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Poor targeting: A gridded spatial analysis of the degree to which aid reaches the poor in Africa

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ABSTRACT

The effects of most kinds of project aid decline over distance, so in order for aid to help the poor it must be targeted to the places where the poor live. This paper examines if aid from the World Bank and African Development Bank flows to the relatively poor within African countries. The unit of analysis is an approximately 50 km × 50 km cell that is tiled across the continent to form a grid of roughly 10,500 cells. I aggregate geotagged aid from each donor into the grid cells in three ways: a binary measure marking if a cell received any aid, the count of aid projects per cell, and each cell's dollar value of aid. I operationalize poverty at the grid cell level in five ways: light at night, mean travel time from the cell to a major city, distance from the centroid of the cell to the recipient's capital city, and cell-level estimates of child malnutrition and infant mortality. I test for the influence of each poverty variable in models that control for the population within each cell and include recipient country fixed effects. Aid flows to richer rather than poorer cells.

If foreign aid is to alleviate poverty, then it should flow to the places where poor people live. This general logic underpins attempts to get donors to send more aid to poorer countries,[1] and for many kinds of aid this logic holds just as strongly within countries as it does across countries. While analyses of aid targeting have traditionally been cross-national (e.g. Alesina & Dollar, 2000; Nunnenkamp & Thiele, 2006), recent work has begun to examine within-country aid targeting. Prior research has shown that, at a sub-national level, aggregate foreign aid does not target poverty in China (Zhang, 2004), India (Nunnenkamp, Öhler, & Sosa Andrés, 2016a), Kenya (Briggs, 2014), Malawi (Nunnenkamp, Sotirova, & Thiele, 2016b), or across a number of countries in Africa (Öhler & Nunnenkamp, 2014; Briggs, 2017).[2] The present article extends this research by examining aid targeting by the World Bank (WB) and African Development Bank (ADB) at a high level of spatial detail across the continent of Africa. It finds that aid does not flow to poorer people within countries. Rather, aid appears to flow to the places that hold the relatively rich.

1. Sub-national aid targeting

The goal of aid, at least from the point of view of the two donors under study in this paper, is to reduce poverty. The World Bank's President Jim Yong Kim describes the mission of the Bank "as ending extreme poverty by 2030 and boosting prosperity among the poorest 40 percent in low- and middle-income countries" (Clemens & Kremer, 2016, p. 60).[3] The ADB is less direct, but notes that their goal is to "promote sustainable economic growth and reduce poverty in Africa." (African Development Bank Group, 2014). Not only do multilateral donors like the WB or ADB want to use aid to reduce poverty, they are thought to be uniquely well positioned to do so because they are more shielded from political influence than are bilateral donors (Rodrik, 1996; Martens, Mummert, Murrell, & Seabright, 2002). Evidence on cross-national aid targeting supports this claim, as multilateral donors tend to send more aid to poorer countries than do bilateral donors (Maizels & Nissanke, 1984; Dollar & Levin, 2006; Nunnenkamp & Thiele, 2006).

While cross-national aid targeting has received more attention than sub-national aid targeting in both research and policy circles, this probably owes more to data availability than to theory. While

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[1] For example, the Commitment to Development Index by the Center for Global Development (2015) favors donors that send more aid to poorer countries.

[2] Nunnenkamp et al. (2016a) find evidence of needs-based targeting when looking at some individual sectors such as health and sanitation and Jablonski (2014) reports limited evidence of needs-based targeting in Kenya along with clear evidence of politically-oriented aid targeting.

[3] Poverty reduction has been a major goal at the Bank for some time. For example, the goal of eradicating absolute poverty was stated by McNamara in 1973 (Clemens & Kremer, 2016, p. 60). The idea that aid should reduce poverty is also clearly laid out in *Assessing Aid* (World Bank, 1998, p. 38) and reiterated for the Sustainable Development Goals on the WB's web page (World Bank, 2015).

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accessible sub-national aid data are fairly new,[4] the theoretical argument for targeting aid to poorer places within countries is not. In fact, the argument for sending aid to poorer places within countries is essentially the same as the argument for sending aid to poorer countries.[5] The argument is as follows: If the goal of aid is to help the poor and if aid provides a good or service that is geographically bound, then aid should be targeted to where poor people live. Thus, money that funds a global public good like vaccine research can be spent anywhere. Aid for national-level programmes should be directed to countries with poorer people. Similarly, aid projects that provide club or local public goods such as health clinics, roads, village electrification, clean water, or schools should be targeted to the places within countries where poorer people live.[6] Thus, there is no theoretical reason for working at the level of countries when examining the degree to which donors target aid to the poor. If aid is intended to reduce poverty, then it should be targeted to poverty according to the geographic scope of its anticipated effect.[7]

The issue of subnational aid targeting is more important if rich and poor people are spatially segregated within countries. This is the case in Africa, where "inequalities between regions as well as urban and rural areas are large" (Bigsten, 2016, p. 6). These differences extend beyond income. For example, "skilled health personnel attend 83% of births in urban areas" of Burundi but only 16% in rural areas (Sahn & Stifel, 2003, p. 583). Not only do "living standards in rural areas lag far behind those in urban areas" but there is also no evidence of convergence (Sahn & Stifel, 2003, p. 591).[8] The issue of spatial inequality would be blunted if the poor were able to easily move to richer parts of countries, but the poor infrastructure that entrenches spatial inequalities also makes migration difficult. In Africa, rates of internal migration from poorer rural areas to richer urban areas are growing but are low by global standards (De Brauw, Mueller, & Lee, 2014).[9] Thus, while aid targeting is important in general, it is especially important if one wants to reach the very poor in Africa.

Given that multilateral donors like the WB and ADB are more insulated from politics and send more aid to poorer countries than most other donors, one might expect that they would also be sensitive to poverty within countries. This should especially be the case for project aid, which is fairly easy for donors to target to specific places (Briggs, 2017). Somewhat counter-intuitively then, research on sub-national aid targeting by these donors has typically found that aid does not target poorer subnational regions within recipient countries (Öhler & Nunnenkamp, 2014; Briggs, 2017).[10]

2. Contributions to the literature

The present paper builds on prior research by making one theoretical intervention, one methodological contribution, and two empirical improvements. The theoretical intervention is the simple but often overlooked point that aid cannot help the poor unless it both works *and reaches the places where poor people live.* This implies that even if we have certain knowledge that aid improves the lives of the people that get aid, we cannot claim that aid is helping any specific group (such as the poor) unless we also know that group is in fact receiving aid. This point is especially important when studying aid to Africa, as spatial inequalities on the continent are high and migration from poorer to richer areas within countries is relatively low. Where aid goes within countries is thus quite important, as it tells us who can benefit from aid (and who cannot).

The paper's methodological contribution follows from the prior theoretical point. The question "Within countries, does foreign aid flow to the places where poorer people live?" is fundamentally descriptive, and so I answer it descriptively. As such, I am not concerned with identifying the effect of poverty on aid allocation. Instead, the goal is to describe the spatial relationship between aid and poverty at a high level of detail and over a large number of countries. The descriptive focus of this work implies that omitted variable bias, including bias caused by spatially correlated variables, is not a concern. While this analysis will not reveal the causal effect of poverty on aid, it will reveal if poorer people are more likely to receive aid than richer people. It may well be that aid does not flow to poorer people because of variables that correlate with poverty rather than because aid is actively avoiding poverty itself. However, given the descriptive question of the paper, controlling for such variables may produce misleading results. Put differently, aid can help the poor only if it reaches the poor—and from this point of view it does not matter if the mechanism causing it to reach the poor is something other than their poverty.

To see this clearly, consider a program whose goal is to give cash to the poorest people in a country and imagine that we have a dataset of all people in the country, their income, how much money they received from the program, and whether or not the person is co-ethnic with the president of the country. It could be the case that the bivariate relationship between how much cash a person received and their income is negative but that this relationship flips to become positive when controlling for co-ethnicity, which itself is positive.[11] This could occur is if aid targeting is influenced by both co-ethnicity and income but that the president's co-ethnic group is much poorer than most other groups in the country. This situation is depicted graphically using simulated data in Fig. 1. The solid line shows the relationship between benefit payout and income across all people. The dashed lines show the relationship between benefit payout and income within co-ethnics and within non-coethnics.

This example highlights that if one wants to answer a descriptive question like "within countries, are poorer people receiving more aid than richer people?" then adding a list of standard control variables can produce misleading results. In the present example, if we condition on co-ethnicity then we might incorrectly conclude that more benefits go to richer people. Control variables can be useful if one is interested in estimating the causal effect of poverty on aid.[12] However, control variables are not useful in all situations and their value depends on the specific question being asked.

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4 Standardized, sub-national aid data have only recently started to become available thanks to the geocoding efforts of AidData.

5 One can also draw a distinction between sending aid to countries with more poor people rather than countries that are poorer on average (Kanbur & Sumner, 2012). For the purpose of the present paper, this distinction is immaterial.

6 The World Bank regularly provides this kind of aid. For example, a pamphlet from the International Development Association, the concessional side of the World Bank, notes "When the poorest are ignored because they're not profitable, IDA delivers. IDA provides dignity and quality of life, bringing clean water, electricity, and toilets to hundreds of millions of poor people" (World Bank, 2014, p. 11).

7 It is possible that an aid-funded good like a road could be built some distance from where poor people live but could still eventually improve some economic outcome for the poor due to second-order effects. However, the same argument applies to cross-national aid targeting and is usually dismissed. For example, aid that aims to improve a national-level variable like the institutional environment in a country could be spent on a richer country that neighbors a poorer one and, if it works, then the poorer one may benefit from having a richer neighbor.

8 The importance of spatial inequalities in Africa is also noted in Beegle, Christiaensen, Dabalen, and Gaddis (2016) and van de Walle (2009).

9 Between 1990 and 2000, the population-weighted rural-urban migration rate in sub-Saharan Africa was only about 1% (De Brauw et al., 2014, p. 34) I'd like to thank a reviewer for raising the issue of internal migration.

10 Investigations of sub-national aid targeting by only the WB find similar results (Zhang, 2004; Nunnenkamp et al., 2016a).

11 This example is essentially a restatement of Simpson's paradox (Simpson, 1951).

12 However, in order to estimate a causal effect in this way from observational data one needs to make exceptionally strong assumptions. For a good summary of the pitfalls of simply adding control variables in an effort to recover causal effects, see the discussion and citations in Samii (2016).

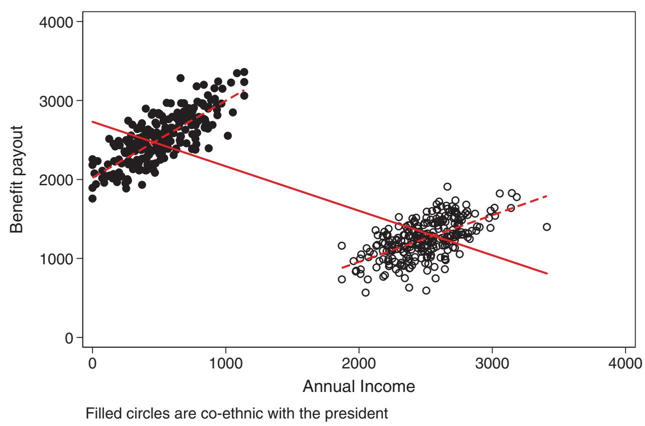

Fig. 1. Stylized example of the pitfalls of adding control variables to a descriptive analysis examining if poorer people receive more aid.

Most prior research examining where aid goes includes a large number of standard control variables, and so this work does not tell us if the poor are in fact receiving more aid. Rather, this work tells us if the poor are receiving more aid conditional on a range of variables such as institutional quality or political patronage. While useful for some research questions, conditioning on variables in this way makes it difficult to know whether poorer people are in fact receiving more aid. The present paper answers this question by comparing poverty and aid across cells and including only recipient fixed effects and cell-level population as covariates.

The paper's first empirical contribution is to analyze aid targeting across about 10,500 grid cells. This approach stands in contrast to all previous work examining how aid targets poverty sub-nationally, which to the best of my knowledge has always aggregated aid into some level of administrative region.[13] Using grid cells is an improvement over using administrative regions because these cells are smaller and consistently shaped. The smaller size of grid cells is important because in smaller spatial units it is less likely that aid will flow to relatively rich people living within a relatively poor spatial unit. This concern is particularly acute when comparing across high-level administrative regions, because rural regions tend to be poorer, larger, and to have higher levels of inequality than urban regions (Sahn & Stifel, 2003). Thus, it is entirely possible that aid flowing to a poor, rural region will actually end up in a portion of that region that holds relatively wealthy people. The likelihood of this happening shrinks as the spatial unit gets smaller. The consistency of the shape of the spatial units also matters, as consistent shape avoids both the *scale* and *zoning* problems that together form the *modifiable areal unit problem* (Wong, 2009). The scale problem occur when points are aggregated into units of different sizes. The issue is that there is no way of knowing if any given result would hold if the points where aggregated at a different level. This problem can be exacerbated if the scale of the aggregation covaries with variables of interest, such as if richer people tend to live in smaller regions. The zoning problem occurs when the shape of the units being analyzed is influenced by variables that are related to the analysis. Gerrymandering is a specific instance of this more general problem.[14] Examining poverty targeting across cells completely avoids the zoning problem. It also helps to address the scale problem by examining the relationship between poverty and aid at a consistent level of aggregation and at a level of aggregation not studied in previous work.

[13] Wood and Sullivan (2015) analyze the relationship between aid and conflict in Africa using grid cells, and so avoid aggregating aid into regions.

[14] For a Ugandan example showing that administrative units are political creations, see Green (2010).

The paper's second empirical contribution is to examine aid targeting from two donors over the entirety of the continent of Africa over a two year period.[15] Past sub-national work has typically focused on either single countries (e.g. Zhang, 2004; Jablonski, 2014; Briggs, 2014; Nunnenkamp et al., 2016a) or a sample of never more than 27 countries with available data (Öhler & Nunnenkamp, 2014; Briggs, 2017). In examining grid cell-level targeting across the continent of Africa, this paper expands the number of countries under study while also examining more nuanced targeting within each country. Thus, this paper's contribution is to descriptively examine where aid from two multilateral donors flows using five measures of poverty and three measures of aid, at a high level of spatial detail, and across the continent of Africa. I show that aid does not flow to the poor within African countries.

3. Data

The unit of analysis in the present paper is a cell in the PRIO-GRID (Tollefsen, Strand, & Buhaug, 2012), which is a standardized, global spatial grid of 0.5×0.5 decimal degrees.[16] Limiting the PRIO-GRID to Africa (including North Africa and islands), reduces the grid to 10,572 cells that form a pixelated map of the continent.[17] In order to examine if aid targets poverty, it is necessary to aggregate aid projects, population measures, and measures of poverty into each cell.

Data on the location of aid projects comes from AidData (Strandow, Findley, Nielson, & Powell, 2011).[18] I examine projects from the WB and ADB that were located in Africa (including North Africa) and approved in 2009 and 2010.[19] Geolocated projects in AidData are given codes that describe the accuracy of the geocoding. I limit the analysis to projects that were either exactly geocoded or were geocoded to a location that is known to be within 25 km of the correct location. This procedure reduces the effective sample by about 50%.[20] While the sample reduction is unfortunate, this reduction is less problematic than it may initially seem because recent research working at the cross-regional level has already shown that aid does not flow to poorer regions within countries (Öhler & Nunnenkamp, 2014; Briggs, 2017). By focusing on aid with more precise geocoding, I provide an additional and more nuanced test of poverty targeting using a subsample of aid that should be uniquely targetable by donors.

I measure grid cell-level aid in three ways. First, as a dummy variable that takes a one if a cell receives any aid and zero otherwise. Second, as the count of the number of projects per cell. Third, as the total value of aid (in millions of USD) within each cell. It is important to note that in the aid dataset, many locations will often correspond to one large project and the cost of the project is only reported at the aggregate level. For example, a project to build schools would report the location of each school but would only give the cost of the total project and not the cost for each school. To calculate the value of aid per grid cell, I assume that the cost

[15] The period of the analysis is 2009–2010, so South Sudan did not yet exist. In some analyses a number of countries are dropped because every cell in the country either did or did not receive aid (the problem of separation).

[16] The cell size is thus about 55 km × 55 km at the equator.

[17] Maps of the grid and all of the variables used in the main text are in the Appendix A.

[18] When I speak of "projects" I refer to the lowest level of the AidData dataset. Technically, these are locations, or sub-projects, that often group together to form projects.

[19] The coverage of the ADB dataset is limited to Africa in 2009 and 2010. The WB dataset was limited to the same region and time periods to increase comparability between the donors.

[20] Forty-seven percent of the WB's projects to Africa in 2009 and 2010 were exactly geocoded. An additional 2% were geocoded to within 25 km. For the ADB, the figures are 57% and 2%, respectively. The analysis thus makes use of about half of the WB's projects and about 60% of the ADB's projects in Africa during this time period.

of each larger project is divided evenly across all of the geolocated sub-projects[21] and then I calculate the sum of the cost of the sub-projects per cell.[22]

To give a sense of how the use of grid cells coarsens the aid data, I graphically depict the count of projects per cell in Kenya in Fig. 2. The shading shows the number of projects per cell and the points show the location of each project. WB projects are colored green and ADB projects are red. The points are drawn with transparency to help reveal overlapping projects. The cell-level count of projects in Kenya ranges from a high of 10 in a cell on Nairobi (black) to zero in about 4/5 of the grid cells (white). While the aggregation of aid projects into cells involves some loss of geographic information, the data retain much more information than in the typical approach of aggregating into sub-national administrative units or countries.

Aggregating aid into grid cells reveals that foreign aid has extensive geographic coverage in Africa. About 10% of Africa's populated grid cells received at least one aid project from the donors under study.[23] This is quite impressive, as I am only looking at two donors over a two year period and I have dropped about half of all of the projects from each donor because they lack the spatial precision necessary to geocode them to a specific cell. The geographic coverage of all aid to Africa is thus likely to be a good deal larger.

The independent variables are also measured at level of the grid cell and each regression includes only a control for the population of the grid cell and one proxy measure of poverty, as well as recipient fixed effects.[24] The population control is critical, as many of the proxies for poverty correlate with population. For example, a grid cell that emits no light at night might be poor, or it might simply contain no people. Given that I am comparing across cells but ultimately care about people, I should control for population. The main text reports results using population measures taken from the History Database of the Global Environment (HYDE) version 3.1 (Klein Goldewijk et al., 2011; Goldewijk et al., 2010) and Appendix A reports results using the Gridded Population of the World dataset, version 3 (CIESIN & CIAT, 2005).[25] I use the count of people per cell from the most recent year before aid was disbursed, which in both cases is 2005.

One drawback of a grid cell analysis is that I lack reliable cell-level measures of poverty, such as the household surveys used in Briggs (2017). Thus, instead of using one precise measure of poverty, I examine how aid correlates with five different proxies for cell-level poverty. The first proxy measures the grid cell's economy, the next two measure how rural is the grid cell, and the final two measure health outcomes.[26] While any one proxy contains some error, we can be fairly confident in the reliability of any aid targeting patterns that are consistent across the proxies.

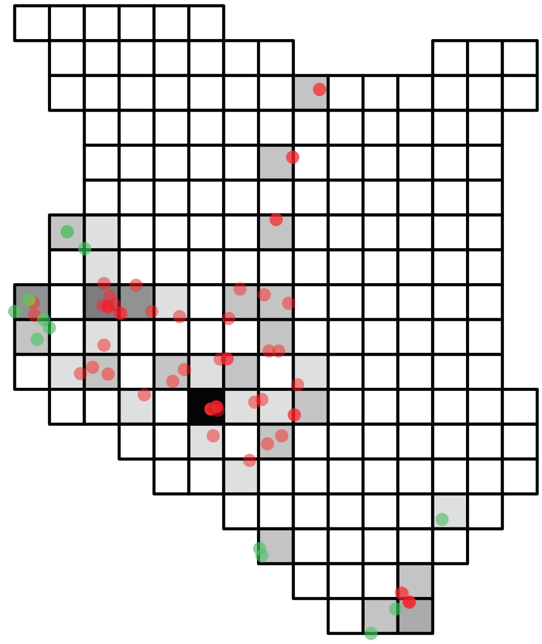

Fig. 2. The location of aid from the WB (green) and ADB (red) in Kenya. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The economic measure is the mean intensity of light at night within each grid cell.[27] This measure has been shown to correlate closely with measures of household wealth (Weidmann & Schutte, 2016). I take the light at night measure from 2008, the year before the 2009/10 period of the aid data.

The next two proxies examine how rural (or remote) is the grid cell and so are based on the notion that rural people tend to be poorer than urban people.[28] By explicitly looking at rural–urban divides, these proxies can also be read as a test for urban bias in aid allocation.[29] To measure how rural is a grid cell, I first use the estimated mean travel time from the pixels in each grid cell to the nearest city with at least 50,000 inhabitants (Uchida & Nelson, 2009).[30] The second measure is the (straight line) distance from the centroid of each cell to the recipient country's capital city in 2008, whose location is taken from the CShapes dataset (Weidmann, Kuse, & Gleditsch, 2010). Distance from the capital captures the cell's distance from what is typically a major urban center with relatively good employment opportunities and relatively good provision of services. It also offers a test of capital city bias in aid allocation.

The final two proxies are estimates of health within the grid cell. The first is the estimated mean rate of the prevalence of child

[21] This assumption is also employed in Briggs (2017).

[22] For the ADB data I use the "project cost" variable, but the results are very similar if I use the "Total Bank Group Funding" variable instead.

[23] Populated is defined as having more than zero people per cell, using the population counts from the 2005 year of the History Database of the Global Environment (HYDE) version 3.1 (Klein Goldewijk, Beusen, Van Drecht, & De Vos, 2011; Goldewijk, Beusen, & Janssen, 2010).

[24] The independent variables come from the PRIO-GRID dataset (Tollefsen et al., 2012), but I report the original sources in the following text.

[25] HYDE takes GPW as one of its inputs and models cell-level population counts. GPW makes efforts to model the population counts as little as possible, relying instead on administrative data. I use the HYDE dataset because a more modeled approach can be useful when the original data may be old or of low quality, which it often is in Africa.

[26] I chose not to report results using a measure of the size of the grid cell's economy from Nordhaus (2006), as the creators of the dataset note that the data are very unreliable in Africa. If used, the gross cell product PPP variable also produces results showing that aid does not target poorer cells.

[27] This is the mean nighttime light emission from the DMSP-OLS Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, and Cloud Free Coverages) and it was standardized to be between zero and one. Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency.

[28] In sub-Saharan Africa, 74% of the rural population (compared to 31% of the urban population) lives in multidimensional poverty (United Nations Development Program, 2016, p. 55). Young, (2013, p. 1728) finds that the "urban–rural gap in living standards is a major source of inequality, accounting for 40% of average inequality." Another overview notes that "the incidence of poverty tends to increase with the distance from major cities" (Thorbecke, 2013, p. i35). This pattern is also noted in Sahn and Stifel (2003). In North Africa, there exist large disparities in health outcomes between rural and urban areas (Boutayeb & Helmert, 2011). For summaries of research on how rural children have worse health outcomes, such as higher rates of stunting, lower weight, and higher infant mortality than urban children, see Smith, Ruel, and Ndiaye (2005, 2007, 2013).

[29] Chambers (1983) remains one of the best references on urban bias and rural development.

[30] The data to create this measure were gathered between 1990 and 2005.

Table 1
Mean of within-country correlations.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR	ln(pop.)
ln(light)	1					
ln(time)	−0.42	1				
ln(dist.)	−0.43	0.50	1			
CMR	−0.20	0.13	0.26	1		
IMR	−0.07	0.00	0.11	0.24	1	
ln(pop.)	0.46	−0.54	−0.42	−0.08	−0.04	1

malnutrition within each cell (CIESIN, 2005). The second health measure combines national and sub-national data on infant mortality to produce grid cell-level estimates of infant mortality (Storeygard, Balk, Levy, & Deane, 2008). Both health variables are transformed into percentages that range from zero to one, with higher numbers indicating worse health. These variables offer fairly crude sub-national coverage and are measured for the year 2000.[31]

I first examine the correlations between the independent variables. I do this by averaging the within-country correlations between each pair of variables over all of the countries in the dataset.[32] The results are shown in Table 1.[33] The correlations between the poverty variables are roughly as expected. Places with more light at night have lower travel times to cities, are closer to capital cities, and have lower rates of child malnutrition and infant mortality, though the latter correlation is weak. Looking at population, places with more light at night, shorter travel time to cities, and shorter distances to capital cities are also more populous. The health variables correlate only weakly with population.

While the variables all correlate in the expected directions, they are not so closely correlated as to render their addition to the analysis superfluous. The health measures in particular stand out as only weakly correlated with the other measures. Rather than aggregating the variables into some form of index, I instead examine how each one relates to within-country aid allocation one at a time. This disaggregated, sequential approach allows us to examine if any proxy produces evidence that aid targets poverty.

4. Analysis

The following analyses are all of a simple form: the dependent variable is a measure of aid and it is explained using one poverty variable, the natural log of the cell's population, and recipient country fixed-effects. The units are grid cells nested within recipient countries. I measure aid per cell in three ways: a binary measure of a cell receiving any aid, a count measure of the number of aid projects per cell, and a measure of the log of the total dollar value of aid per cell. The binary analysis uses a linear probability model and a logistic model and the count analysis uses a negative binomial model and a Poisson model.[34] The analysis of the dollar value of aid is done using OLS, but I present results from an analysis of all grid cells and an analysis restricted to the grid cells that received at least one aid project. All analyses include recipient fixed effects and cluster standard errors on the recipient country. The addition of the recipient fixed effects means that the results are not driven by recipient-level factors such as the size of the recipient's economy or the quality of the recipient's democracy. It also rules out bias associated with recipient-specific under or over-reporting of their population or infant mortality figures, for example.

The analyses make use of three different operationalizations of aid, two different models or sample adjustments per operationalization, and five proxies for poverty. This setup leads to 30 tests of the within-recipient, grid cell-level relationship between poverty and foreign aid with each test producing two coefficients, one for population and one for the poverty proxy used in that test. In order to present all of these results as efficiently as possible, I do not report the coefficient for population and I group the results into three modified statistical tables based on the level of measurement of the aid variable. Table 2 reports results from a binary measure capturing if a cell received any aid, Table 3 reports results using a count of aid projects per cell, and Table 4 reports results using the dollar value of aid. Each table thus reports the results of 10 unique tests, and the column headings in each table name the poverty proxy whose coefficient is presented in that column rather than the dependent variable. I at no time find that, conditional on a cell's population, aid flows to poorer cells. Rather, aid often flows to grid cells that are richer.

Table 2 examines if grid cells with more poverty are more likely to receive any aid than richer grid cells. I show results from both a linear probability model in Panel A and a logistic model in Panel B. The linear probability model has the advantage of not dropping recipients with cells that all received or all did not receive aid. The logistic model drops such recipients,[35] but has the advantage of bounding predicted probabilities between zero and one. There is no need to defend any specific model, as the results are largely in agreement. As noted above, the column headings report the relationship between aid and the key *independent* variable from each test. Conditional on the (logged) population in each cell, cells that have more light at night are more likely to receive at least one aid project. Aid projects are also more likely to be present in cells that have shorter travel times to cities and in cells that are closer to the capital city. The health variables are consistently negatively signed, but are not consistently significant and have highly variable magnitudes. Across both models and all five proxies for poverty, it is easy to reject the hypothesis that cells with more poverty are more likely to receive at least one aid project.

Table 3 reports results where aid is operationalized as the number of projects per cell. The dependent variable is an overdispersed count variable, and so I present results from both a negative binomial model and a Poisson model. Aid does not flow to poorer places within countries. Cells receive more aid projects if they have more light, shorter travel times to major cities, shorter distances to the capital, and lower rates of child malnutrition. The results for infant mortality are negative but not consistently statistically significant.

[31] 2000 is the most recent year in each dataset.

[32] The Seychelles, Sao Tome and Principe, Mauritius, and Cape Verde were dropped because they either did not have enough cells or had too much missing data to estimate the correlations.

[33] The measures that exhibit skew are logged in the table and in the main analysis. The population variable has zero values, and so I add one (e.g. one person) before taking the log.

[34] For a discussion of the merits of each count model, see Cameron and Trivedi (2010).

[35] Burundi and Rwanda are the only countries where every cell received at least one aid project. In Cape Verde, Equatorial Guinea, Libya, Madagascar, the Seychelles, Somalia, Swaziland, and Zimbabwe no cells received a project.

Table 2
Analyzing if a Cell Received Any Aid.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Linear Probability Model					
	0.19***	−0.06***	−0.05***	−0.11	−0.51
	(0.05)	(0.02)	(0.01)	(0.11)	(0.39)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: Logistic Model					
	0.93**	−0.67***	−0.31***	−2.61*	−11.17**
	(0.40)	(0.24)	(0.12)	(1.43)	(4.91)
Num. cells	9257	9257	9257	9008	9059
Num. recipients	41	41	41	41	41

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is a binary indicator marking if a cell received any aid (1 = yes). All regressions include recipient fixed effects and control for logged population.
Panel A has robust standard errors clustered on recipients in parentheses. Panel B has bootstrapped standard errors based on 1000 replications and 41 country clusters in parentheses.
*** p < .01, ** p < .05, * p < .1.

Table 3
Analysis of the Count of Projects.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Negative Binomial Model					
	0.67***	−0.48***	−0.28***	−1.84**	−3.61
	(0.14)	(0.16)	(0.07)	(0.76)	(2.55)
Num. cells	9279	9279	9279	9030	9081
Num. recipients	44	44	44	44	44
Panel B: Poisson Model					
	0.51***	−0.65***	−0.27***	−1.95***	−5.30***
	(0.18)	(0.17)	(0.07)	(0.58)	(1.91)
Num. cells	9279	9279	9279	9030	9081
Num. recipients	44	44	44	44	44

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the count of the number of projects per cell. All regressions include recipient fixed effects and control for logged population.
Panel A has bootstrapped standard errors based on 1000 replications and 44 country clusters in parentheses. Panel B has robust standard errors clustered on recipients in parentheses.
*** p < .01, ** p < .05, * p < .1.

Table 4
Analysis of the Dollar Value of Aid.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: OLS					
	1.07***	−0.26***	−0.23***	−0.93*	−3.66**
	(0.27)	(0.07)	(0.06)	(0.51)	(1.49)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: OLS, sample restricted to cells that received aid					
	1.09***	−0.32*	−0.20**	−2.91***	−6.67*
	(0.31)	(0.16)	(0.10)	(0.98)	(3.69)
Num. cells	900	900	900	883	889
Num. recipients	45	45	45	45	45

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the natural log of the total (+0.1) value of aid per cell in millions of USD. All regressions include recipient fixed effects and control for logged population.
Panels A and B have robust standard errors clustered on recipients in parentheses.
*** p < .01, ** p < .05, * p < .1.

As with the binary models, there is no evidence that aid is flowing to areas of poverty within countries and there is fairly strong evidence that aid is flowing to the relatively rich.

Finally, I operationalize aid as the natural log of each cell's dollar value of aid.[36] The results across all cells are shown in Panel A of Table 4. Taking the log plus a small constant leads to a bimodal distribution with many small values (from the majority of cells that received no aid) and then a roughly normal distribution over the cells that received at least one aid project. Panel B shows the same analysis when the sample is restricted to the cells that received at least one aid project. The interpretation of Panel B is that it answers if aid-receiving cells get more aid (in dollar terms) if they are poorer. In line with the previous results, richer cells receive more aid. A 1% increase in light at night leads to about a 1% increase in the dollar value of aid. A 4% increase in travel time to a city or in distance to the capital leads to about a 1% decrease in the dollar value of aid. As before, the health variables are less consistent but broadly show that places with better health receive more aid.

[36] Most cells receive no aid, and so I add 0.1 to the aid value to prevent these cells from being dropped from the analysis. The results are quite similar if I add one (meaning one million dollars as the aid variable is measured in millions) instead.

Across all of the models and operationalizations of aid, places with more light, shorter travel times, and shorter distances to the capital receive more aid.[37] The health variables are not always significantly different from zero, but their coefficients are always negative. In fact, none of the 30 tests produce a single coefficient (even a statistically insignificant one) that suggests that aid flows to cells with more poverty.

4.1. Robustness

The results reported thus far have included different operationalizations of aid, different models, different proxies of poverty, and different sample restrictions. Across the results, aid either flowed to richer places within countries or the relationship between the poverty proxy and aid was not significantly different from zero. This section briefly summarizes a small number of additional robustness tests. Full results are presented in the Appendix A.

First, I consider how mismeasured cell-level population counts could bias the results. If the cell-level population variable is measured with error, which it probably is, then the coefficients for variables that correlate with (true) population, such as light at night, may be partially picking up the effect of a cell having more people than is recorded in the population variable. This implies that aid that simply targets larger (true) populations could appear in the results as aid that is targeting light at night, conditional on (mismeasured) population. This concern can be met in two ways. First, I re-ran all of the above analyses using a different cell-level population variable. The results are quite similar to those in the main text. In no case do I find even a statistically insignificant coefficient that suggests that aid is being targeted to the poor.

The second way of examining the influence of mismeasured population is to consider more closely the variables that should correlate more weakly with population. Light at night, for example, should in theory have a close correlation with population as it is proxying for total local economic activity rather than economic activity per capita. Indeed, in the data under study the within-country relationship between light at night and population is fairly strong (see Table 1). However, the within-country relationship between child malnutrition or infant mortality and population is considerably more ambiguous in theory and in the data (again, see Table 1). Thus, if we see anti-poor targeting in the travel time or light at night variables but pro-poor targeting in the health variables then this is a good indicator that mismeasured population is causing a great deal of bias. While the health variables do not show the consistent, anti-poor targeting that appears in the other variables, they also show no evidence of pro-poor targeting. Both health variables are consistently negative and often statistically significantly different from zero.

Finally, it is worth noting that for mismeasured population to be causing bias not only must cell-level population be measured with error but also donors must somehow be targeting aid according to true cell-level population. It is not clear how donors would have the information required to do this. This suggests that while mismeasured population may be causing some bias, it is unlikely that the core result that aid does not flow to the poor is being driven simply by mismeasured population.

Next, I explore whether the treatment of spatial autocorrelation is causing misleadingly small standard errors. In the main results, standard errors are clustered at the level of recipient countries. To examine if this choice is too liberal, I replicate the OLS results (Panel A in Table 2 and the entirety of Table 4) but adjust standard errors to account for spatial dependence as in Conley (1999).[38] I do this twice, once assuming that spatial autocorrelation decreases linearly in distance up to a cutoff of 200 km and once with a distance cutoff of 1000 km. In both cases, I use the centroids of the grid cells to mark if a cell is within either the 200 or 1000 km boundary. Using either cutoff leads to standard errors that are smaller than those reported in the main text.

Silva et al. (2006) have shown that log-linearized models estimated by OLS (such as the results in Table 4) may produce inconsistent estimates if the model suffers from heteroskedasticity. As an alternative, they propose a Poisson pseudo-maximum likelihood method and show that it provides reliable estimates across a wide range of situations (Silva et al., 2011). I replicated Table 4 using their method. Aid still flows disproportionately to richer cells and there is no evidence of it flowing to poorer cells.[39]

Finally, I disaggregated the two donors and reran all of the analyses from the main text for each. The results are again quite similar to those reported in the main text. In general, aid from both donors flows to cells with more light, shorter travel times to major cities, and shorter distances to capital cities. The health variables offer less consistent evidence, but any time that the health variables are statistically significant it is in the direction of healthier places receiving more aid. I find no evidence that pooling the donors together for the main analysis masks interesting differences between them.

The main text and the robustness tests in the Appendix A in total present 155 tests of the relationship between a proxy for poverty and aid.[40] None of the tests yields a statistically significant pro-poor result at $p < 0.1$, and in only one test is there a positive (but statistically insignificant) coefficient for the effect of poverty on aid.[41] One hundred and eight of the 155 tests (70%) produce a statistically significant effect at p <.05, suggesting that aid flows to richer areas. While error in the population variable may well be creating some bias towards a finding of pro-rich targeting in some of the variables, the overall results are clearly at odds with the idea that aid flows to poorer places within countries.

5. Discussion

This paper examined the spatial relationship between aid and poverty across approximately 10,000 cells covering the continent of Africa. It showed that aid does not flow to poorer places within countries. Rather, the bulk of the evidence suggests that aid flows to places of relative wealth. This finding has implications for our understanding of aid effectiveness, inequality, and urban bias.

First, realizing that aid skews towards areas of relative wealth within countries should temper our optimism about the ability of aid to help end extreme poverty. This is unfortunate, as ending extreme poverty is the first Sustainable Development Goal and achieving it is expected to involve "targeting the most vulnerable" (United Nations Development Program, 2016). This paper found no evidence of such targeting in aid allocations. This lack of poverty

[37] Additionally, conditional on the poverty variables, aid clearly targets more populous cells. The population variable is significant (p < .05) in all specifications except for the Table 4, Panel B, the model which measures poverty using light at night.

[38] To complete this portion of the analysis, I made use of code used originally in Hsiang (2010) and Fetzer (2014).

[39] I'd like to thank a reviewer for pointing me to Silva et al. (2006).

[40] Main paper (30 tests), GPW population control (30), Conley standard errors (30), PPML (5), ADB tests (30), WB tests (30). With the exception of the Conley standard errors and PPML, the setup of each batch of 30 tests is the same as those presented in the main paper. The Conley standard error section replicates Panel A of Table 2 and all of Table 4 with a distance cutoff of 200 km and then with distance cutoff of 1000 km. The PPML robustness test replicates Panel A of Table 4, but the dependent variable is not logged in the PPML tests.

[41] This only occurs when the sample is restricted to aid from the World Bank, when the dependent variable is a count measure of aid, and when a fixed effects negative binomial model is used. The positive relationship does not exist when a fixed effects Poisson model is used with an otherwise identical setup.

targeting means that the poorest will not be able to benefit from aid that provides goods like schools or clinics, but it also means that the poorest are least likely to benefit from aid that boosts national economic growth. This is because the local benefits of national economic growth diminish as one moves towards more remote parts of countries (Christiaensen, Demery, & Paternostro, 2003; Christiaensen, Demery, & Paternostro, 2005). Thus, even aid that boosts economic growth is unlikely to have a large impact on the alleviation of extreme poverty unless it coincides with investments that decrease the remoteness of the very poor, such as improvements in infrastructure. Targeting resources to the places where the poorest live is thus very important if one wants to end extreme poverty.

Second, aid as it is currently allocated has the potential to increase inequality by funding the provision of goods and services in the parts of countries that hold the relatively wealthy. This is not likely to be a major concern to donors if they take a global interpersonal view of inequality, as places of relative wealth in low-income countries still hold many people that are at the low end of the global distribution of wealth (Milanovic, 2012). However, if donors view reducing inequalities within countries as an important standalone goal, then the current spatial allocation of foreign aid is problematic.

Finally, the current results reinforce prior work on urban bias in international development. An analysis of within-country inequality from a decade ago found "no overall evidence of declining differences in urban and rural living standards despite the (at least) rhetorical emphasis on rural development as the central pillar in the strategies of international organizations, development agencies, and non-governmental organizations" (Sahn & Stifel, 2003, p. 591). Perhaps one reason for a lack of convergence in living standards across urban and rural areas is that neither African governments nor donors are making serious investments in linking remote areas to urban centers. While this is partially conjecture, the findings of this paper support this explanation.

The present work has shown that aid does not skew towards the poorer parts of recipient countries, but it is silent as to *why* this is occurring. However, the robustness of the core finding across different levels of measurement of aid rules out some intuitive explanations for donor behavior. For example, one might believe that any apparent bias towards the rich is simply due to donors giving some aid to lots of places but giving more aid to places with cities. It is true that donors give more aid to places closer to cities (even after conditioning on cell-level population). However, there is no evidence that poorer places are more likely to be selected to receive aid. Rather, richer cells are both more likely to be selected to receive some aid and are also more likely to receive more aid once they are selected. Further, this pattern is not being driven by differences in the number of people that live in each cell. That aid does not flow to the poor within countries is a durable result.

Any explanation of why aid tends not to flow to the poor within countries will have to grapple with both the donor and recipient side of the relationship. If one assumes that the multilateral donors under study want to target aid towards poverty, then the present finding is a bit of a puzzle. One way of resolving the puzzle would be to show that donors prioritize recipient government preferences over targeting aid towards the poorest. Another way to resolve the puzzle would be to show that donors lack the detailed information necessary to push for pro-poor targeting.[42] It could also be the case that donors have calculated that the per dollar effect of aid on some development outcome is larger when spent on the relatively rich within poor countries, perhaps due to the fact that the relatively poor live in places that have worse local institutions or infrastructure.

At the recipient level, it is unclear whether aid avoids the poorest because of factors inherent to poverty itself or because of factors that simply covary with poverty. An example of the former would be if the poorest tended to receive less aid because their poverty means that they lack the political voice to demand their share of resources. An example of the latter would be if recipient governments are less likely to prioritize projects that are farther from urban or more industrial areas, either because they are more expensive or perhaps because the government has calculated that the return from investing in urban areas is larger.

6. Conclusion

This article demonstrated that aid does not flow to the poor within recipient countries. Rather, the weight of the evidence suggests that aid flows to richer areas. This finding is consistent with past work that aggregated aid into administrative regions and found that aid was either insensitive to measures of need or tended to flow to richer regions, though this work typically estimated only the partial relationship between poverty and aid (Zhang, 2004; Öhler & Nunnenkamp, 2014; Dreher et al., 2015; Briggs, 2017; Nunnenkamp et al., 2016a). The present work is unique in its continental coverage, its use of a spatial grid, its range of operationalizations of aid, its diverse measures of poverty, and its focus on describing if aid is flowing to the poor. Writing in 2014, Öhler & Nunnenkamp, (2014 p. 420) noted that "very limited evidence exists on the allocation of aid within recipient countries." A few years later, we now have a fairly consistent finding that aid from poverty-sensitive multilateral donors does not flow to the poor within recipient countries. One important goal of future work is to identify the causal forces explaining why aid is not reaching the poor.

Conflicts of interest

None.

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Appendix A

This appendix first presents additional statistical results, then shows some additional information about the population variables, then presents the code used to produce Fig. 1, then shows maps of the variables in the main analysis.

The first set of statistical robustness tests replicates Tables 2–4 but use a population control from GPW instead of HYDE. The second set of tests replicates Panel A of Table 2 and all of Table 4 but uses Conley (1999) standard errors instead of clustering at the recipient country level. The third set of tests uses a Poisson pseudo-maximum-likelihood method to replicate Table 4. The fourth set of robustness replicates Tables 2–4 but examines aid from the ADB and then WB separately. All of these result are presented in Tables 5–17.

I present the statistical robustness checks without additional commentary as their interpretation is straightforward: Across all of these robustness tests, there is not one statistically significant coefficient that suggests that aid is targeting poverty and every coefficient except one (Table 16, Panel A, IMR) points in the direction of pro-rich aid targeting.

[42] For a fuller description of these explanations, see Briggs (2017).

A.1. GPW population control

Table 5
Replication of Table 2 (Binary DV), using GPW.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Linear Probability Model					
	0.16***	−0.04***	−0.03***	−0.11	−0.37
	(0.05)	(0.01)	(0.01)	(0.12)	(0.36)
Num. cells	10,674	10,667	10,674	10,410	10,460
Num. recipients	53	53	53	53	52
Panel B: Logistic Model					
	1.21***	−0.87***	−0.25**	−1.62	−9.27**
	(0.42)	(0.14)	(0.10)	(1.43)	(4.32)
Num. cells	9331	9329	9331	9072	9124
Num. recipients	43	43	43	43	43

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is a binary indicator marking if a cell received any aid (1 = yes). All regressions include recipient fixed effects and control for logged population.
Panel A has robust standard errors clustered on recipients in parentheses. Panel B has bootstrapped standard errors based on 1000 replications and 43 country clusters in parentheses.
*** p <.01, ** p <.05, * p <.1.

Table 6
Replication of Table 3 (Count DV), using GPW.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Negative Binomial Model					
	0.81***	−0.65***	−0.28***	−1.44	−2.62
	(0.16)	(0.10)	(0.07)	(0.96)	(3.01)
Num. cells	9351	9349	9351	9092	9144
Num. recipients	45	45	45	45	45
Panel B: Poisson Model					
	0.75***	−0.84***	−0.27***	−1.43*	−3.67*
	(0.14)	(0.15)	(0.07)	(0.75)	(1.93)
Num. cells	9351	9349	9351	9092	9144
Num. recipients	45	45	45	45	45

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the count of the number of projects per cell. All regressions include recipient fixed effects and control for logged population.
Panel A has bootstrapped standard errors based on 1000 replications and 45 country clusters in parentheses. Panel B has robust standard errors clustered on recipients in parentheses.
*** p <.01, ** p <.05, * p <.1.

Table 7
Replication of Table 4 (Continuous DV), using GPW

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: OLS					
	0.95***	−0.18***	−0.15***	−0.93*	−3.02**
	(0.28)	(0.06)	(0.05)	(0.53)	(1.36)
Num. cells	10,674	10,667	10,674	10,410	10,460
Num. recipients	53	53	53	53	52
Panel B: OLS, sample restricted to cells that received aid					
	1.25***	−0.39**	−0.20*	−2.75**	−6.66*
	(0.32)	(0.16)	(0.10)	(1.06)	(3.58)
Num. cells	902	901	902	885	891
Num. recipients	45	45	45	45	45

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the natural log of the total (+0.1) value of aid per cell in millions of USD. All regressions include recipient fixed effects and control for logged population.
Panels A and B have robust standard errors clustered on recipients in parentheses.
*** p <.01, ** p <.05, * p <.1.

A.2. Conley standard errors

Table 8
Replication of Panel A in Table 2 (Binary DV), using Conley SEs.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Linear Probability Model, 200 km					
	0.19***	−0.06***	−0.05***	−0.11	−0.51**
	(0.02)	(0.01)	(0.01)	(0.07)	(0.24)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: Linear Probability Model, 1000 km					
	0.19***	−0.06***	−0.05***	−0.11	−0.51*
	(0.04)	(0.01)	(0.01)	(0.11)	(0.29)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is a binary indicator marking if a cell received any aid (1 = yes). All regressions include recipient fixed effects and control for logged population.
Panel A has standard errors adjusted for spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 200 km. Panel B has standard errors similar to Panel A, but the autocorrelation linearly decreases up to a cutoff of 1000 km.
*** p <.01, ** p <.05, * p <.1.

Table 9
Replication of Table 4, using Conley SEs at 200 km.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: OLS, 200 km cutoff					
	1.07***	−0.26***	−0.23***	−0.93***	−3.66***
	(0.14)	(0.03)	(0.04)	(0.32)	(0.99)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: OLS, restricted to cells that received aid, 200 km cutoff					
	1.09***	−0.32**	−0.20***	−2.91***	−6.67*
	(0.27)	(0.13)	(0.07)	(0.79)	(3.47)
Num. cells	900	900	900	883	889
Num. recipients	45	45	45	45	45

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the natural log of the total (+ 0.1) value of aid per cell in millions of USD. All regressions include recipient fixed effects and control for logged population.
Panel A and B have standard errors adjusted for spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 200 km.
*** p <.01, ** p <.05, * p <.1.

Table 10
Replication of Table 4, using Conley SEs at 1000 km.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: OLS, 1000 km cutoff					
	1.07***	−0.26***	−0.23***	−0.93**	−3.66***
	(0.20)	(0.05)	(0.04)	(0.45)	(1.15)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: OLS, restricted to cells that received aid, 1000 km cutoff					
	1.09***	−0.32**	−0.20**	−2.91***	−6.67**
	(0.27)	(0.15)	(0.08)	(0.83)	(3.09)
Num. cells	900	900	900	883	889
Num. recipients	45	45	45	45	45

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the natural log of the total (+0.1) value of aid per cell in millions of USD. All regressions include recipient fixed effects and control for logged population.
Panel A and B have standard errors adjusted for spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 1000 km.
*** p <.01, ** p <.05, * p <.1.

A.3. Poisson estimation of continuous DV

At the suggestion of one reviewer, I also report the results from Table 4 using a Poisson model (Silva et al., 2006; Silva et al., 2011).

Table 11
Replication of Table 4 (Dollar Value of Aid), using Poisson model.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
	1.12***	−0.50*	−0.78***	−1.30	−22.45***
	(0.15)	(0.28)	(0.14)	(3.95)	(4.95)
Num. cells	9279	9279	9279	9030	9081
Num. recipients	44	44	44	44	44

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the total value of aid per cell in millions of USD. All regressions include recipient fixed effects and control for logged population.
Robust standard errors clustered on recipients in parentheses.
*** p <.01, ** p <.05, * p <.1.

A.4. ADB Targeting

Table 12
Replication of Table 2 (Binary DV), only ADB aid.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Linear Probability Model					
	0.15***	−0.03***	−0.03***	−0.10	−0.16
	(0.05)	(0.01)	(0.01)	(0.09)	(0.33)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: Logistic Model					
	0.79*	−0.61***	−0.30**	−2.57	−8.00
	(0.42)	(0.20)	(0.14)	(2.20)	(6.64)
Num. cells	7577	7577	7577	7492	7543
Num. recipients	37	37	37	37	37

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is a binary indicator marking if a cell received any aid (1 = yes). All regressions include recipient fixed effects and control for logged population.
Panel A has robust standard errors clustered on recipients in parentheses. Panel B has bootstrapped standard errors based on 1000 replications and 37 country clusters in parentheses.
*** p <.01, ** p <.05, * p <.1.

Table 13
Replication of Table 3 (Count DV), only ADB aid.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Negative Binomial Model					
	0.79***	−0.45***	−0.32***	−2.53	−4.74
	(0.25)	(0.14)	(0.09)	(1.65)	(5.08)
Num. cells	7588	7588	7588	7503	7554
Num. recipients	39	39	39	39	39
Panel B: Poisson Model					
	0.47	−0.69***	−0.28***	−1.78**	−5.39**
	(0.34)	(0.18)	(0.08)	(0.74)	(2.72)
Num. cells	7588	7588	7588	7503	7554
Num. recipients	39	39	39	39	39

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the count of the number of projects per cell. All regressions include recipient fixed effects and control for logged population.
Panel A has bootstrapped standard errors based on 1000 replications and 39 country clusters in parentheses. Panel B has robust standard errors clustered on recipients in parentheses.
***p <.01, ** p <.05, * p <.1.

Table 14
Replication of Table 4 (Continuous DV), only ADB aid

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: OLS					
	0.65***	−0.14***	−0.15***	−0.84**	−2.09*
	(0.22)	(0.04)	(0.04)	(0.37)	(1.18)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: OLS, sample restricted to cells that received aid					
	1.06**	−0.23	−0.29**	−2.89	−11.46**
	(0.43)	(0.24)	(0.11)	(2.04)	(5.07)
Num. cells	497	497	497	491	496
Num. recipients	40	40	40	40	40

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the natural log of the total (+ 0.1) value of aid per cell in millions of USD. All regressions include recipient fixed effects and control for logged population.
Panels A and B have robust standard errors clustered on recipients in parentheses.
*** p <.01, ** p <.05, * p <.1.

A.5. WB Targeting

Table 15
Replication of Table 2 (Binary DV), only WB aid.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Linear Probability Model					
	0.11***	−0.04***	−0.03***	−0.06	−0.39
	(0.04)	(0.01)	(0.01)	(0.07)	(0.28)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: Logistic Model					
	0.78**	−0.69**	−0.28*	−2.48**	−9.68
	(0.38)	(0.30)	(0.15)	(1.19)	(6.09)
Num. cells	7500	7500	7500	7251	7302
Num. recipients	34	34	34	34	34

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is a binary indicator marking if a cell received any aid (1 = yes). All regressions include recipient fixed effects and control for logged population.
Panel A has robust standard errors clustered on recipients in parentheses. Panel B has bootstrapped standard errors based on 1000 replications and 34 country clusters in parentheses.
*** p <.01, ** p <.05, * p <.1.

Table 16
Replication of Table 3 (Count DV), only WB aid.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: Negative Binomial Model					
	0.56***	−0.50**	−0.23*	−0.79	2.46
	(0.17)	(0.25)	(0.12)	(1.05)	(4.85)
Num. cells	7,500	7,500	7,500	7,251	7,302
Num. recipients	34	34	34	34	34
Panel B: Poisson Model					
	0.55***	−0.60**	−0.25**	−2.28**	−5.39
	(0.14)	(0.24)	(0.12)	(0.96)	(3.83)
Num. cells	7,500	7,500	7,500	7,251	7,302
Num. recipients	34	34	34	34	34

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the count of the number of projects per cell. All regressions include recipient fixed effects and control for logged population.
Panel A has bootstrapped standard errors based on 1000 replications and 34 country clusters in parentheses. Panel B has robust standard errors clustered on recipients in parentheses.
*** p <.01, ** p <.05, * p <.1.

Table 17
Replication of Table 4 (Continuous DV), only WB aid.

	ln(light)	ln(time)	ln(dist.)	CMR	IMR
Panel A: OLS					
	0.65***	−0.16***	−0.13***	−0.34	−1.88*
	(0.21)	(0.05)	(0.04)	(0.32)	(1.07)
Num. cells	10,572	10,572	10,572	10,323	10,374
Num. recipients	52	52	52	52	52
Panel B: OLS, sample restricted to cells that received aid					
	0.46**	−0.20	−0.02	−1.89***	−4.23
	(0.21)	(0.13)	(0.10)	(0.63)	(3.80)
Num. cells	512	512	512	498	502
Num. recipients	34	34	34	34	34

Each cell comes from a unique regression and each coefficient is for the independent variable named in the column heading. In all cases the dependent variable is the natural log of the total (+ 0.1) value of aid per cell in millions of USD. All regressions include recipient fixed effects and control for logged population.
Panels A and B have robust standard errors clustered on recipients in parentheses.
*** p <.01, ** p <.05, * p <.1.

A.6. More on the population controls

I make use of two grid cell-level population counts in the analyses (HYDE in the main text and GPW in the appendix). The logs of these variables are highly correlated (r = 0.79), as is shown in the right pane of Fig. 3. The largest difference between the two variables is that the HYDE population estimates have many more small and zero values. This is probably due to the fact that the GPW models the data less and so is more prone to spreading sub-national population counts over cells that are unlikely to contain many people. The population variables are both positively skewed, and the left pane of Fig. 3 shows how taking the logs of the variables corrects for the skew. It also reveals that the logged variables contain a lot more cross-cell variation than is apparent in the map in Fig. 10 (Fig. 10 shades cells based on linear population rather than logged population) (see Figs. 4–9).

A.7. Simulation code

The following Stata code produces and analyzes the data shown in Fig. 1.

Fig. 4. Black cells received at least one aid project.

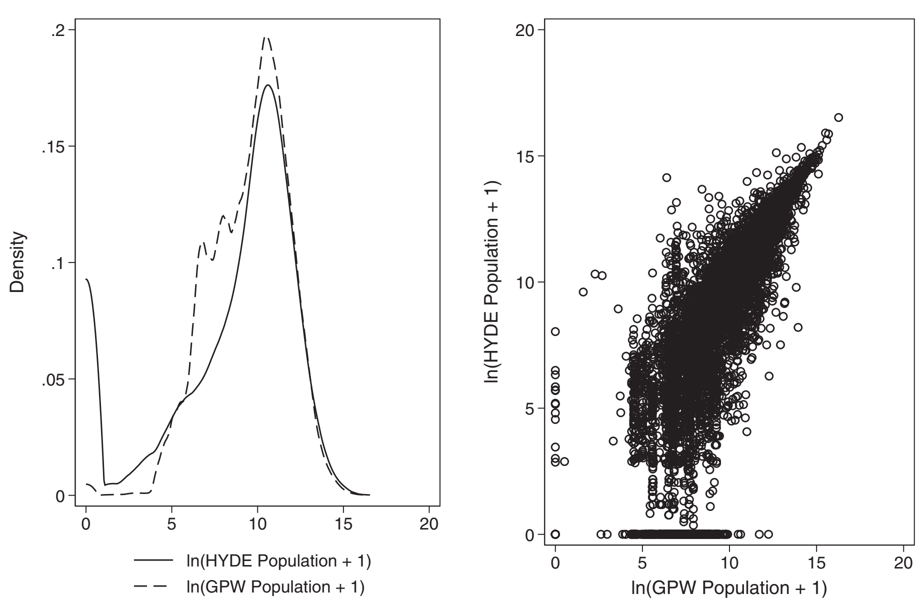

Fig. 3. Relationship between population variables.

Fig. 5. Darker cells have more light at night.

Fig. 6. Darker cells are more distant from the country's capital.

```
clear
* setup data, pay homage to the 90s
set seed 90210
set obs 500
* generate coethnic dummy
gen coethnic = runiformint(0, 1)
* generate income
gen income = rnormal(500, 250) if coethnic == 1
replace income = rnormal(2500, 250) if coethnic == 0
replace income = 0 if income < 0
* generate benefit payouts
gen benefit = income + rnormal(2000, 200) if coethnic
== 1
replace benefit = income/2 + rnormal(0, 200) if
coethnic == 0
replace benefit = 0 if benefit < 0
* plot results
```

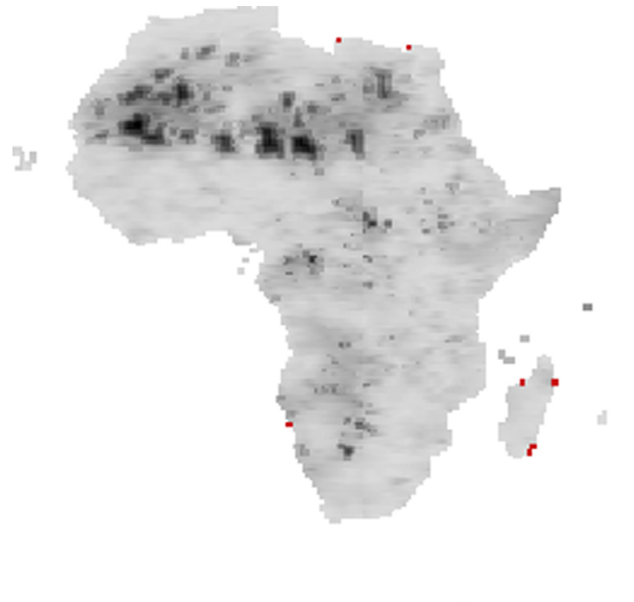

Fig. 7. Darker cells have longer travel times to major cities.

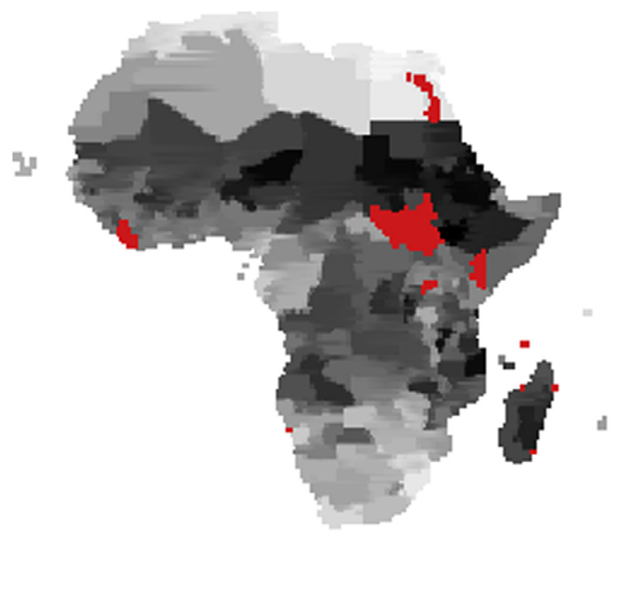

Fig. 8. Darker cells have higher estimated rates of child malnutrition.

```
* benefits go to poorer people, but not when control-
ling for ethnicity
separate benefit, by(coethnic)
scatter benefit0 benefit1 income || ///
lfit benefit0 income, lcolor(red) || ///
lfit benefit1 income, lcolor(red) || ///
lfit benefit income, lcolor(red) xtitle("Annual
Income")///
ytitle("Benefit payout")///
caption("Filled circles are co-ethnic with the
president")///
legend(off)
* regressions
* coefficient for income is negative in the first and
positive in the second
```

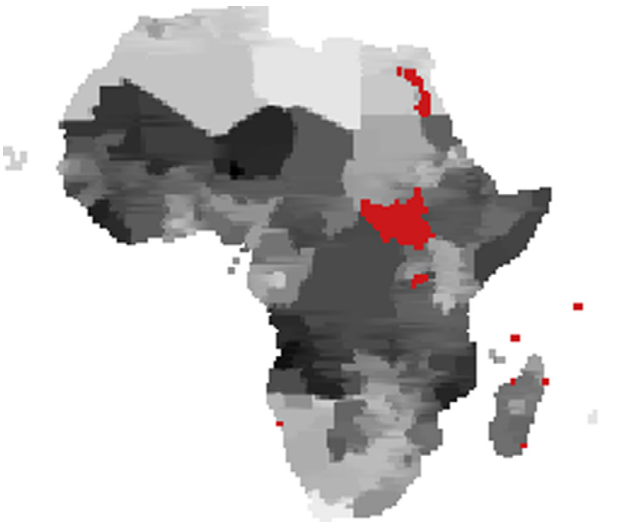

Fig. 9. Darker cells have higher estimated rates of infant mortality.

Fig. 10. Darker cells hold more people (HYDE).

```
reg benefit income, robust
reg benefit income coethnic, robust
```

A.8. Maps

The following maps present complete grid cell-level information for each variable in the main paper. In all cases, darker shades mean that the cell has more of the mapped variable and the highest value of each mapped variable is set to be completely black. The relationship from dark to light is always linear (not logged, as many variables are in the analysis). The minimum value per map is light, but it is not always white, as drawing the minimum-value cells in white would make the border of Africa unreadable in some maps. The light at night and population maps show especially strong skew, with very few dark values and very many light ones. This is why these variables (and others, as described in the text) are logged in the analysis. The child malnutrition and infant mortality variables show a good deal of variation in the maps and are not logged in the analysis. Only the latter four maps (time to major city, child malnutrition, infant mortality, HYDE population) have missing values, and these cells are colored red.

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