Appendix A: Making the Wealth Variables

This appendix first discusses how countries were selected into the sample in more detail and then discusses the construction of the wealth variables. The sample of countries was composed of every sub-Saharan African country that had at least one regionally geolocated aid project from the WB or ADB in 2009 or 2010,[1] and that had a DHS survey that:

1. was published between 1999 and 2008,
2. was constructed to allow for estimates at the regional level,
3. included the wealth index, and
4. used the country's standard ADM1 regions.

If a country had more than one such DHS survey in the ten-year window, the most recent one was selected. Most of the countries that were cut from the sample were cut because they either did not have any DHS surveys or they did not have one in the decade before aid was disbursed. Additionally, six countries were not considered because they received no new commitments of aid from the WB or ADB in 2009 or 2010. This selection process produced a sample of seventeen countries. The countries and the dates of their DHS surveys are listed in Table A1.

DHS surveys with the wealth index also include information placing each household within one of five wealth quintiles. These quintiles are constructed from questions asking about ownership of various assets such as televisions, toilet facilities, or the type of flooring material. The quintiles are constructed so that they should reflect the respondent's placement within the de jure household population. This is different from the population of individuals surveyed because it includes people younger than fifteen and older than forty-nine.

To calculate shares of wealth quintiles across regions, I divided the number of surveyed households in a given wealth quintile in each region by the total number of surveyed households in that quintile. In essence, this approach takes advantage of the fact that all of the DHS surveys under examination

[1] At least one project had to be geolocated to the regional level or better. All data on aid projects comes from AidData (Strandow, Findley, Nielson et al. 2011).

Table A1: DHS Survey Years

Country	Year of DHS Survey
Benin	2006
DRC	2007
Ethiopia	2005
Ghana	2008
Guinea	2005
Kenya	2003
Lesotho	2004
Malawi	2004
Mali	2006
Mozambique	2003
Namibia	2006
Niger	2006
Nigeria	2008
Rwanda	2007-2008
Sierra Leone	2008
Tanzania	2004-2005
Zambia	2007

at some point divide the country into ADM1s and then sample within regions with probability proportionate to population. All calculations were done while weighting the figures by both the probability of being sampled and de jure household membership. In practice, these "household membership weights" are constructed by multiplying the sample weight (typically hv005) by household size (typically hv012). This allows us to take into consideration the fact that some small populations are oversampled and the fact that households vary in size (in ways that are not caught by the sampling because they include people younger than fifteen and older than forty-nine). While the use of the weights is clearly best practice because it corrects for oversampling and for different sizes of households (outside of the 15–49 year sampling frame), in practice the use of the weighting scheme leads to only small changes when compared to similar calculations without the use of the weights.

While a wealth share variable constructed in this way from the DHS surveys must include some random error, it also produces estimates of regional populations that are very close to national censuses, as was shown in Figure 2. This section presents tables that show the raw data behind Figure 2. Table A2 reproduces Table 1 but also includes three extra columns. The first extra column estimates the fraction of the total Kenyan population in each region from the DHS wealth quintile distributions. It does this by multiplying every percentage in each row by 20 and then summing the resulting numbers. This number is then compared to the regional population distributions from the Kenyan censuses of 1999 and 2009 (the DHS report was carried out in 2003). The DHS and census results align closely.

Table A3 repeats the same procedure for Ghana. As with Kenya, the censuses and the manipulated DHS quintiles produce similar results and there is no obvious bias. While Accra has a smaller population in the DHS output than in the Ghanaian census data, Nairobi is similar in the Kenyan census data and the DHS output. While the DHS figure for the rather poor Upper East is larger than the census figure in the Ghanaian data, the DHS figure for the similarly poor North Eastern is smaller than the Kenyan census data. No DHS estimate misses its nearest census by more than 1.5 percentage points and most differences fall much closer to 0. These similarities, as well as the good match between quintile distributions within countries and prior expectations (e.g. Nairobi is rich, North Eastern is poor and lightly populated, Rift Valley is populous), reinforce the utility and validity of this way of measuring the distribution of people according to wealth across regions

Table A2: DHS Wealth Quintiles Compared to Kenyan Census Reports

	Poorest	2nd Poorest	Middle	2nd Richest	Richest	Total	Census (1999)	Census (2009)
Central	1.2%	10.9%	19.5%	24.7%	11.9%	13.6%	13.0%	11.4%
Coast	11.4%	4.9%	6.4%	6.5%	11.6%	8.2%	8.7%	8.6%
Eastern	12.5%	18.8%	23.4%	22.5%	6.4%	16.7%	16.1%	14.7%
Nairobi	0.0%	0.0%	0.0%	0.8%	36.3%	7.4%	7.5%	8.1%
North Eastern	10.3%	1.7%	1.1%	0.7%	0.5%	2.8%	3.4%	6.0%
Nyanza	19.4%	23.7%	15.0%	9.8%	8.5%	15.3%	15.3%	14.1%
Rift Valley	32.1%	21.9%	17.8%	26.7%	21.5%	24.0%	24.4%	25.9%
Western	13.0%	18.2%	16.8%	8.3%	3.3%	11.9%	11.7%	11.2%

within countries. This is significant—it is difficult to construct nuanced, subnational, and cross-nationally comparable measures of wealth in Africa.

Table A3: DHS Wealth Quintiles Compared to Ghanaian Census Reports

	Poorest	2nd Poorest	Middle	2nd Richest	Richest	Total	Census (2000)	Census (2010)
Ashanti	5.6%	18.3%	21.0%	24.6%	21.5%	18.2%	19.1%	19.4%
Brong Ahafo	11.7%	11.2%	10.6%	9.9%	3.1%	9.3%	9.6%	9.4%
Central	1.5%	13.5%	14.9%	11.7%	6.4%	9.6%	8.4%	8.9%
Eastern	6.4%	13.5%	13.7%	11.4%	5.3%	10.1%	11.1%	10.7%
Greater Accra	0.5%	1.8%	5.8%	18.1%	45.8%	14.4%	15.4%	16.3%
Northern	32.9%	9.6%	7.0%	4.2%	2.3%	11.2%	9.6%	10.1%
Upper East	21.2%	3.7%	1.4%	1.5%	1.8%	5.9%	4.9%	4.2%
Upper West	7.1%	3.0%	1.7%	1.3%	0.5%	2.7%	3.0%	2.8%
Volta	8.7%	12.7%	13.3%	7.3%	3.4%	9.1%	8.6%	8.6%
Western	4.3%	12.8%	10.6%	10.0%	9.9%	9.5%	10.2%	9.6%

Appendix B: Additional Information

This appendix holds additional statistical tables and robustness checks. It presents: summary statistics for the variables used in the regressions, a table showing that the richest people are more likely to live in regions that hold capital cities, scatter plots showing how logging the wealth share variables improves fit but does not significantly alter the results, an analysis replicating Table 3 but carried out on a smaller sample of countries, an analysis replicating Table 3 but including a control for regional inequality, three different analyses that take into account the fact that the dependent variables that are represented in percentages (share of total value of aid or share of total number of projects) are bound at 0 and 1, a replication of Table 3 that re-weights each region so that each country contributes equally to the analysis, a set of tests that runs the regressions from Table 3 while sequentially excluding each country in the sample, an analysis of ethnic aid targeting, a selection model that examines the factors influencing which regions get any aid, a comparison of poverty targeting across the two donors, a table that counts the total number of tests and the number of tests that found significant results for the poorest and richest wealth quintiles, and finally a map of the aid projects under study.

To start, Table B1 shows the summary statistics for variables included in the regressions. Variables that had true 0s or 1s are expressed without decimal points. The first three variables are the dependent variables from the main analysis.

Table B1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
% OF AID VALUE	195	0.0872	0.1574	0	1
% OF COUNT OF PROJECTS	195	0.0872	0.1483	0	1
LN(AID VALUE)	195	1.5928	2.6612	-2.3026	7.1862
% OF POOREST	195	0.0872	0.0976	0	0.4959
% OF RICHEST	195	0.0872	0.1289	0.0014	0.6962
LN(% OF POOREST)	195	-3.2767	1.6087	-6.9078	-0.6994
LN(% OF RICHEST)	195	-3.2480	1.3054	-6.0529	-0.3607
CAPITAL	195	0.0872	0.2828	0	1
% OF BATTLES	195	0.0769	0.1880	0	1
BATTLES	195	5.3436	21.2995	0	227
% OF AREA	195	0.0872	0.0934	0.0002	0.5263
LN(AREA)	195	9.9851	1.7336	4.0584	13.3468

Table B2 provides support for the argument, expressed in the main text, that the rich are more likely to live in regions with capital cities. The unit of observation is the region and the dependent variable is the region's share of the wealthiest people in a country (*% OF RICHEST*). The regressions are estimated with OLS and include country fixed effects. The capital dummy is substantively large and statistically significant. In these countries, the capital dummy alone explains about half of the within-country variation in the location of the richest quintile of the population.

Table B2: Explaining Where the Wealthy Live

	(1)	(2)
CAPITAL	0.30***	0.27***
	(0.050)	(0.054)
LN(AREA)		-0.01
		(0.009)
Fixed Effects	Yes	Yes
R-squared	0.50	0.51
Number of Regions	195	195
Number of Countries	17	17

Robust standard errors clustered on countries in parentheses
* p<0.1; ** p<0.05; *** p<0.01.

In footnote 44, I note that I take the log of the wealth share variables because they are skewed and that the logged variables produces the best fit. This is supported by Figure B1, which shows the bivariate relationship between the log of the total dollar amount of aid to each region and either the fraction of the poorest or richest quintile or the log of the fraction of the poorest or richest quintile. In all cases the variables are demeaned using the country-level means of the relevant x and y variables. This allows me to graphically show all data points in a scatter plot while still maintaining the logic of a country fixed effects regression. As noted, aid does not flow to places with more of the poorest people but it does flow to areas with more of the richest. Both results hold with and without the log transformation of the quintile variables, though the fit is clearly better when the quintile variables are logged.

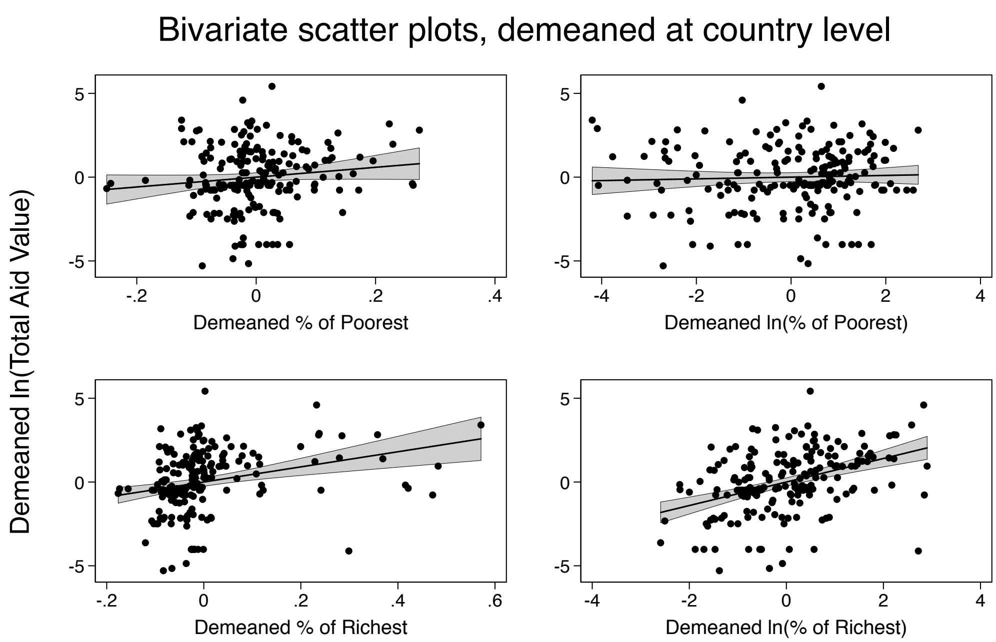

Figure B1: Scatter plots of bivariate results (demeaned).

Table B3 replicates Table 3 but drops any country that has fewer than five regions or received fewer than 5 aid projects during the two years under study. This drops Malawi, Sierra Leone, and Niger from the analysis. The results for the rich stay the same while the (already weak) results for the poor are weakened further.

Table B3: Main Analysis on Trimmed Sample

	(1) Value	(2) Projects	(3) ln(Value)
% OF POOREST	0.28	0.20	
	(0.207)	(0.160)	
LN(% OF POOREST)			0.10
			(0.095)
% OF RICHEST	0.61**	0.61**	
	(0.236)	(0.231)	
LN(% OF RICHEST)			0.72***
			(0.215)
CAPITAL	0.03	-0.03	1.20
	(0.079)	(0.062)	(0.837)
% OF BATTLES	-0.06	-0.01	
	(0.080)	(0.073)	
BATTLES			0.00
			(0.002)
% OF AREA	0.33	0.45*	
	(0.269)	(0.244)	
LN(AREA)			0.36***
			(0.081)
Fixed Effects	Yes	Yes	Yes
Number of countries	14	14	14
Number of regions	180	180	180
R-squared	0.22	0.23	0.25

Robust standard errors clustered on countries in parentheses
* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table B4 replicates Table 3 but includes a control for within-region inequality. The inequality measure is not typical because I do not have absolute measures of wealth but rather a division of people into quintiles of the population according to wealth. The inequality control is thus a measure that captures the extent to which the region has more people at the first and fifth quintile relative to the middle quintile. The exact formula is: % OF POOREST + % OF RICHEST - 2 * % OF MIDDLE. While this measure makes sense on its own, in practice almost no regions have high shares of the poorest and richest and also low shares of people in the middle quintile. One of the only examples of this kind of inequality is Katanga in the DRC. Katanga has 17.5 percent of the poorest quintile, 17 percent of the richest quintile, and 7 percent of the middle quintile.

In general, the richest quintile tends to live in regions with below averages shares of the middle quintile while the poorest quintile tends to live in regions with above-average shares of the middle quintile (see Table 2). This implies that the inequality measure is mostly being driven by regions that have high shares of the rich and low shares of the middle. These are usually capital regions.

Table B4: Main Analysis with Inequality Control

	(1) Value	(2) Projects	(3) ln(Value)
% OF POOREST	0.30	0.26*	
	(0.179)	(0.134)	
LN(% OF POOREST)			0.10
			(0.085)
LN(% OF RICHEST)	0.67***	0.76***	
	(0.186)	(0.186)	
LN(% OF RICHEST)			0.73***
			(0.195)
CAPITAL	0.04	-0.01	1.25
	(0.071)	(0.056)	(0.927)
% OF BATTLES	-0.09	-0.04	
	(0.082)	(0.080)	
BATTLES			-0.00
			(0.002)
% OF AREA	0.36	0.41*	
	(0.225)	(0.203)	
LN(AREA)			0.31***
			(0.079)
INEQUALITY	-0.09	-0.14	-0.48
	(0.121)	(0.113)	(1.333)
Fixed Effects	Yes	Yes	Yes
Number of countries	17	17	17
Number of regions	195	195	195
R-squared	0.23	0.26	0.24

Robust standard errors clustered on countries in parentheses
* p<0.1; ** p<0.05; *** p<0.01.

The dependent variables that measure regional aid as a share of total aid have censoring at 0 and 1, which could bias the results of the analysis. Table B5 examines the data using a random effects tobit model that takes this censoring into account and shows consistent favoritism to the rich and a lack of favoritism to the poor. The dependent variable in models (1) and (2) is each region's share of the country's total dollar value of aid and the dependent variable in models (3) and (4) is the region's share of the total number of projects. Models (1) and (3) use the full sample and models two and four drop countries with fewer than five projects or regions. The effect of the richest is similarly significant ($p < 0.05$), and the effect of the poorest is similarly insignificant, in tobit models with country dummies instead of random effects, and these models are reported in the "count of all models" discussion in the robustness section of the main text. Code to produce the fixed-effects tobit models is present in the replication files but the results are not reproduced here.

Table B5: Tobit Models

	Share of Value		Share of Projects	
	(1)	(2)	(3)	(4)
	Main	Small Sample	Main	Small Sample
% OF POOREST	0.21	0.19	0.16	0.11
	(0.154)	(0.178)	(0.142)	(0.162)
% OF RICHEST	0.66***	0.68***	0.70***	0.67***
	(0.136)	(0.147)	(0.125)	(0.134)
CAPITAL	0.02	0.02	-0.04	-0.04
	(0.063)	(0.068)	(0.058)	(0.062)
% OF BATTLES	-0.08	-0.03	-0.04	0.02
	(0.071)	(0.078)	(0.065)	(0.071)
% OF AREA	0.36**	0.35*	0.42***	0.47***
	(0.164)	(0.195)	(0.151)	(0.178)
Random Effects	Yes	Yes	Yes	Yes
Number of Regions	195	180	195	180
Number of Countries	17	14	17	14

Standard errors in parentheses
* p<0.1; ** p<0.05; *** p<0.01.

The tobit model used here is not ideal because it assumes that I have a censored set of observations of a variable that is not logically or practically bound. In my case, the share of aid variables are truly bound at 0 and 1. Another approach is to use a generalized linear model with a logistic link function and binomial distribution. This has the effect of "condensing" the predictions from the model into the range of 0 and 1 (or, similarly, one can view the logistic link as "spreading" the dependent variable out along the real number line for modeling). As with all of these robustness tests, I do not intend to heavily defend the assumptions of any one model. Rather, I am emphasizing that the core result holds across a wide variety of specifications and models. I use the same specification as models (1) and (2) in Table 3 but rather than using OLS I use a GLM with a logistic link. Standard errors are clustered on countries. For clarity, I present the results graphically in Figure B2 rather than in tabular form. The dependent variable in the top two panels is each region's share of the total count of projects per country. The dependent variable in the bottom two panels is each region's share of the total cost of projects per country. As is evident from the graphs, the effect of the richest is highly statistically significant ($p < 0.01$) and the effect of the poorest is not.

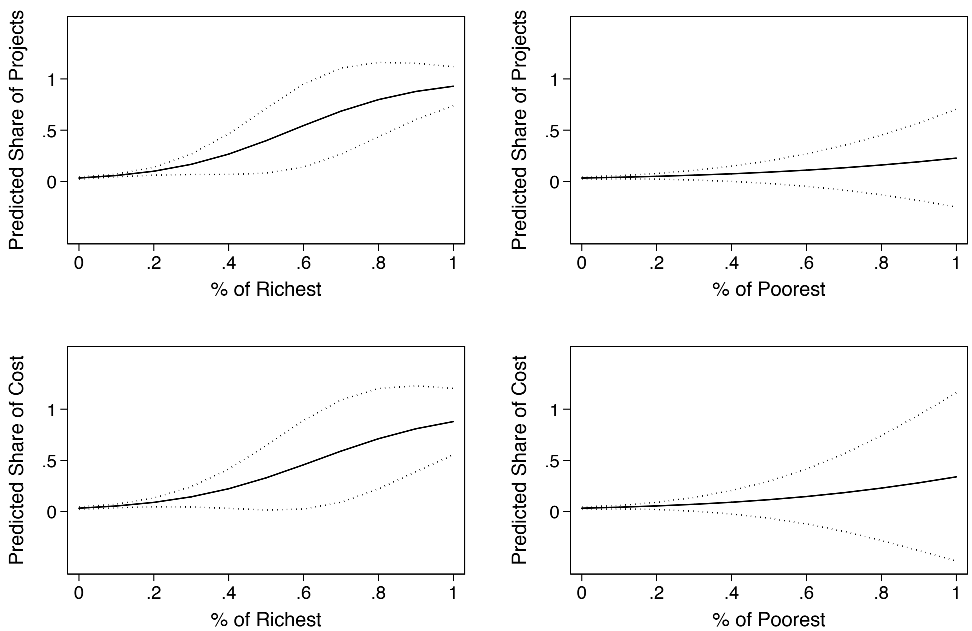

Figure B2: Relationship between wealth shares and aid shares.

Given that regions are the unit of analysis, countries with more regions will contribute more to the analysis if all regions are weighted equally. Table B6 presents results using weights that make each country count equally in the analysis rather than each region. This is done by giving each region a weight that is equal to 1 divided by the total number of regions in each country. The effect of the poorest is significant ($p < 0.05$) in only model 2 (share of projects). This result goes away if the percent of poorest variable is logged (not shown). The effect of the richest segment of the population on aid is consistently significant.

Table B6: Weighted Regions

	(1) Value	(2) Projects	(3) Ln(Value)
% OF POOREST	0.35*	0.31**	
	(0.186)	(0.120)	
LN(% OF POOREST)			0.13
			(0.095)
% OF RICHEST	0.66**	0.81***	
	(0.227)	(0.232)	
LN(% OF RICHEST)			0.73***
			(0.131)
CAPITAL	0.00	-0.08	0.82
	(0.075)	(0.064)	(0.525)
% OF BATTLES	-0.08	-0.05	
	(0.106)	(0.096)	
BATTLES			0.00
			(0.002)
% OF AREA	0.39	0.47*	
	(0.253)	(0.223)	
LN(AREA)			0.23**
			(0.085)
CONSTANT	-0.04	-0.06	1.70
	(0.036)	(0.035)	(1.114)
Fixed Effects	Yes	Yes	Yes
Number of countries	17	17	17
Number of regions	195	195	195

Robust standard errors clustered on countries in parentheses
Obs. (regions) weighted so each country contributes equally
* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

I now show that the results are robust when individual countries are excluded from the sample. Figure B3 shows coefficients and 95 percent confidence intervals for % OF POOREST and % OF RICHEST for a set of regressions where each country in the dataset is sequentially excluded. This implies that the first estimate for each coefficient reports the result when Benin is excluded, the second reports results when dropping the DRC, and so on. The left pane is based on model (1) in Table 3 and the right pane is based on model (2). Model (3) is presented on the following page. The figure examines if the results are sensitive to the exclusion of possibly outlying countries. The results for the richest segment of the population are always significant. The results for the poorest become significant at $p < 0.05$ in only model (2) if Namibia or Guinea are excluded.

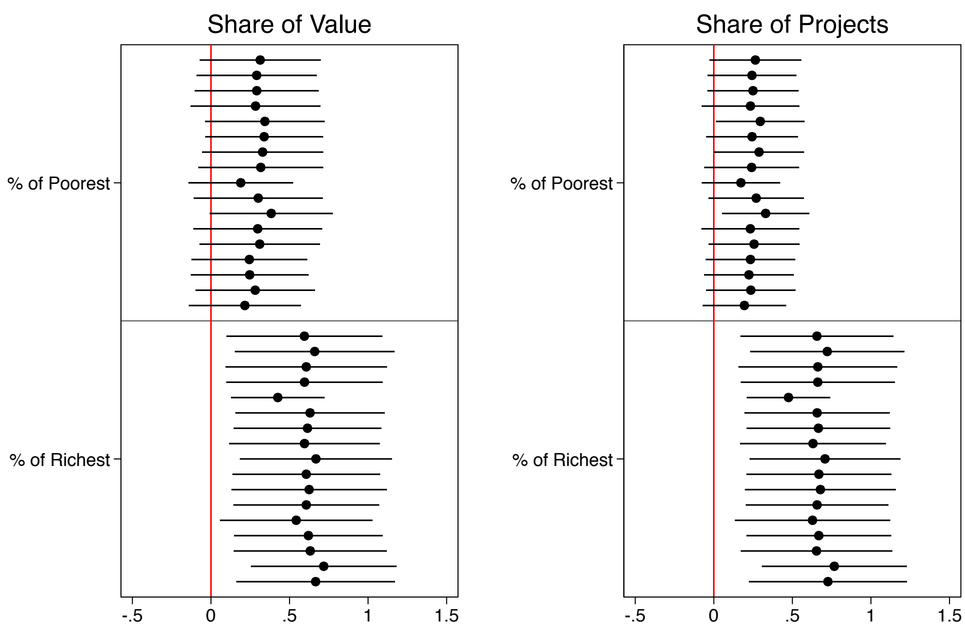

Figure B3: Aid targeting to the poorest and richest, dropping one country at a time

Figure B4 is the same as Figure B3, but it is based on the preferred specification of model (3) (logged variables) in Table 3. As before, each point estimate per coefficient corresponds to one regression and each excludes one country from the sample. The logged model is less sensitive to dropping countries. In no regression is the flow of aid to the poorest significantly different from (0). All regressions show significant effects for the richest, though when Nigeria is excluded the point estimate of LN(% OF RICHEST) drops to 0.45 and the p-value increases to 0.024. Across all of the manipulations in all of the models, the richest are always significantly favored with aid.

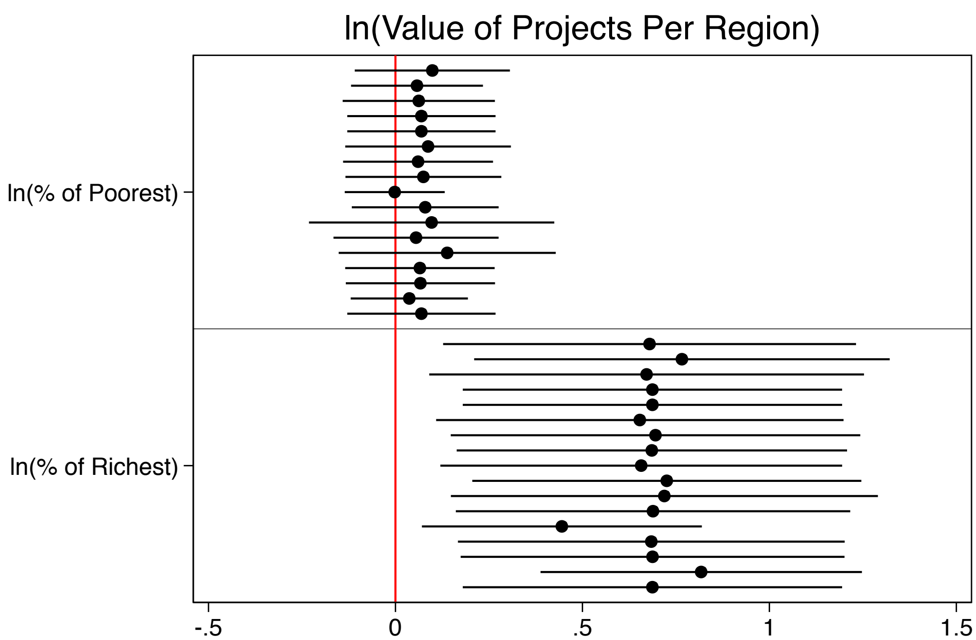

Figure B4: Aid targeting to poorest and richest, logged variables, dropping one country at a time

To examine ethnic aid targeting, I replicated Table 3 but added a dummy variable (PRES.) that took a value of 1 if the country's president (in 2008) was born in the region,[1] I then run another model where I interact the dummy marking the president's birth region with the share of the poorest and richest people to see if the poorest or richest people within the president's home region are disproportionately favored with aid. As before, the richest people are consistently favored but sharing the president's ethnicity—as proxied by being in a region that holds the president's hometown—is not an important factor in explaining the location of aid projects.

Model (1) in Table B7 is similar to Model (1) in Table 3, but it includes the PRES. dummy and has a smaller sample size. Model (2) interacts PRES. with % OF POOREST and % OF RICHEST, which reveals if the rich or poor are favored more if they live in the president's hometown. None of the hometown variables or interaction terms are statistically significant. Models (3) and (4) carry out the same analysis on the natural log of the total value of aid per region, and the results are similar. As before, the wealth variables are consistently important but sharing the president's ethnicity—as proxied by being in a region that holds the president's hometown—is not an important factor in explaining the location of aid projects. When the dependent variable is the share of the total number of projects instead of the share of the value of aid and models (1) and (2) in table B7 are estimated, the % OF RICHEST p-value is consistently less than 0.05. PRES. and % OF POOREST are not statistically significant in these regressions. These results are included in the replication code and counted in the table that counts all tests, but are not presented here.

[1] Using a dummy for the president's home region has the benefit of reducing ambiguity around ethnicity (especially when some presidents come from mixed backgrounds), but it drops countries where the president was not born inside the country. I also drop countries where the president in 2008 lost power before the end of 2010. This results in Ghana, Guinea, and Zambia being dropped from this portion of the analysis. Ghana had an election in 2008 and John Kufuor of the New Patriotic Party (NPP) was term limited. Nana Akufo-Addo ran for the NPP and lost, giving Ghana its second electoral turnover. Lansana Conté, former president of Guinea, died in 2008. Rupiah Banda was president of Zambia from 2008 to 2011, but he was born in what is now Zimbabwe.

Table B7: Ethnicity Interactions

	(1) Value	(2) Interaction	(3) ln(Value)	(4) Interaction
PRES.	0.12	0.09	0.67	1.34
	(0.075)	(0.115)	(0.512)	(1.216)
% OF POOREST	0.21	0.17		
	(0.205)	(0.220)		
PRES. × % OF POOREST		0.56		
		(0.430)		
% OF RICHEST	0.41**	0.39**		
	(0.164)	(0.172)		
PRES. × % OF RICHEST		-0.40		
		(0.441)		
LN(% OF POOREST)			0.07	0.07
			(0.092)	(0.098)
PRES. × LN(% OF POOREST)				0.09
				(0.201)
LN(% OF RICHEST)			0.69**	0.67**
			(0.235)	(0.247)
PRES. × LN(% OF RICHEST)				0.16
				(0.299)
CAPITAL	0.01	0.03	0.84	0.86
	(0.070)	(0.072)	(0.844)	(0.867)
% OF BATTLES	-0.14	-0.11		
	(0.090)	(0.094)		
BATTLES			-0.00	-0.00
			(0.002)	(0.002)
% OF AREA	0.45*	0.43*		
	(0.227)	(0.237)		
LN(AREA)			0.35***	0.35***
			(0.095)	(0.092)
Fixed Effects	Yes	Yes	Yes	Yes
Number of countries	14	14	14	14
Number of regions	168	168	168	168
R-squared	0.22	0.24	0.24	0.24

Robust standard errors clustered on countries in parentheses
* p<0.1; ** p<0.05; *** p<0.01.

On the suggestion of one reviewer, I now examine if the fraction of rich or poor people influences the likelihood of a region getting any aid. Accordingly, the dependent variable now takes a 0 if a region received no aid and one if a region received at least one aid project. I show results with and without control variables. While a (conditional) fixed-effects logistic regression is appropriate given the binary nature of the dependent variable, it also leads to separation. This means that seven countries (66 regions) are dropped because all regions received at least one aid project.[2] To show robustness, I present results in Table B8 using a logit model and an OLS (linear probability) model. Regions with more of the richest people are consistently more likely to receive at least one aid project, and the results are substantively large (e.g. Models (1) and (2) have odds ratios above 2). The effect of the rich is similar but a little weaker in the linear probability models. The estimated effect of the poorest is almost exactly 0.

[2]The countries dropped because of separation are: DRC, Kenya, Malawi, Mali, Rwanda, Sierra Leone, and Tanzania.

Table B8: Binary DV

	(1) Logit 1	(2) Logit 2	(3) LPM 1	(4) LPM 2
LN(% OF POOREST)	0.05	-0.12	-0.01	-0.04
	(0.190)	(0.230)	(0.019)	(0.024)
LN(% OF RICHEST)	0.85***	0.95***	0.08***	0.08***
	(0.272)	(0.308)	(0.026)	(0.026)
CAPITAL		1.34		0.04
		(1.452)		(0.079)
BATTLES		-0.03		-0.00
		(0.036)		(0.000)
LN(AREA)		0.58**		0.05*
		(0.271)		(0.025)
Fixed Effects	Yes	Yes	Yes	Yes
Number of countries	10	10	17	17
Number of regions	129	129	195	195
R-squared			0.08	0.11

Robust standard errors clustered on countries in parentheses
* p<0.1; ** p<0.05; *** p<0.01.

The main results are qualitatively similar when the two donors are analyzed separately. Figure B5 replicates the right (logged variable) portion of Figure 3, but analyzes the World Bank and African Development Bank resources separately. The results are generally similar, with the poorest two quintiles not being statistically significant and the top two having significant effects. Across both donors, aid is flowing to the richest and not the poorest.

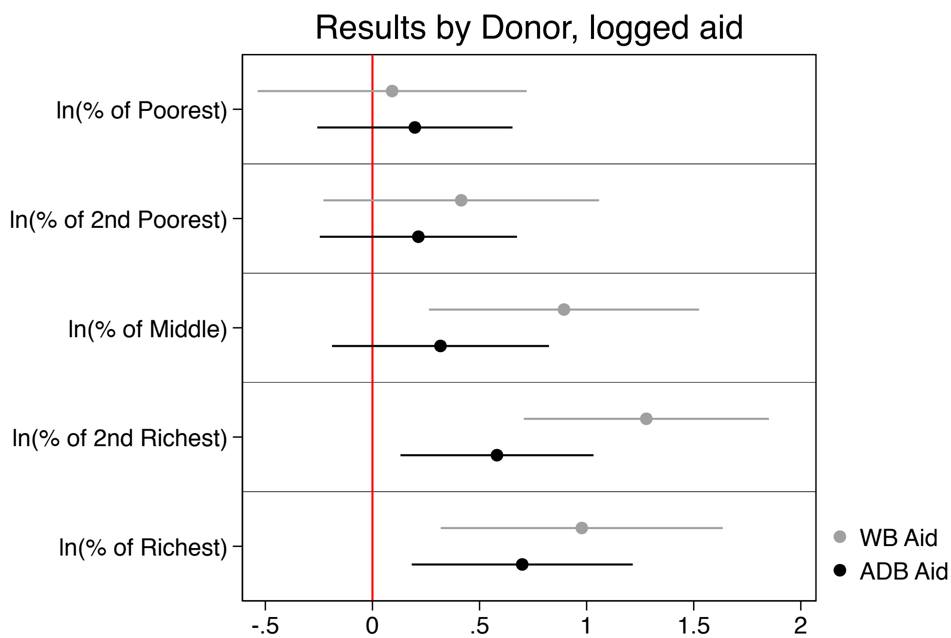

Figure B5: Bivariate (fixed effects) results, by donor.

Table B9 shows that the degree to which each donor sends aid to the richest or poorest remains similar when most control variables are added. The dependent variable in models (1) and (2) is logged aid per region from the African Development Bank and models (3) and (4) show logged aid from the World Bank. Models (1) and (3) drop the capital city control, and models (2) and (4) include the control. Neither donor's targeting to the rich is caused by the level of conflict in the region nor the size of the region. However, the table reveals that the African Development Bank's skew to the rich is primarily as a result of capital city bias, while the World Bank's skew to the rich is not. While this difference in mechanism is interesting, neither donor has a pro-poor aid allocation within the countries under study.

Table B9: Targeting By Donor

	(1) ADB NoCap	(2) ADB	(3) WB NoCap	(4) WB
LN(% OF POOREST)	0.51	0.64*	-0.01	-0.03
	(0.309)	(0.320)	(0.096)	(0.111)
LN(% OF RICHEST)	0.77***	0.51*	1.09***	1.14***
	(0.227)	(0.245)	(0.301)	(0.342)
CAPITAL		3.16***		-0.58
		(0.860)		(1.245)
BATTLES	0.01**	0.02**	-0.01	-0.01
	(0.006)	(0.006)	(0.008)	(0.008)
LN(AREA)	-0.19	-0.05	0.52**	0.49**
	(0.300)	(0.307)	(0.196)	(0.215)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	182	182	163	163
Number of countries	16	16	13	13
R-squared	0.09	0.13	0.21	0.21

Robust standard errors clustered on countries in parentheses
* p<0.1; ** p<0.05; *** p<0.01.

Table B10 counts all of the times that I tested for the statistical significance of the relationship between either the poorest or richest wealth quintiles and aid. It also records how many times each test yielded a statistically significant ($p < 0.05$) result. The "Num. Test" column is not a count of the number of unique regressions but rather a count of the number of unique statistical tests for the effect of the richest or poorest quintile on aid (both wealth variables were tested an equal number of times). The models are listed in the order that they appear in the text and appendix. While the text and appendix do not present an exhaustive specification search, these results should increase our confidence in the relationships reported in the main text.

Table B10: Counts of Models and Significant Results

Model	Poor Sig.	Rich Sig.	Num. Tests
Bivariate	0	3	3
Table 3	0	3	3
Bivariate Scatter	0	1	1
Trimmed	0	3	3
Unequal	0	3	3
RE Tobit	0	4	4
FE Tobit	0	4	4
GLM Logit	0	2	2
Re-weighted	1	3	3
Drop 1, Share of Value	0	17	17
Drop 1, Share of Project	2	17	17
Drop 1, log Value	0	17	17
Pres. Interaction	0	6	6
Binary DV (selection)	0	4	4
Disag. Donor Bivariate	0	2	2
Disag. Donor	0	3	4
Sum	3	92	93
Percent Significant	3%	99%	

Finally, Figure B6 maps the regional-level (ADM1) boundaries of the countries in the sample (in black) and the location of many, but not all, of the aid projects used in the analysis. More specifically, the map plots all aid projects—covering both donors and both years under study—provided that the project could be geolocated at a level of precision that was better than the regional level (a level of precision of less than 4 in the AidData coding scheme). The analysis in the text uses all projects with a precision coding of less than 5, meaning that it include projects that were geolocated to a region but where the precise location of the project within the region is unknown. It makes little sense to plot these regionally geolocated projects in the map and so they were dropped for this purpose only.

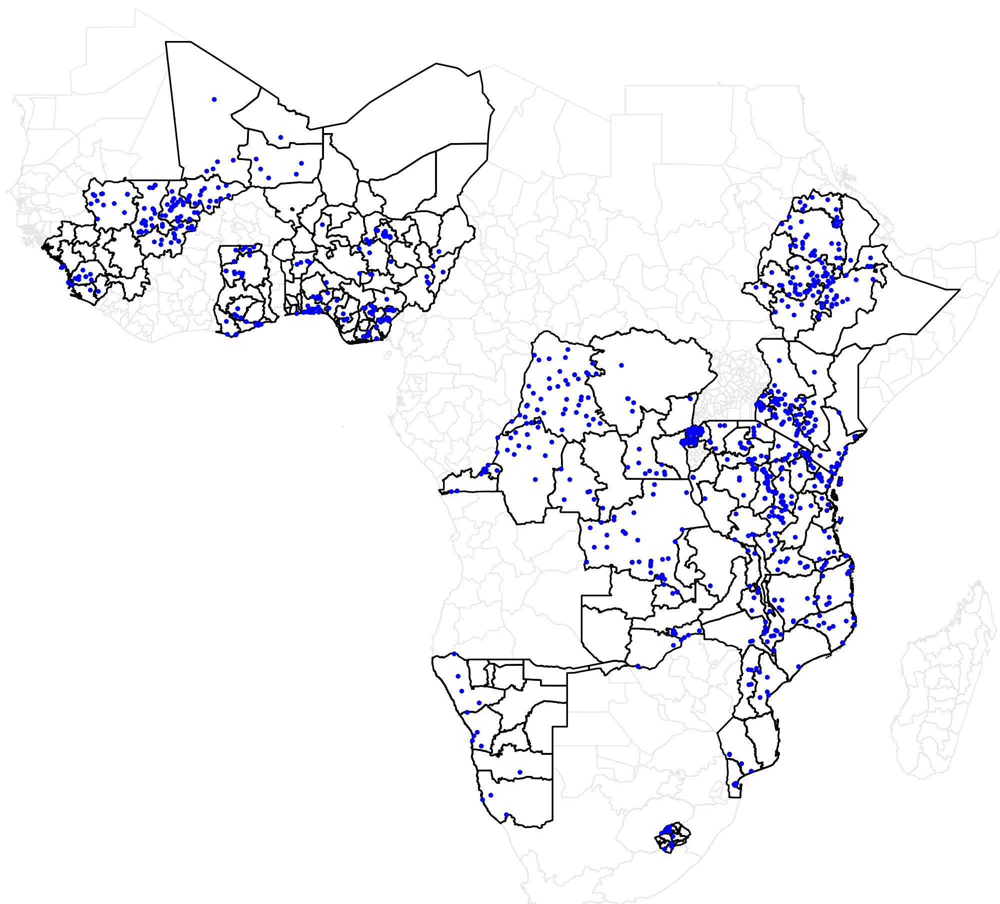

Figure B6: Regions in the Sample and Aid Projects.