the sample by 5 years. The coefficient for the WB aid are different compared to Table 3 and lose statistical significance.

Table 62: ADM1 IV (WB Aid - Same Years as Chinese Aid)

	(1)	(2)
Panel A: WB Aid		
IV Second Stage: World Bank		
$\ln(World\,Bank\,Aid_{\text{t-1}})$	-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		
$\ln(Chinese\,Aid_{\text{t-2}})$	-0.2582	-0.1886
	(0.4282)	(0.5256)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	36.578	31.190
IV First stage: China		
$Chinese\,Commodity_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-14.0193***	-12.6964***
	(2.3180)	(2.2734)
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 dependent variable is a binary conflict incidence indicator (100 if BRD≥5, 0 if BRD<5). The sample includes first order subnational regions in African countries for the 1995-2012 (WB) and the 2000-2012 period (China). Standard errors in parentheses, two-way clustered at the country-year and regional level. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interpretation: The table shows the results when restricting our estimations for WB aid to the years with available information for Chinese aid, which reduces the sample by 5 years. The coefficient for the WB aid are similar to those when including Chinese aid jointly, indicating that using both aid variables in separate equations in our main approaches does not introduce a large bias.