Journal of International Development
J. Int. Dev. **30**, 904–910 (2018)
Published online 25 March 2018 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/jid.3357

SHORT NOTE

LEAVING NO ONE BEHIND? A NEW TEST OF SUBNATIONAL AID TARGETING

RYAN C. BRIGGS*,†
Department of Political Science, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA

Abstract: The Sustainable Development Goals endeavour to leave no one behind. This note tests whether or not donors have traditionally acted on this rhetoric by examining if aid targets areas of poverty within Nigeria, Senegal, and Uganda. Unlike prior research on aid targeting, the analysis covers aid from nearly all donors and does not aggregate variables into spatial regions. Instead, I measure the distance from geotagged survey data tracking poverty to aid projects started just after each survey wave. I show that projects are placed closer to richer people. This effect holds within countries and within first-level administrative regions. Copyright © 2018 John Wiley & Sons, Ltd.

The Sustainable Development Goals endeavour to 'leave no one behind' and to ensure that resources 'reach first those who are furthest behind' (United Nations Statistics Division, 2017). Targeting aid to poorer places within countries makes sense if the goal of aid is to eradicate poverty, as the effects of most kinds of aid decline over distance (Briggs, 2018).

However, recent research has demonstrated that aid does not disproportionately flow to poorer places within countries (Öhler & Nunnenkamp, 2014; Briggs, 2017; Custer *et al.*, 2017; Öhler *et al.*, 2017; Briggs, 2018). However, all prior research testing subnational aid allocations across multiple countries examined only aid from multilateral donors and always aggregated aid into large spatial regions.[1] Examining multilateral donors only is unfortunate, as the factors influencing multilateral aid targeting may differ from the factors

*Correspondence to: Ryan C. Briggs, Department of Political Science, Virginia Polytechnic Institute and State University, 531 Major Williams Hall (0130), 220 Stanger Street, Blacksburg, VA, USA.
E-mail: ryancbriggs@vt.edu
†Department of Political Science, Virginia Tech. I would like to thank Paddy Carter and Nicolas Van de Sijpe for helpful comments on an earlier draft. Any errors are my own.

[1] A partial exception is Briggs (2018), who aggregates aid into approximately 3000 km^2 grid cells instead of administrative regions.

influencing bilateral donor targeting (Rodrik, 1996; Dollar & Levin, 2006). Aggregating into spatial regions is also unfortunate because the scale of aggregation can change the results of an analysis because of the modifiable areal unit problem (Wong, 2009).

This note address both issues. First, it focuses on aid targeting within three countries in Africa for which I have close-to-complete aid data. In doing so, it provides the first subnational analysis of aid from essentially all donors active in three countries. Second, I do not aggregate the aid or poverty variables into spatial units but rather measure the distance from enumeration areas (EAs) in three rounds of Afrobarometer surveys to aid projects that were to be started within 2 years after each survey. This avoids the modifiable areal unit problem and enables a test of within-region aid targeting in addition to a within-country test.

I show that, conditional on a proxy for population density, future aid projects are placed further from poorer people. This relationship holds within countries and within first-level administrative regions within countries.

1 DATA AND ANALYSIS

I examine the poverty sensitivity of aid by measuring the distance from geotagged survey respondents to the nearest aid project that will be built within 2 years after each survey. This allows me to directly answer the question: are aid projects being targeted to places that are closer to a country's poorest citizens? I show that, conditional on a proxy for local population density, aid targets the relatively wealthy.

I start by selecting countries that both had an Aid Information Management System (AIMS) set up in conjunction with AidData and multiple Afrobarometer surveys. AIMS is incorporated into recipient country government planning processes and allows one to track much of the aid flowing into a country. Only Nigeria (AIMS v1.3.1), Senegal (AIMS v1.5.1) and Uganda (AIMS v1.4.1) had Afrobarometer surveys during the time in which they also had an AIMS, and so I focus on these three countries.[2] Nigeria's AIMS tracked aid from 1988 to 2014. It covered 28 different donors and records 1843 locations of aid projects. Senegal's AIMS tracked aid from 2000 to 2012 and records 1124 project locations from 79 donors. Uganda's AIMS includes aid from 1978 to 2014 and includes 2426 project locations from 56 donors. I use data from Afrobarometer rounds 3, 4 and 5, and in total, I have eight country-survey rounds of data.[3] While these countries were selected based on data availability and not on the degree to which they represent the broader continent, it is worth noting that I have countries in both East and West Africa and countries that were colonized by the British and French.

The unit of analysis is the survey respondent. These respondents are nested in EAs that are dispersed across the territory of each country. I do not aggregate the respondents into spatial units like administrative regions or grid cells.

The dependent variable measures how far each EA is from its closest future aid project, where future is defined as starting either the year after the survey or the year after that. To do this, I make use of the fact that both the aid data and the Afrobarometer surveys are geocoded.[4] I restrict the aid data to locations geocoded with a precision code of less than

[2]Malawi had a similar aid management system in place, but it lacks the standardized reporting of the other countries and so was not included.
[3]I have three rounds for Nigeria and Uganda but only two for Senegal. I cannot use data from Afrobarometer round 5 in Senegal because the aid data stop in 2012 and Afrobarometer round 5 was carried out in 2013.
[4]The geocoding procedure for the Afrobarometer surveys is described in BenYishay *et al*. (2017).

DOI: 10.1002/jid

four, and I restrict the Afrobarometer EAs to those coded with a precision code of less than three.[5] By analysing the distance to the closest future aid project, I decisively rule out the concern that any correlation between aid and poverty is driven by aid affecting poverty.[6] The dependent variable enters the analysis as the natural log of one plus the distance to the nearest future aid project in kilometres.

The key independent variables are drawn from the Afrobarometer surveys and are based on questions that measure deprivations. These questions ask respondents 'Over the past year, how often, if ever, have you or anyone in your family gone without': and then give five goods: 'Enough food to eat', 'Enough clean water for home use', 'Medicines or medical treatment', 'Enough fuel to cook your food' and 'A cash income'. For each of the five questions, the answers are never (0), just once or twice (1), several times (2), many times (3) and always (4). I use these questions to measure poverty, so higher scores indicate more poverty. I make use of individual questions and also an average across all five questions.[7]

While I do not aim to identify the causal effect of poverty on aid, I control for the population density around each EA.[8] I do this to limit the very likely possibility that aid targets denser places because then it can reach more people and that these denser places are also richer. Thus, controlling for the number of people around each EA allows one to test if aid targets poorer people once the number of people in each location is held constant. The Afrobarometer surveys have a rural–urban variable, but a binary variable is a very crude way to measure population. Instead, I leverage the fact that Afrobarometer selects their EAs with probability proportionate to population size. I create a variable that counts the number of other EAs within 50 km of each EA in each survey round. This variable has much more variation than a rural–urban division. EAs near major cities are sometimes near more than 20 other EAs in the same survey round, while remote and rural EAs often are not within 50 km of any other EA.[9] To control for population density flexibly, I add a set of dummy variables marking every value of this variable to each regression.

Every analysis also includes either country-survey round fixed effects or region-survey round fixed effects. This ensures that I am always comparing within either countries or regions at one point in time. All analyses include the standard cross-national Afrobarometer survey weights, but these are reweighted so that each country contributes equally to the analysis regardless of how many rounds of Afrobarometer data it contributes.

2 RESULTS

Table 1 shows the baseline results. Conditional on population density, aid is targeted further from people with more extreme deprivations. Model 1 includes country-survey

[5]Locations (aid or EAs) given a precision code of three are geolocated only to the second-level administrative unit, and the recorded spatial point is marked as the centroid of the administrative unit. Thus, if I retain both aid and EAs with a precision code of three, then I will have a number of EAs that incorrectly appear to be directly targeted by aid because both will be geocoded to ADM2 centroids. Projects geocoded with a precision code of one or two are within 25 km of the correct location.
[6]This approach is similar in spirit to how Kotsadam *et al*. (2017) use future aid to measure selection effects for the placement of aid.
[7]When calculating the average, I keep observations that lack data on some (but not all) of the deprivation questions. Very few respondents have missing data on any of the deprivation questions. For example, for the question on food, 0.003 per cent of respondents have missing data.
[8]See Briggs (2018) for an explanation of why a descriptive (rather than causal) analysis is most useful when one is asking a question of targeting, such as 'who is receiving this good?'
[9]I demonstrate this variation graphically in the appendix.

Table 1. DV: ln(Distance from Closest Future Aid Project)

	(1)	(2)
Mean of deprivations	0.13*** (0.03)	0.05*** (0.02)
EA count dummies	Yes	Yes
Country-round fixed effects	Yes	No
Region-round fixed effects	No	Yes
Observations	7501	7501

Robust standard errors clustered on 946 enumeration areas (EAs) in parentheses.
***$p < 0.01$.

round fixed effects. Within countries, moving 1 point up the mean deprivation scale implies living about 13 per cent further from the site of a future aid project. Model 2 includes region-survey round fixed effects. The relationship between deprivations and distance to future aid is weaker within subnational regions, but it remains significant and points in the same direction.

The above results assume that each of the four steps in the ordinal scale from 'never' experiencing a deprivation to 'always' experiencing a deprivation has the same relationship to the distance from future aid. I test this assumption by running the same analysis but including each level of the ordinal deprivation variables as its own dummy variable (with the dropped base level being 'never' experiencing the deprivation). Table 2 presents the results for the variables measuring deprivations in food and water. As mentioned earlier, I flexibly control for population density by including a set of dummy variables marking the number of other EAs within 50 km of each EA, and I alternatively include country-round or region-round fixed effects.

The results support those of Table 1. People who said that they or members of their family 'always' went without enough food to eat live almost 50 per cent further from a future aid project than people who said that they 'never' went without food. Those who report always going without enough clean water for home use in the past year live 30 per cent further from a future aid project than those who never experienced this

Table 2. DV: ln(Distance from Closest Future Aid Project)

	Food		Water	
	(1)	(2)	(3)	(4)
Just once or twice	0.12** (0.05)	0.03 (0.03)	0.11** (0.05)	−0.00 (0.03)
Several times	0.16*** (0.05)	0.08*** (0.03)	0.09* (0.06)	0.03 (0.03)
Many times	0.26*** (0.08)	0.07 (0.06)	0.16** (0.07)	0.06 (0.05)
Always	0.48*** (0.10)	0.18** (0.07)	0.30*** (0.10)	0.15** (0.06)
EA count dummies	Yes	Yes	Yes	Yes
Country-round fixed effects	Yes	No	Yes	No
Region-round fixed effects	No	Yes	No	Yes
Observations	7485	7485	7488	7488

The base category in all regressions is 'none'. Robust standard errors clustered on 946 enumeration areas (EAs) in parentheses.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

deprivation. There is also pro-rich targeting within subnational regions, but the results are less dramatic. Within regions, the only consistently significant effect is that those who always went without enough food or water over the past year live about 15 per cent further from future aid than those that never experienced these deprivations. Across the models, average distance from the closest future aid project generally increases as the level of deprivation increases.

3 CONCLUSION

This note presented a new test of the within-country relationship between aid and poverty. When compared with prior work on aid targeting, the present test used different data sources, a wider array of donors, new ways of measuring aid targeting, new ways of measuring poverty, and a different unit of analysis. Despite this, its results are consistent with those of Öhler and Nunnenkamp (2014), Briggs (2017, 2018), Öhler *et al*. (2017) and Custer *et al*. (2017). The present note shows, however, that prior work likely underestimates the extent to which aid targets the relatively rich within countries. This is because prior work aggregated aid into spatial regions and showed that aid targets richer regions within countries. The present note confirms the finding that aid targets richer people within countries, but it also shows that aid targets richer people *within regions*. This note also showed for the first time that pro-rich aid targeting is not unique to the World Bank or African Development Bank but instead exists across a wide range of donors.

As noted in Briggs (2017), these results have implications beyond the practical question of who is able to benefit from aid. If donors are sincere in their stated desire to target aid to the poorest, then the fact that they are failing to do this suggests that they lack either will or ability. One natural interpretation of the results is that donors defer subnational targeting choices to aid recipients. This kind of deference to recipients is in line with common codifications of appropriate donor action like the Paris Declaration on Aid Effectiveness or the Global Partnership for Effective Development Cooperation. The idea that donors largely defer to recipients when targeting aid subnationally is consistent with prior case study work showing that recipient governments can target aid according to local political factors (Briggs, 2014; Jablonski, 2014; Masaki, 2014). However, it clashes with research suggesting that donors exercise fairly strong control over aid (Collier, 2006; Morrison, 2012; Winters, 2014).

The present note should not be read as showing that aid is being targeted badly. It is entirely possible that aid is flowing to the places where it can be used most effectively and that those places tend to be places of relative wealth. However, if donors are sincere about reaching first those who are furthest behind, then subnational aid targeting will have to change dramatically to achieve this goal.

REFERENCES

BenYishay A, Rotberg R, Wells J, Lv Z, Goodman S, Kovacevic L, Runfola D. 2017. Geocoding Afrobarometer rounds 1–6: methodology & data quality. *AidData* http://geo.aiddata.org

Briggs RC. 2014. Aiding and abetting: project aid and ethnic politics in Kenya. *World Development* **64**: 194–205.

Briggs RC. 2017. Does foreign aid target the poorest? *International Organization* **71**(1): 187–206.

Briggs RC. 2018. Poor targeting: a gridded spatial analysis of the degree to which aid reaches the poor in Africa. *World Development* **103**: 133–148.

Collier P. 2006. Is aid oil? An analysis of whether Africa can absorb more aid. *World Development* **34**(9): 1482–1497.

Custer, S., DiLorenzo, M., Masaki, T., Sethi, T., and Wells, J. (2017). Beyond the tyranny of averages: development progress from the bottom up. *AidData Policy Report*.

Dollar D, Levin V. 2006. The increasing selectivity of foreign aid, 1984–2003. *World Development* **34**(12): 2034–2046.

Jablonski R. 2014. How aid targets votes: the impact of electoral incentives on foreign aid distribution. *World Politics* **66**(2): 293–330.

Kotsadam, A., Østby, G., Rustad, S. A., Tollefsen, A. F., and Urdal, H. (2017). Development aid and infant mortality. *AidData Working Paper*.

Masaki, T. (2014). The political economy of aid allocation in Africa: evidence from Zambia. *Working Paper*.

Morrison K. 2012. What can we learn about the "resource curse" from foreign aid? *The World Bank Research Observer* **27**(1): 52–73.

Öhler, H., Negre Rossignoli, M., Smets, L., Massari, R., and Bogetic, Z. (2017). Putting your money where your mouth is: geographic targeting of World Bank projects to the bottom 40 percent. *World Bank policy research working paper*.

Öhler H, Nunnenkamp P. 2014. Needs-based targeting or favoritism? The regional allocation of multilateral aid within recipient countries. *Kyklos* **67**(3): 420–446.

Rodrik D. 1996. Why is there multilateral lending? In *Annual World Bank Conference on Development Economics, 1995*, Bruno M, Pleskovic B (eds). International Monetary Fund: Washington, DC; 167–193.

United Nations Statistics Division (2017). Leaving no one behind – SDG indicators. https://unstats.un.org/sdgs/report/2016/leaving-no-one-behind.

Winters MS. 2014. Targeting, accountability and capture in development projects. *International Studies Quarterly* **58**(2): 393–404.

Wong D. 2009. The modifiable areal unit problem (MAUP). In *The SAGE Handbook of Spatial Analysis, Chapter 7*, Fotheringham AS, Rogerson PA (eds). Sage: London, UK.

DOI: 10.1002/jid

APPENDIX A

This appendix presents supporting material. I break histograms of the population density measure down over countries and over the Afrobarometer-coded urban/rural variable. I show that my count variable captures more variation than Afrobarometer's urban/rural coding, although both are in general agreement.

Figure A1 shows that observations coded as being within urban EAs by Afrobarometer have more other EAs within 50 km than observations coded as being within rural EAs. However, there is also a good deal of variation in the number of other EAs within 50 km from each EA within each panel. This variation is likely to be meaningful in sorting big cities from small ones or isolated small towns from more clustered rural areas. This is why I condition on a full set of dummies marking the number of EAs within 50 km (as well as country-round or region-round fixed effects) rather than just using Afrobarometer's urban/rural status variable.

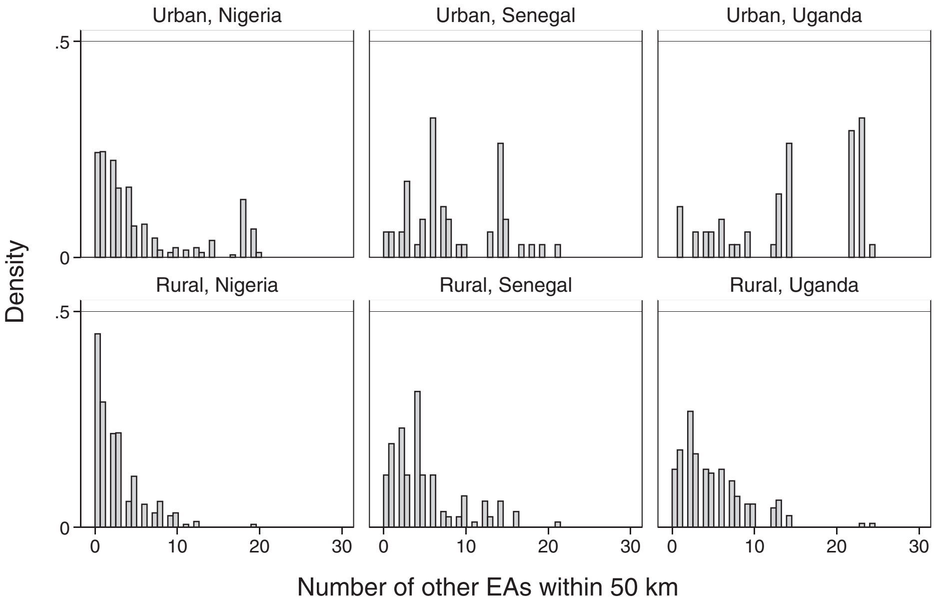

Figure A1. Histograms of enumeration areas (EAs) within 50 km, by country and urban/rural status

DOI: 10.1002/jid