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Where Does the Money Go? Spatial Patterns in the Distribution of World Bank Foreign Aid Projects *

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Abstract

Does foreign aid target the poorest people in developing countries? We examine this question in the context of World Bank foreign aid projects at the local level in 50 countries worldwide. We combine geo-referenced data on World Bank foreign aid projects with remote-sensing data on nighttime light intensity, micro-geographic conditions, and household survey data to analyze the determinants of the spatial distribution of World Bank foreign aid projects. We employ an inner-outer buffer matching approach to identify treatment and control locations and estimate the effect of the determinants of sub-national foreign aid allocation. Our results suggest that the allocation of World Bank foreign aid projects is driven by a combination of distance-based measures, bio-geographic variables, remote-sensing data, and socio-economic variables based on household survey data. We find that locations with better living conditions, such as higher nighttime light intensity, better access to water and sanitation, or higher educational attainment, are generally more likely to receive aid projects. Our results further suggest that substantial heterogeneity exists in the factors that are relevant to the allocation of aid projects across sector classifications. This suggests that the allocation decisions on aid projects are driven rather by efficiency considerations than the needs of the local population. Additional robustness analyses further confirm our main findings.

Keywords: Foreign Aid; Geo-Referenced Aid Projects; The World Bank Group; Favoritism; Foreign Aid Allocation; Buffer Analysis; GIS Data; Spatial Analysis

JEL Classification Numbers: D61, D73, F35, R11, R58

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1 Introduction

The implementation of foreign aid projects in recipient countries is often tied to high expectations of improving the living conditions of the local population. Accordingly, scholars expect to find a positive relationship between the allocation of aid projects and economic outcomes, such as, for example, economic growth or increased night-time light intensity (Bitzer and Gören, 2024; Khomba and Trew, 2022; Dreher et al., 2021a; Civelli et al., 2018; Dreher and Lohmann, 2015). However, the actual allocation of aid projects can be subject to political, economic, and social considerations that do not necessarily align with the needs of the local population (Dreher et al., 2019; Oehler and Nunnenkamp, 2014; Briggs, 2018b).

This paper aims to shed light on the determinants of the sub-national spatial distribution of World Bank foreign aid projects across a large set of recipient countries and periods. The effectiveness of foreign aid in promoting economic development has been and still is a topic of intense debate in the literature on development economics. In addition to the question of whether foreign aid is effective in promoting economic development, the question of how foreign aid is allocated across countries and regions is of particular interest. The motives of donor countries and organizations in allocating foreign aid could go beyond the mere promotion of economic development and include, for example, humanitarian, political, or strategic considerations.

We combine geocoded household data from the Demographic and Health Surveys (DHS) with georeferenced data on World Bank projects and remote-sensing data on night-time light intensity, micro-geographic conditions, socio-economic, and bio-geographic variables to analyze the determinants of the spatial distribution of World Bank foreign aid projects. We propose an inner and outer buffer approach to identify treatment and control locations, which allows us to estimate the causal effect of the determinants of aid allocation. Specifically, we identify the relevant DHS locations within a 5 km radius of the project location as the treatment group, whose characteristics are expected to affect the likelihood of a project being implemented in a given location (inner buffer sample). As the control group, we consider DHS locations within a 5 km to 50 km radius of the project location (outer buffer observations). Observations outside the 50 km radius are not considered in the analysis, as they are not expected to affect the decision process of the World Bank of a project being implemented in a given location. To avoid reverse causality, we only consider DHS locations that have been surveyed no more than six years before the project implementation. The survey data are further matched with remote-sensing data to capture the geographic, climatic, and socio-economic living conditions in the respective areas. We provide a systematic and comprehensive empirical analysis of the determinants of foreign aid allocation across a large set of recipient countries, periods, and data sources.

We explore empirically which factors drive the spatial distribution of World Bank foreign aid projects. For this purpose, the scope of our analysis is gradually narrowed down to the most micro-level of analysis, the project location. The intention is to create a systematic and comprehensive empirical analysis of the determinants of and competing hypotheses on foreign aid allocation across a large set of recipient countries and periods. We gradually introduce different sets of variables to our empirical analysis, starting with distance-based measures, bio-geographic variables, remote-sensing data, and micro-level variables based on DHS household survey data.

As a starting point, we consider the role of distance-based measures, such as, for example, the distance from the survey location to the capital city, the nearest largest settlement (population $\geq 100{,}000$), or the nearest road, which are often used in the literature as proxies for the cost of delivering aid. Almost unanimously, our distance-based measures show a negative relationship with the likelihood of a project being implemented in a given location, indicating that, in line with efficiency considerations, the cost of delivering aid is a crucial factor in the allocation decision.

In addition, we consider bio-geographic variables, such as, for example, the elevation (in meters above sea level), fraction of crop or pasture land, or climate variables, which serve as proxies for the natural conditions in the respective areas. We find the likelihood of a project being implemented in a given location to be negatively related to the share of crop land, the share of pasture land, and the elevation, while precipitation (as an indicator of temperate regions) shows a positive relationship with the likelihood of a project being implemented in a given location.

Further, we include socio-economic factors, such as, for example, the night-time light intensity, which is often used as a proxy for economic activity, the incidence of violent conflicts, or the number of natural disasters as well as socio-economic variables, such as, for example, the population size, the number of ethno-linguistic groups, the birthplace of the incumbent political leader, and the malaria prevalence rate. We find that night-time light intensity is positively related to the likelihood of a project being implemented in a given location, while, for example, disaster-prone areas show a negative relationship. We also find that the likelihood of a project being implemented in a given location is positively related to the birthplace of the incumbent political leader, which is in line with the literature on political favoritism in aid allocation.

Moreover, we consider the role of the DHS survey location-based variables that visibly capture the standard of living of the affected population, such as, for example, the housing conditions, educational attainment of household members, the access to water and sanitation, the access to electricity, broadcast media or road infrastructure, or household demographics. This set of variables is particularly interesting, as it allows us to uncover heterogeneity at the project level, which is not possible with aggregated remote-sensing data that we have employed in the previous steps of our analysis. The results show that the likelihood of a project being implemented in a given location is predominantly positively related to the housing conditions, the educational attainment of household members, the access to water and sanitation, and the access to electricity, broadcast media or road infrastructure. In terms of heterogeneity, we find that the factors that are relevant to the allocation of aid projects differ across sector classifications, such as, for example, health, education, or infrastructure projects.

We conduct a series of robustness analyses that test the sensitivity of the regression model to the spatial and temporal matching approach and the selection of control variables. Here, we establish the robustness of our main results in three ways. First, the central results hold for different, broader definitions of the treatment group within larger inner buffer radii around the project location and similarly also for restricting the sample to only aid project locations with the two levels of highest precision in the geocoding process. Second, our main results are also not affected by alternative definitions of the temporal matching of the household survey data with the foreign aid project data. Third, the results remain consistent even when employing post-model selection estimators, such as OLS applied to control variables selected through LASSO-type methods (e.g., PDSLASSO).

This paper contributes to the literature on the sub-national allocation of foreign aid in several ways. The majority of empirical studies on foreign aid allocation consider sub-national aggregates of foreign aid, for example administrative divisions at varying levels, such as provinces or sub-regions (ADM1; e.g., Oehler and Nunnenkamp, 2014; Rosvold, 2020; Oehler et al., 2019), districts (ADM2; e.g., Dreher et al., 2019; Briggs, 2014; Gonschorek, 2021), or more fine-grained (ADM3 or higher; e.g., Eichenauer et al., 2020; Jablonski, 2014). Further studies that follow grid cell approaches can be seen as refinements of the administrative regions (Briggs, 2018b; Alpino and Hammersmark, 2020), but face similar issues of data aggregation that potentially blurs decisive localized factors in the allocation decision. In contrast, this present study is best located among the empirical studies that are detached from data aggregation to administrative regions and employ project-specific locations instead (Briggs, 2016; Dellmuth et al., 2021; Briggs, 2018a). Using project-specific locations gives the advantage of providing a realistic picture of the local conditions at the actual project site, in a radius that, for example, corresponds to walking distances. Therefore, this paper endeavors to analyze determinants of project aid location across 50 countries in a time period between 1992 and 2014 based on consistent, objective, and comparable indicators, measuring the geographic, climatic, and socio-economic living conditions in the respective areas. The project locations are matched with geocoded survey data that effectively measure the standard of living of the affected population and make it possible to uncover heterogeneity at the level of sub-national aggregates, such as districts or regions.

The remainder of the paper is organized as follows. Section 2 provides an outline of the relevant literature on sub-national allocation of foreign aid. Section 3 describes the data sources and the variables employed in our empirical analysis. Section 4 presents the empirical strategy. Section 5 discusses the main results and provides a series of robustness analyses. Finally, Section 6 concludes by summarizing the main findings and discussing their implications for future research.

2 Review of the Relevant Literature

The sub-national allocation of foreign aid has been the subject of a large and still growing body of literature, where primarily the role of corruption and aid capture has been addressed. Prior experience has led donor organizations to shift from program aid (that is, large-scale, multi-locational programs) to project aid (that is, a localized provision of aid at specific sites), thereby limiting recipient countries' leeway for spending resources and money while enabling more effective tracking of sub-national allocation (Briggs, 2014).

Especially in recent years, the resulting availability of rich geo-referenced data on aid flows to project locations (AidData, 2017b; Dreher et al., 2021b) has led to the emergence of a growing strand of literature analyzing the allocation of foreign aid resources at the sub-national level (e.g., Dreher et al., 2019; Briggs, 2014; Eichenauer et al., 2020). A significant share of these studies at the sub-national level focuses on aid allocation and various forms of favoritism in individual countries with large economic, cultural, and religious differences, at times adorned with anecdotal evidence or very country-specific idiosyncrasies. Only a few notable exceptions study larger samples of countries and thereby produce more generalizable results (see, for example, Oehler and Nunnenkamp, 2014; Briggs, 2018a,b, 2016; Oehler et al., 2019; Dreher et al., 2019; Marineau and Findley, 2020). Nevertheless, it is possible to identify some recurring influences discussed within the literature that are often interrelated to some extent. Most prominently, these include the needs orientation of aid allocation, the availability of basic infrastructure, as well as various forms of favoritism, such as political, ethnic, and religious favoritism. These factors serve as a guideline for a structured analysis of determinants of foreign aid allocation across countries and sectors.

We provide a brief overview of the literature on these factors in the following. A structured overview of the literature in terms of the spatial unit of analysis, the countries considered, the main topics addressed, and the data and aid measures used is provided in Table 1.

Needs Orientation of Aid Allocation. While research has identified several factors impacting the allocation of foreign aid, economic need is often considered the most relevant determinant. For example, the World Bank's International Development Association (IDA), a major institution involved in poverty reduction, states its main motive for development assistance as fighting poverty by providing help to the poorest countries and populations in the world (World Bank Group, 2021). Accordingly, a needs-based allocation of foreign aid raises the expectation that, on the sub-national level, aid flows should be observed to go to regions of relative poverty and highest need.

However, the empirical literature does not provide clear evidence in support of this rather idealistic view. In particular, needs orientation could show different patterns depending on the type of foreign aid project. For the case of disaster aid, Dellmuth et al. (2021) highlight the role of needs-related factors in the allocation of UN aid outflows. They find that UN aid flows to countries are higher when, for example, a higher number of people is affected, when the disaster is more severe, or when the state is fragile and thus unable to provide emergency aid itself. Similarly, Eichenauer et al. (2020) show that in the aftermath of the 2015 earthquake, Nepalese districts were allocated more aid projects and more funding if they suffered more immediate or aftershock damage. We account for these factors by including a set of disasters in the ADM2 region of the unit, as well as the incidence of violent conflict events within a 10 km radius from the DHS location in our regression models.

In contrast, these findings are less clear for regular aid projects. Here, studies come to mixed conclusions, speaking in favor of needs-based targeting or finding no evidence supporting this hypothesis.[1] Some studies even find evidence for the exact opposite of the needs-based targeting hypothesis. For example, some aid resources are not allocated to regions facing shortages of food or water (e.g., Briggs, 2018a, find such households to be up to 30–48 percent farther away from foreign aid projects). Other studies observe that the poorest regions

[1]For example, Rosvold (2020) finds that provinces with a higher human development index receive less aid, whereas Oehler and Nunnenkamp (2014) find no statistically significant association between the prevalence of malnutrition or infant mortality rate and the allocation of foreign aid funds.

or districts of a country by income distribution are less likely to receive aid (Zhang, 2004; Nunnenkamp et al., 2016). This pattern varies widely across regions, with positive, negative, or no significant associations between local levels of poverty and aid allocation being reported (Oehler et al., 2019).

In the literature, various explanations are brought forward to put results contradicting a needs-based targeting hypothesis into perspective. For example, Briggs (2018a) concludes that it is conceivable that aid flows to places of relative wealth within the country, as the provided resources can be employed more efficiently there. Similarly, Marineau and Findley (2020) hypothesize that more affluent sub-regions are chosen for foreign aid project implementations, so that donors are able to successfully complete their projects. Accordingly, aid donors face a trade-off between the recipients' needs and the project's effectiveness and might therefore decide to provide aid projects to regions where they expect the probability of success to be higher. We account for multiple dimensions of need by including in our regressions variables measuring the intensity of night-time lights, the prevalence of malaria, and socio-economic and demographic controls from household surveys of the local population.

Basic Infrastructure. The idea behind the basic infrastructure hypothesis is that foreign aid projects are more likely to be allocated to regions where they can be implemented more efficiently. For example, the availability of roads (Briggs, 2014; Nunnenkamp et al., 2016; Oehler et al., 2019), electricity, water, and sanitation (Gonschorek et al., 2018), public health services, or education (Alpino and Hammersmark, 2020) could be crucial for the successful implementation of foreign aid projects.

If aid allocation is indeed based on efficiency considerations, the presence of basic infrastructure could affect the allocation of foreign aid projects for merely practical reasons, as a consequence of the location's accessibility. In a study based on first-order administrative regions in African countries, Oehler et al. (2019) describe basic infrastructure and accessibility, measured by the travel time to the respective country's capital city, as a prerequisite for efficient aid provision. In their regressions, however, no significant association with the share of funding received is found, albeit possibly due to the coarse level of aggregation.

At the district level in India, Nunnenkamp et al. (2016) show that both the share of the population in poverty as well as lower paved road density cause the district to be less likely to receive aid in general, whereas access to electricity is found to increase this overall probability. They hypothesize that central and accessible regions are chosen by donors preferably, in an effort to enhance visibility and impress shareholders through successful project implementation. In addition, Briggs (2018b) observes a similar pattern at an even lower level of aggregation and shows that grid cells with a longer travel time to the nearest city or which are farther away from the capital city have a significantly lower probability of aid allocation, receive fewer total projects, and ultimately less aid in terms of value.

We account for these aforementioned factors by including a set of distance-based controls in our baseline regressions. We include distance measures of the DHS survey location to road, railroad, electricity grid, coast, river, nearest largest settlement, and capital city, as well as distance to UNESCO world heritage sites in our regressions, in order to account both for the accessibility, as well as the visibility of the project location.

If aid allocation was indeed aligned by the prospect of successful implementation, the presence of basic infrastructure (e.g., roads, electricity, and sanitation) could be expected to be sufficient for attracting foreign aid projects. However, Binetti and Steinwand (2019) speaks more in favor of a needs-based allocation and presents for Nepal a weak pattern of post-conflict regions with better infrastructure receiving less aid. Upon distinguishing aid projects by their sectors, Nunnenkamp et al. (2016) find the relevant indicators of need (such as, for example, paved road density for transport projects or child mortality rate for health projects) to mostly show the expected effects, that is, greater need is associated with a higher probability of aid allocation in the respective sector. As opposed, agricultural productivity and access to electricity, which at first glance would appear highly relevant for projects implemented in the sectors of agriculture and energy and mining, have no significant influence on aid allocation in these sectors. Gonschorek et al. (2018) finds a similarly mixed pattern for Indonesia, where districts with more access to water and safe water are less likely to receive grants. As opposed, districts with higher access to electricity receive more grants. Regarding access to paved roads, no significant impact is found.

The above mentioned, mixed findings illustrate that efficiency considerations in aid allocation cannot be explained solely by physical infrastructure. For example, Alpino and Hammersmark (2020) presume that the World Bank's strategy of aid allocation aims at the efficient provision of resources. In their grid-cell-based empirical analysis, they show that regions which are near to the location of historical Christian missions could be more suited for successful aid implementation because of higher levels of human and social capital in the population. As opposed, Song et al. (2020), in a study based on Indian districts, find districts with higher literacy rates to be less likely to receive education-related aid projects, a finding which could be read in favor of a needs-based aid targeting. In the spirit of Alpino and Hammersmark (2020), we include a distance measure to Christian missions in our regressions to account for the potential role of human and social capital in the allocation of foreign aid projects.

Political, Ethnic, and Religious Favoritism. A major concern of donors regarding the sub-national distribution of aid is political, religious, or ethnic favoritism. This would imply that, contrary to the main goal of foreign aid, resources are not allocated to the population in need but rather based on membership in ethnic (Briggs, 2014), political (Dreher et al., 2019; Oehler and Nunnenkamp, 2014), or religious groups (Rosvold, 2020). Political targeting and favoritism among ethnic groups have been confirmed empirically even in closely monitored projects (Briggs, 2014).

A recurring pattern observed across many studies is that aid is captured and redistributed by the governing party, often to the home city or district, or birthplace of the political leader (see, for example, Dreher et al., 2019; Gonschorek, 2021; Oehler and Nunnenkamp, 2014; Nunnenkamp et al., 2016). Such patterns of political favoritism have been observed in various countries, including Kenya (Briggs, 2014), Indonesia (Gonschorek, 2021), and India (Nunnenkamp et al., 2016), and have been confirmed for both World Bank and Chinese aid projects (Dreher et al., 2019; Oehler and Nunnenkamp, 2014). Consequently, other areas in the recipient countries have received rather low resource allocations, even if those are characterized by objectively higher need and hardship (Briggs, 2014). Oehler and Nunnenkamp (2014) illustrate that this pattern is especially prevalent for foreign aid projects earmarked for physical infrastructure investment, suggesting a heterogeneous

Table 1: Overview of the Literature on the Sub-National Allocation of Foreign Aid

Authors	Spatial Unit	Countries	Main Topic(s)	Needs orientation	Basic Infrastructure	Political Favoritism	Religious Favoritism	Ethnic Favoritism	Aid Data	Aid Measure	Period
Oehler and Nunnenkamp (2014)	Subregion	19 Sub-Saharan African countries, 8 Asian and Latin American Countries	Needs orientation, Political Favoritism	x		x			WorldBank AidData, AfDB	Number of Project Locations	2005–2011
Anaxagorou et al. (2020)	Province / ADM1	14 Sub-Saharan-African Countries***				x		x	Chinese Aid	Real aid commitments	2000–2012
Briggs (2012)	Province / ADM 1	Ghana	Political favoritism			x			National Electrification Project	Aid disbursements	1999-2000
Rosvold (2020)	Province / ADM1	Philippines	Needs orientation, Religious favoritism	x			x		WorldBank AidData	Aid Project Start Indicator	1996–2012
Zhang (2004)	Province / ADM1	China	Needs orientation, Commercial interests, Political favoritism	x		x			WorldBank AidData	Total aid received	1980–2001
Oehler et al. (2019)	Province / ADM1	58 Countries	Needs orientation, Basic infrastructure, Donor coordination	x	x				WorldBank AidData	Share of funding received by administrative unit	2005–2014
Dreher et al. (2019)	Province / ADM1	47 African Countries	Political favoritism, Needs orientation, Basic infrastructure	x	x	x			Chinese Aid	Aid commitments	2000–2011
Briggs (2014)	District / ADM2	Kenya	Ethno-political favoritism, Needs orientation, Basic infrastructure	x	x	x		x	Kenyan data set	District-level Resource Distribution	1989–1995
Dipendra (2020)	District / ADM2	Nepal	Needs orientation, Political Favoritism	x		x			NGO and INGO funding	Aid Value per 10,00 Residents	2011–2017
Marineau and Findley (2020)	District / ADM2	Uganda, Nigeria, DRC, Senegal, Malawi	Donor coordination, Needs orientation	x					Multi- and bilateral Aid Data from Aid Management Platform	Aid Commitments per Person	1978–2014
Marty et al. (2017)	District / ADM2	Malawi	Needs orientation, Ethno-political favoritism, Basic infrastructure	x	x	x	x		WorldBank AidData	Health-targeted aid, binary measure and disbursements per capita	2004–2011
Masaki (2018)	District / ADM2	Zambia	Political favoritism			x			WorldBank AidData, JICA, AfDB	Number of projects	1991–2010
Nunnenkamp et al. (2016)	District / ADM2	India	Needs orientation, Political favoritism, Commercial interests	x	x	x			WorldBank AidData	Amount of Project Aid	2006–2011
Song et al. (2020)	District / ADM2	India	Political favoritism		x	x			WorldBank AidData	Binary Indicator for District Primary Education Project (DPEP)	1994–2001
Binetti and Steinwand (2019)	District / ADM2	Nepal	Needs orientation, Basic infrastructure, Political favoritism	x	x	x			Government of Nepal's Aid Information Management System (AIMS)	Aid commitments	2008–2013
Gonschorek (2021)	District / ADM2	Indonesia	Political favoritism			x			Indonesian Database for Policy and Economic Research	Share of grants in district to total grants in province	2005–2013
Eichenauer et al. (2020)	Municipality / ADM3	Nepal	Needs orientation, Basic infrastructure, Ethno-political favoritism	x	x	x		x	WorldBank AidData	Number of Projects, Financial Amount (both proposed and funded)	2015
Jablonski (2014)	Municipality / ADM3	Kenya	Ethno-political favoritism			x		x	WorldBank AidData, AfDB	Project total committed value	1992–2010
Briggs (2018b)	Grid Cell	African continent	Needs orientation, Basic infrastructure	x	x				WorldBank and ADB data	Binary Measure, Project Count, Total Dollars	2009–2010*
Alpino and Hammersmark (2020)	Grid Cell	African continent	Ethno-political favoritism, Basic infrastructure		x	x	x		WorldBank AidData	Indicator: "Ever received aid"	1995–2014
Briggs (2016)	Project Location	17 African Countries**	Needs orientation	x					WorldBank AidData	Aid Value, Number of Projects	2009–2010*
Dellmuth et al. (2021)	Project Location	Recipient Countries of UN Disaster Aid	Needs orientation, Commercial interests	x					UN disaster aid (CERF; OCHA; CBPF)	Aid disbursements	2006–2017
Briggs (2018a)	Project Location	Nigeria, Senegal, Uganda	Needs orientation	x					WorldBank AidData	Distance from nearest aid project	1988–2014
Gonschorek et al. (2018)	District / ADM2	Indonesia	Needs orientation, Political alignment	x	x	x			Indonesian Database for Policy and Economic Research		
Dreher et al. (2021a)	Province / ADM1 and District / ADM2	47 African Countries	Political Favoritism			x			Chinese Aid	Binary Measure (First Stage Regression)	2001–2012

* Projects approved in this time period

** Benin, DRC, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Malawi, Mali, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sierra Leone, Tanzania, Zambia

*** Angola, Botswana, Cameroon, Cape Verde, Ghana, Guinea-Bissau, Lesotho, Malawi, Mozambique, Sierra Leone, South Africa, Tanzania, Togo, Zambia effect by sector classification. Political favoritism has further been observed to coincide with political motives, such as the need to strengthen either the incumbent party's position in the upcoming elections (Gonschorek et al., 2018; Jablonski, 2014; Briggs, 2012) or to influence voting behavior in areas of opposition (Masaki, 2018). To account for the potential role of political favoritism in the allocation of foreign aid projects, we include a distance measure to the capital city, as well as a dummy variable indicating whether the project location is the birthplace of the political leader in our regressions.

A different strand of literature focuses on the role of religious and ethnic favoritism in the allocation of foreign aid projects. For example, evidence of an increased likelihood of aid allocation to districts hosting major ethnic groups has been reported (Marty et al., 2017; Song et al., 2020). In particular, districts with higher population shares of scheduled castes and tribes in India are found to be successful in attracting more World Bank foreign aid projects (Song et al., 2020), whereas Marty et al. (2017) report mixed evidence for Malawi, where the president's ethnic group receives less aid per capita, but his birth district is allocated higher amounts of foreign aid funds. Regarding religious favoritism, Rosvold (2020) shows that in the Philippines, provinces with higher shares of Christian settlement areas have received significantly more aid, especially in reaction to the incidence of armed conflicts. These dimensions of favoritism affecting the allocation of foreign aid projects are accounted for in our regressions by including a measure of the number of ethno-linguistic groups in the region, as well as a distance measure to Catholic and Protestant missions.

3 Data and Variables

Geocoded foreign aid data. The main dependent variable of this study is taken from the AidData international research lab hosted at the William and Mary's Global, that provides geocoded data of World Bank foreign aid projects (AidData, 2017b). This data set comprises of foreign aid projects implemented as part of the World Bank IBRD/IDA lending lines. In a time period between 1995 and 2014, commitments and disbursements for a total of $5,684$ projects across $61,243$ locations are provided, along with the geographic coordinates (latitude and longitude) of the respective project locations. As the geographical exactness of the project locations is crucial for the analysis, we rely on an assessment of the geographical precision of the project locations. As suggested by the International Aid Transparency Initiative's (IATI), AidData distinguishes between different location classes, based on the size of the targeted unit of the projects. The precision codes for the exactness of geographical locations list administrative regions, populated places, structures, and other topographical features as descriptions of the project location.[2] This information is complemented with an assessment of the accuracy of the geographical coordinates by AidData, that is, whether the location is exact or approximate (AidData, 2017a). AidData then combines these specifications into an indicator similar to the IATI's geographical precision scale. This precision code indicator ranges from 1 (coordinates correspond to an exact location)

[2]See the description at IATI's website at https://iatistandard.org/en/iati-standard/203/codelists/geographiclocationclass/.

to 8 (location can only be related to an independent political entity).[3] For our analysis, we rely on projects or project locations with a precision code of up to 3, that is, locations *near*, *in the area of*, or up to 25 km away from the given coordinates. This reduces the number of projects, as well as project locations employed in the study, to $2,644$ projects and $44,447$ project locations, respectively.[4]

The data on World Bank foreign aid projects and project locations can be broken down further by the individual and project-specific aid sectors, in order to account for different allocation patterns by project type. The sector coding of the projects is based on the OECD's Development Assistance Committee (DAC) sector classification and allows for a categorization of the projects into a plethora of sectors and sub-sectors. In our sample, we rely on the nine main sector codings of either *Education*, *Health*, *Water Supply and Sanitation*, *Government and Civil Society*, *Other Social Infrastructure*, *Economic Infrastructure and Services*, *Production Sectors*, *Industry, Mining and Construction*, as well as *Multi-Sector/Cross-Cutting* projects.

For our analysis, we employ the coordinates and the timing of the project implementation (as given by the reported starting date) to match the projects with the household survey data and construct our definition of treated and control DHS locations. The location of the project is taken as the center of the project area and therefore constitutes the reference point for the buffer approach, which we employ to construct our spatial units of analysis.

Demographic and Health Survey (DHS) data. To define *treated* and *control* locations, and as a measure of local living conditions, we rely on geo-referenced survey data from the DHS program. The detailed survey data account for the localized living conditions that might be relevant to the World Bank's aid allocation decisions. The DHS program consists of individual- and household-level data, which have been collected across multiple phases and waves since 1984. While the DHS program's primary focus is on health-related indicators with varying questionnaire modules, the data sets also include core questions on household demographics, education, and nutrition, among others.

The country-level data sets of the DHS program are provided as repeated cross-sections, with a varying set of countries participating in each wave at irregular intervals. Within each country and wave, a number of geographical locations (so-called DHS clusters) are surveyed, with the latitude and longitude of the locality being recorded with added random displacement of the coordinates to ensure the anonymity of individuals. For example, urban clusters are displaced by up to 2 km, while rural clusters are displaced by up to 5 km from the reported location. An additional 1% of the rural clusters are displaced by up to 10 km.[5] For the sample of this study, we rely on those DHS data sets that are complemented with GPS coordinates from the years 1992 to 2014, as we are restricted by the availability of both the night-time light emissions and the foreign aid data.[6]

[3] The precision codes are described in greater detail at IATI's website at https://iatistandard.org/en/iati-standard/203/codelists/geographicalprecision/.

[4] Figure B5 in the appendix provides a graphical representation of the distribution of the foreign aid projects across the countries and years.

[5] See the technical description provided on the DHS program's website at https://dhsprogram.com/Methodology/GPS-Data.cfm.

[6] While the DHS program dates back to 1984, the complementary GPS data sets, which provide specific information on the DHS

We use the DHS household data to obtain, for each DHS cluster, the population shares having certain characteristics related to the local living conditions. The emphasis is on finding measures of localized basic need, in order to evaluate the needs-orientation hypothesis at more granular levels. The survey questionnaires include various sections aimed at different household members (for example, women, men, or children living in the household), as well as, where applicable, the household as a whole. The latter is the most comprehensive section and includes detailed information on household demographics, education, material resources, and wealth, mostly based on household possessions (Howe et al., 2009). For each DHS cluster, a varying number of households, again comprising multiple individuals, exist. Due to the availability of individual and household weights, the data can be aggregated to be representative of the respective DHS cluster population. Note that upon aggregation, household-level variables are interpreted as *percentages of households* in the respective DHS cluster, while individual-level variables are interpreted as *percentages of individuals* in the respective DHS cluster.

We derive five sets of variables from the DHS data, which are thought to reflect the basic needs and living conditions of the local population. First, this includes the main building material used for the dwelling's floor, which is thought to reflect the relative wealth of the household (Rutstein and Johnson, 2004). We rely on the broad categories that are consistently used across countries and waves, that is, a distinction between natural (e.g., earth, sand, or clay), rudimentary (e.g., wood planks, mats), and processed (e.g., tiles, carpet, or vinyl) floor material. We argue that floor material is an objective criterion that can easily be assessed by the interviewer, thus providing a valid proxy for household wealth and economic need. Second, as an addition, the availability of basic resources and infrastructure to the household is utilized. This includes the share of households with access to electricity, to radio broadcasting (as measured by possession of a radio device), and basic mobility, measured by the possession of a bicycle. While, similar to the floor material, these three items reflect basic needs of the households, they at the same time allow for drawing conclusions about the households' access to basic infrastructure in the survey area. Third, and with a similar intuition, the availability of basic sanitation to the household is employed. The access to piped water as a main water source, as well as the presence of a flush toilet, provides an assessment of the hygienic conditions and household wealth. Consistent with needs-based targeting, the absence of improved household sanitation has been shown to be correlated with a higher probability of foreign aid allocation (Gonschorek et al., 2018). In general, higher quality access to water and sanitation is associated with a lower incidence of bacterial and parasitic infections and therefore improved health outcomes (Tate et al., 2012). Fourth, the educational level of the individuals is recorded, where it is distinguished between no education, primary, secondary, or higher attainment. While the level of education in the population reflects the local level of development, it similarly accounts for the availability of a trained labor force in the area of the survey location. Fifth and last, demographics, that is, the average number of members per household, the mean age of the survey population, and the share of households with a male household head, are included. The latter factor is used to examine whether the World Bank projects are more likely to be allocated to areas where the household is not male-headed (i.e., female-headed), to facilitate gender

clusters (or survey locations), have been increasingly available only since 1988.

equality and empowerment.[7]

Distance indicators. To account for the broad location of the DHS clusters within the respective country, distance-based variables are constructed. The overall location within the country is measured by the distance to the country's capital city. Capital cities have been observed to receive higher than normal funding by the World Bank on average, possibly due to higher visibility and better infrastructural conditions (Oehler et al., 2019). In addition, proximity to the capital city might also reflect the general level of development and political stability in the area. The same hypothesis holds for the remoteness of the cluster, which is measured by the distance to the nearest largest settlement (i.e., with a population size $\geq 100,000$ people). Access to transport networks or basic infrastructure is measured by the distance to the closest river, railroad, road, or power transmission line. With a similar intuition, the distance to the country's border or coastline is included. These variables could affect the probability of foreign aid allocation, especially across different sectors, as has been shown by Nunnenkamp et al. (2016). The distance to historical Christian missions is included to account for possible differences in human and social capital (Alpino and Hammersmark, 2020). Lastly, the distance to UNESCO world cultural heritage sites is employed to account for the consideration of visibility and scenic beauty in the foreign aid allocation decision (comparable to the *planting of flags* described by Nunnenkamp et al., 2016).

Bio-geographic and climatic indicators. In addition, we control for the general topographic and climatic conditions in the area of the DHS clusters using a set of four types of bio-geographic controls. First, this includes the absolute values of the latitude and longitude of the DHS cluster location. We further incorporate several raster data sources, aligning them with our data through the following approach: When required, we aggregate the raster values to a 0.1 decimal degree reference grid. Subsequently, we map the corresponding raster value at the geographic coordinates of the DHS cluster and the survey date to the respective DHS cluster location.

Our second source, the mean and standard deviation, respectively, of terrain elevation (in meters above sea level) in the area of the survey location, are included in order to account for the area's terrain ruggedness and accessibility, which might affect aid allocation decisions. We rely on the Shuttle Radar Topography Mission (SRTM) data set, which provides a global coverage of terrain elevation at a resolution of 3 arc-seconds. We aggregate the raster data to the 0.1 decimal degree reference grid and assign the contemporaneous raster value at the geographic coordinates of the DHS cluster to the respective cluster.

Third, as a measurement of land surface characteristics affecting land use, for example for agricultural purposes, we include the share of crop as well as pasture land. We hypothesize that a larger agricultural sector could affect the institutional and employment structures (Easterly and Levine, 2003) and thereby also sectoral aid allocation patterns. For this purpose, we rely on the extent and global distribution of cropland and pasture land in the year 2000, as provided by Ramankutty et al. (2008). The raster data sets are available at a resolution of five arc-minutes (approximately 10 km $\times$ 10 km at the equator). Again, we aggregate the raster data to

[7] This is an open hypothesis, as we do not have a clear theoretical prediction on the direction of the effect.

the 0.1 decimal degree reference grid and assign the resulting raster value to the geographic coordinates of the DHS cluster.

Fourth, to control for variation in meteorological and climatic conditions which could affect basic needs in the general population, we include the mean ground-level temperature, the average precipitation, and the 12-month Standardized Precipitation Evapotranspiration Index (SPEI), which measures drought episodes. The SPEI is a multi-scalar drought index that combines precipitation and temperature data to assess the severity of drought episodes (Vicente-Serrano et al., 2010b,a). The SPEI has a mean of 0 and a standard deviation of 1, where negative values indicate drought episodes and positive values indicate wet episodes. It has been shown that variability in precipitation as well as drought episodes affect rural livelihoods through income shocks (Kazianga and Udry, 2006), which in turn could affect needs-oriented foreign aid allocation. The temperature and precipitation rasters are available at a resolution of 0.5 decimal degrees as part of the Climatic Research Unit Time Series (CRU TS Version 4.05) data set (Harris et al., 2020). Similarly, the SPEI values are also available at a resolution of 0.5 decimal degrees as part of the Global SPEI database.[8] We keep the raster data at the original resolution as the data has much lower spatial resolution than our reference grid. We then assign the contemporaneous raster value to the geographic coordinates of the DHS cluster.

Additional geo-spatial indicators: socio-economic and health factors. We further include a set of seven socio-economic and health-related factors that are thought to affect the allocation of foreign aid projects.

First, as a local indicator of economic activity, we consider a measure of night-time light intensity. This variable has frequently been employed as a proxy for economic activity and development (Henderson et al., 2012; Bruederle and Hodler, 2018). We combine data from two series of satellite imagery to obtain night-time light emissions for the complete sample period (NOAA-NGDC, 2015; Ghosh et al., 2021).[9] These yearly raster data sets are available at different resolutions of 30 arc-seconds (1992 to 2013) and 15 arc-seconds grids (from 2014 onwards). We construct a coherent and inter-temporally comparable time series dataset of global night-time light emissions at a 30 arc-seconds resolution for the period 1992 to 2019. The resulting raster data takes values between 0 and 63, which is proportional to radiance values of satellite-detected night-time light emissions. We then take the sum of pixel-level brightness values within the 0.1 decimal degree reference grid cell and assign the contemporaneous raster value to the geographic coordinates of the DHS location.

Second, we account for the population size in the area of the DHS survey location. The population raster data is taken from the Gridded Population of the World (GPW) data set (CIESIN, 2017). The original raw data is available at a resolution of 5 arc-minutes and only at five-year intervals. We interpolate the population data for the missing years using a linear interpolation method. We then aggregate the raster data to the 0.1 decimal degree reference grid and assign the contemporaneous raster value to the geographic coordinates of the DHS cluster.

Third, the incidence of violent conflict might deter donors from allocating aid to certain areas. Accordingly,

[8] See https://spei.csic.es/database.html for more information on data construction and sources.

[9] See the appendix, Section D, for additional details on sources and data construction.

we include the number of conflict events within a 10 km radius of the survey location in the year of the survey. This information is taken from the UCDP/PRIO Georeferenced Event Dataset (UCDP GED) (Sundberg and Melander, 2013).

Fourth, as shown in Hodler and Knight (2011), ethnic fractionalization is detrimental to aid effectiveness, as it might lead to a misallocation of resources. We therefore include the number of ethno-linguistic groups in the area of the survey location as a proxy for ethnic fragmentation. In particular, we use the spatial distribution of ethno-linguistic groups as provided by the World Language Mapping System (Global Mapping International, 2016) to construct the number of ethno-linguistic groups within our 0.1 decimal degree reference grid. We then assign this value to the DHS survey location.

Fifth, to account for political considerations in the allocation of foreign aid (Oehler and Nunnenkamp, 2014; Dreher et al., 2019), we include the birthplace of the incumbent political leader. The data on the birthplaces of the political leaders is taken from The Political Leader's Affiliation Database (PLAD) compiled by Dreher et al. (2020).[10] The data contains information on the birthplaces of political leaders in 177 countries from 1989 to 2023. Birthplaces of the political leaders are geocoded and matched to the sub-national administrative regions 2 (ADM2) level of the DHS survey locations. The variable is an indicator that takes the value of 1 if the DHS survey location is located in the administrative region of the birthplace of the incumbent political leader and zero otherwise.

Sixth, the occurrence of natural disasters has reportedly affected the allocation of foreign aid (Dellmuth et al., 2021; Eichenauer et al., 2020), we take the count measure of natural disasters in the ADM2 region of the survey location in the year of the survey from the Geocoded Disasters data set (Rosvold and Buhaug, 2021b,a).

Seventh and last, we include the average number of malaria cases per $1,000$ population in the area of the survey location as a proxy for the health needs of the population and the disease environment. This disease environment might also influence the World Bank decision process on the allocation of foreign aid projects due to the potential health risks for the staff.[11] This information is taken from the Malaria Atlas Project, which provides a global coverage of malaria prevalence as a raster data set at a resolution of 5 km (Hay and Snow, 2006). Again, we aggregate the raster data to the 0.1 decimal degree reference grid and assign the contemporaneous raster value to the respective DHS survey location.

4 Empirical Approach

4.1 Buffer Analysis with Geocoded Microdata

In this section, we formalize the identification strategy for estimating the effect of localized geography and living conditions on the probability of foreign aid allocation. A standard approach to estimate the effect of

[10] The data can be accessed at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/YUS575.

[11] Unfortunately, we cannot completely differentiate between the health-needs orientation of the local population and the World Bank staff health-security argument.

local conditions on aid allocation is to use an inner and outer buffer approach around the aid project location to define treated and control areas. We assume that the World Bank's decision on where to allocate aid projects incorporates the characteristics of the relevant target population prior to the project implementation. We retrieve the relevant characteristics of the target population from the DHS data.

We combine the geographic information provided for the World Bank foreign aid project locations with rich household-level survey data obtained from the DHS program based on spatial proximity. This approach has the advantage of not being bound to administrative units (or pseudo-administrative units, such as grid cells) and allows for a very localized and detailed measurement of the living conditions and socio-demographics in the project implementation or *treated areas*. However, employing exact project locations as the unit of investigation introduces the challenge of initially not being able to observe any *non-treated areas* in the original sample; that is, we cannot directly infer which areas were decided upon not to receive any aid allocation.

We resolve this issue by implementing a two-step buffer approach in order to select a treatment and a control group from the DHS survey data, based on the timing and location of the World Bank foreign aid projects. We hypothesize that the World Bank's decision on where to allocate aid projects incorporates the characteristics of this relevant target population prior to the project implementation and that these individuals are the ones who are later expected to benefit from the aid project allocation. We observe a sample of DHS survey locations i at different points in time s with geocoded locations $\theta_i = (x_i, y_i)$, where x_i and y_i are the longitude and latitude coordinates of the DHS survey location. Geocoded foreign aid projects a are located in space at point locations $\theta_a = (x_a, y_a)$. Thus, DHS survey locations differ in their distance to the aid project locations, defined as $Dist_{ia} = d(\theta_i, \theta_a)$. We define targeted areas as those DHS survey locations i that are located within a certain distance d_t for all units in the subsample $\mathscr{D}_t \equiv \{i : Dist_{ia} \leq d_t\}$. Hence, $\mathscr{D}_t$ contains DHS units that are regarded as targeted locations for foreign aid projects. Similarly, we define non-targeted areas as those DHS survey locations i that are located outside the distance d_t but within a certain maximum distance $\bar{d}$ as $\mathscr{D}_c \equiv \{i : d_t < Dist_{ia} \leq \bar{d}\}$.

Figure B1 illustrates the buffer approach for the identification of treated and control areas. The figure shows the distribution of DHS survey locations in the vicinity of a foreign aid project location. The inner buffer is defined as a radius of $d_t = 5$ km around the aid project location, while the outer buffer is defined as a radius of $\bar{d} = 50$ km around the aid project location.[12] DHS survey locations that are located within the inner buffer are considered as treated, while DHS survey locations that are located within the outer buffer are considered as control units. Regarding the latter, these survey locations can still be considered as fairly proximate, so that they could have plausibly served as an alternative project location to the World Bank, but they are sufficiently far away from the project location that they are not likely to draw benefits from its implementation.

It is important to note that the inner buffer approach results in one-to-many relationships between foreign aid projects and DHS survey locations, as one DHS survey location can be located within the inner buffer of many other foreign aid projects. We prefer this approach over the one-to-one relationship, as it allows us to exploit the full richness of the DHS survey data and to estimate the effect of localized geography on the probability

[12] We test for alternative distance ranges as part of the robustness analyses.

of foreign aid allocation with a higher degree of precision. Nevertheless, we account for the one-to-many relationships in the econometric analysis by clustering standard errors at the DHS survey level to account for spatial correlation between DHS survey locations across different foreign aid project locations.

To avoid reverse causality, we only consider DHS survey locations that have been surveyed before but no more than 6 years prior to the project implementation, i.e., $\Delta T_{ai} = date_a - date_i \leq 6$, where $date_a$ is the implementation date of the foreign aid project and $date_i$ is the survey date of the DHS survey location. This time restriction ensures that the DHS survey locations are observed before the implementation of the foreign aid project, so that the observed characteristics of the target population are not influenced by the project implementation.[13]

Furthermore, we ensure that DHS survey locations classified as part of the control group have not been previously affected by any World Bank foreign aid projects. However, the possibility of future *treatment* is deemed acceptable. This precaution is crucial to prevent contamination of the control group by prior aid interventions, which might have altered the living conditions of the target population and potentially introduced bias into the estimation of the effect of localized geography on the likelihood of foreign aid allocation.

4.2 Econometric Specification

We employ the spatial distribution of foreign aid projects to assess how localized geography and living conditions influence the probability of aid allocation, using the following regression framework:

$$AID_{i(a)s} = D'_{i(a)s}\Omega + B'_{i(a)s}\Gamma + S'_{i(a)s}\Delta + H'_{i(a)s}\Sigma + \alpha + \lambda_{i(r)} + \lambda_{i(s)} + \varepsilon_{i(a)s}, \tag{1}$$

where a indexes foreign aid projects, i DHS survey locations, s time, $i(r)$ the country region r in which the DHS survey i is located, and $i(s)$ the survey year s in which the DHS survey i was conducted. The notation $i(a)$ refers to the DHS survey location i that is linked to the foreign aid project a. The dependent variable $AID_{i(a)s}$ is a dichotomous variable that takes on a value of 100 if a relevant DHS survey location i lies in the inner buffer $d_t = 5$ km of World Bank foreign aid project a, and zero otherwise if i is situated in the outer buffer region, so that the distance to the project location is between $d_t = 5$ km and $\bar{d} = 50$ km.[14] Again, we do not consider cases where the distance is greater than $\bar{d} = 50$ km, as these locations are considered irrelevant for the aid allocation decision and to function as a control group.

The control variables are constructed separately for the inner and outer buffer samples based on the distance criteria outlined earlier. The vector $D'_{i(a)s}$ includes distance-based indicators such as proximity of the DHS location to the capital city, major roads, and national borders. The vector $B'_{i(a)s}$ captures bio-geographic characteristics, including elevation and land use types. Socio-economic factors, such as population density, night-time light intensity, conflict incidence, and malaria prevalence, are represented in the vector $S'_{i(a)s}$. Household-level

[13] We test for alternative time ranges as part of the robustness analyses.

[14] We use the definition $AID_{i(a)s} = 100$ to indicate the presence of a DHS location in the inner buffer, and $AID_{i(a)s} = 0$ otherwise to facilitate the interpretation of the regression results in terms of percentage point changes.

attributes, including housing quality, education levels, and wealth indices from DHS survey i, are summarized in the vector $H'_{i(a)s}$. The term α represents a constant, while $\lambda_{i(r)}$ and $\lambda_{i(s)}$ denote fixed effects for DHS country×region and survey year, respectively. The error term $\varepsilon_{i(a)s}$ accounts for unobserved idiosyncratic variation. To address spatial correlation, standard errors are clustered at the DHS location level.

It is important to note that this specification controls for a wide range of potential confounding factors that could influence the spatial distribution of foreign aid projects and the living conditions of the target population, respectively. The inclusion of ADM1 region, within-country, fixed effects $\lambda_{i(r)}$ accounts for any time-invariant unobserved heterogeneity of social and economic conditions that might influence the socio-economic and demographic characteristics of the target population. This is particularly important, as the World Bank's allocation of foreign aid projects might be influenced by the level of economic development, political stability, or other factors that vary across regions within a country. The inclusion of time (i.e., survey year) fixed effects $\lambda_{i(s)}$ around the survey date controls for any time-varying factors that might influence the allocation of foreign aid projects. Again, the World Bank's allocation of foreign aid projects could be influenced by the occurrence of natural disasters, political events, or other exogenous shocks. Proper control of these unobserved factors is therefore crucial to ensure that the estimated effect of localized geography on the probability of foreign aid allocation is not biased by any of these omitted factors.

4.3 Descriptive Statistics

Table C1 provides an overview of the descriptive statistics for the primary variables utilized in the empirical analysis. The statistics are presented for the overall sample of foreign aid projects and DHS survey locations, as well as separately for the inner and outer buffer samples. The final estimation sample includes 281,996 DHS survey locations within the inner and outer buffers of foreign aid projects. Approximately 9.19 percent (25,923 observations) are located in the inner buffer, while 90.81 percent (256,073 observations) are in the outer buffer.[15]

The inner and outer buffer samples exhibit distinct characteristics. The inner buffer sample shows higher levels of secondary and tertiary education, greater wealth, and improved housing conditions compared to the outer buffer sample. Additionally, the inner buffer sample is closer to capital cities, larger settlements, railroads, and roads. Economic activity, as measured by night-time light intensity, and population size are also higher in the inner buffer sample.

Figure B2 illustrates the distribution of the time difference between the implementation dates of foreign aid projects and the survey dates of DHS locations. Among the 900,872 potential DHS and foreign aid project links, 66.79 percent of DHS survey locations were surveyed within six years prior to the implementation of the foreign aid project (see Table C2). In the final estimation sample, 22.60 percent (63,720 observations) were surveyed

[15]The average distance between DHS survey locations and foreign aid projects is 29.11 km (Std. Dev. = 14.37 km), ranging from 0.0033 km to 50.00 km. For the inner buffer, the average distance is 2.85 km (Std. Dev. = 1.29 km), with a range of 0.0033 km to 5.00 km. For the outer buffer, the average distance is 31.77 km (Std. Dev. = 12.27 km), ranging from 5.00 km to 50.00 km.

in the same year as the project implementation, while 17.45 percent (49,195 observations) were surveyed one year prior, 16.17 percent (45,611 observations) two years prior, 14.71 percent (41,483 observations) three years prior, 10.98 percent (30,963 observations) four years prior, 8.40 percent (23,674 observations) five years prior, and 9.70 percent (27,350 observations) six years prior.

Figures B3 and B4 depict the distribution of DHS and foreign aid links for the inner and outer buffer samples, respectively. As expected, the outer buffer sample contains a higher number of DHS and foreign aid links due to its larger size. Notably, DHS locations in the outer buffer can be linked to multiple foreign aid project locations, serving as potential control observations for the analysis. Although these DHS locations are not treated, they remain critical for estimating the effect of localized geography on the probability of foreign aid allocation.[16]

5 Empirical Results

5.1 Geocoded Distance Indicators

This section introduces the initial regression results for distance-based control variables, which are incorporated to evaluate the basic infrastructure and needs-based orientation hypotheses in sub-national aid allocation. The corresponding estimates are presented in Table A1.

The rationale for this analysis is to investigate the sub-national distribution of foreign aid using coarse geographic indicators that reflect key national features, often derivable from maps. Distance-based indicators have been extensively utilized in prior empirical studies on sub-national aid allocation.[17] These results primarily aim to test the basic infrastructure hypothesis and, to some extent, the needs-based orientation hypothesis in spatial aid targeting.

All specifications include fixed effects for DHS country-by-region and DHS survey year. Columns (1) to (7) estimate equation (1) by incorporating each distance-based control variable individually. These variables include the log-transformed distances of DHS survey locations to the capital city, the nearest large settlements, UNESCO cultural heritage sites, historic Christian missions, the country's border, the coast or rivers, roads or railroads, and the national power grid.

Consistent with Briggs (2018b) and the basic infrastructure hypothesis, all distance measures exhibit statistically significant negative coefficients. This indicates that the likelihood of foreign aid allocation decreases as the distance to these features increases. Thus, World Bank foreign aid projects tend to be concentrated near capitals, large settlements (i.e., cities with populations $\geq$ 100,000), and existing infrastructure such as roads or railroads.

When analyzed individually, these results appear to challenge the needs-based orientation hypothesis, which posits that aid should target the most remote and underserved regions.

[16] Robustness analyses include alternative time and distance ranges.

[17] See, for instance, Briggs (2018b); Alpino and Hammersmark (2020); Dreher et al. (2019) for detailed discussions.

However, the findings shift in column (8), where all distance-based control variables are included simultaneously. In this specification, the coefficients for distance to the coast and distance to power transmission lines become positive and statistically significant. This suggests that, conditional on other distance measures, aid is more likely to be allocated to locations farther from rivers or power transmission lines. While this could be interpreted as partial support for the needs-based targeting hypothesis, the overall results strongly align with the basic infrastructure hypothesis in explaining sub-national aid allocation.

In summary, distance measures predominantly exhibit significant negative effects on the probability of aid allocation, underscoring the importance of basic infrastructure in sub-national targeting. Nonetheless, this broad geographic approach explains only a limited portion (approximately one-third) of the variation in the dependent variable, even when accounting for country-by-region and survey year fixed effects. This indicates that geographic factors alone are insufficient to fully explain sub-national aid allocation patterns.

5.2 Bio-geographic Factors

Next, we incorporate bio-geographic factors into the regression model, as detailed in Table A2. These variables aim to capture environmental living conditions at the survey locations and are added alongside the distance-based controls from Table A1. This analysis primarily evaluates the needs orientation hypothesis, which suggests that aid should target regions with adverse environmental conditions indicative of higher needs.

Column (1) introduces the absolute latitude and longitude of the DHS survey locations as proxies for climatic conditions. The coefficients are statistically significant at the 10% and 5% levels, respectively, indicating a weak tendency for aid projects to be allocated closer to the equator but farther from the prime meridian. This aligns with the geographic concentration of aid projects in Sub-Saharan Africa, as illustrated in Figure B5.

Columns (2) through (7) examine additional bio-geographic indicators. Aid allocation does not appear to be significantly influenced by terrain ruggedness (column (2)). However, regions with a lower share of agricultural or pasture land (column (3)) are less likely to receive aid, suggesting a focus on remote areas with lower agricultural productivity, consistent with needs-based targeting. Conversely, locations in tropical regions (column (4)), with higher average temperatures (column (5)), or lower precipitation (column (6)) are less likely to be targeted, which challenges the needs-based hypothesis. The 12-month drought index (column (7)) shows no significant effect on aid allocation.

When all bio-geographic indicators are included simultaneously in column (8), the significance of mean temperature diminishes, while other coefficients remain consistent with their individual specifications.

In summary, the bio-geographic factors reveal a mixed pattern. While aid projects are more likely to target areas with higher precipitation, there is no strong evidence of donor strategies addressing agricultural vulnerability (e.g., as discussed in Kazianga and Udry, 2006).

5.3 Socio-economic Conditions

Table A3 extends the baseline model by incorporating variables that capture socio-economic, political, and health-related conditions at the DHS survey locations. These variables primarily address the influence of needs-based targeting, political favoritism, and ethnic diversity on foreign aid allocation.

Column (1) introduces the natural logarithm of night-time lights intensity as a proxy for local economic activity. The positive and statistically significant coefficient suggests that foreign aid projects are more likely to be allocated to economically active and developed areas, favoring efficiency over needs-based targeting.

Column (2) includes population size in the regression model. The positive and significant coefficient indicates that aid projects are more frequently allocated to densely populated areas, further supporting efficiency considerations in sub-national aid allocation (Nunnenkamp et al., 2016).

In column (3), the number of conflict events within a 10 km radius of the DHS survey location is added. The results show that each additional conflict event increases the probability of foreign aid allocation by approximately 0.82 percentage points, reflecting a tendency to address humanitarian needs in conflict-prone areas.

Column (4) examines the impact of natural disasters within the ADM2 region of the DHS cluster. Contrary to expectations, the occurrence of natural disasters has a negative and significant effect on the likelihood of aid allocation. This finding diverges from prior studies (e.g., Eichenauer et al., 2020), likely due to differences in aid classification, as this study excludes disaster response or humanitarian aid projects.

Column (5) investigates the role of ethnic diversity by including a measure of ethno-linguistic diversity. The positive and significant coefficient suggests that aid projects are more likely to be allocated to ethnically diverse areas, potentially to address distributional conflicts or diverse needs (Hodler and Knight, 2011). Accordingly, when trying to achieve the same preferred outcome (e.g., economic growth), more foreign aid projects would be needed to be allocated to ethnically diverse areas compared to more homogenous regions.

Column (6) incorporates a dummy variable for survey locations in the birth region of the incumbent political leader. The positive and significant coefficient indicates that such locations are, on average, 0.99 percentage points more likely to receive foreign aid, highlighting the prevalence of political favoritism in sub-national aid allocation.

Column (7) combines all previously discussed variables into a single regression model. Most coefficients remain significant and stable, except for the number of conflict events, which loses significance in this specification.

Columns (8) to (10) focus on a reduced sample with data on malaria *plasmodium falciparum* prevalence rates. Column (8) shows that higher malaria prevalence is associated with a lower likelihood of aid allocation. Column (9) confirms the robustness of the full specification from column (7) within this reduced sample. Column (10) includes both socio-economic controls and malaria prevalence, with results remaining consistent, except for the loss of significance for conflict events and the leader's birthplace. The remaining regression coefficients exhibit consistent patterns, further challenging the notion of needs-based targeting in foreign aid allocation.

In summary, the socio-economic variables provide limited support for the needs-based targeting hypothesis. Instead, most variables speak more in favor of an efficiency-oriented targeting approach. Foreign aid projects appear to be implemented rather in more populated areas, with greater economic activity (consistent, for example, with Nunnenkamp et al., 2016) and do not seem to consider adverse health outcomes (Oehler and Nunnenkamp, 2014). Additionally, the results suggest political favoritism, such that DHS clusters in the political leader's birth region are more likely to benefit from foreign aid projects (in line with Oehler and Nunnenkamp, 2014; Dreher et al., 2019), again indicating the recipient's influence in the sub-national allocation of foreign aid projects.

5.4 DHS Individual and Household Controls

Table A4 incorporates additional local survey data on living standards, education, and demographics. These variables, measured at the individual or household level, provide a more granular perspective to refine the empirical analysis.

Column (1) uses the primary floor material of households' dwellings as an indicator of wealth, development, and living standards (Rutstein and Johnson, 2004). The analysis includes variables for the share of households with rudimentary and processed floors, with natural floors serving as the baseline category. Interestingly, the results reveal that foreign aid is more likely to be allocated to locations where households have either processed or rudimentary floor materials compared to natural floors. This outcome challenges the expectation of aid being primarily directed toward the most underprivileged areas.

In column (2), we include the population shares with varying levels of educational attainment: primary, secondary, and higher education, with the reference category being those with no education (including *does not know*). All three categories are positively and significantly associated with the likelihood of receiving foreign aid. Among these, the coefficient for secondary education is the largest, followed by higher and then primary education. This suggests that locations with a higher proportion of uneducated populations are less likely to receive aid, highlighting efficiency-oriented considerations in the allocation process.

In column (3), we include variables representing the share of households with access to piped water and flush toilets as proxies for water supply and sanitation. Both coefficients are positive and statistically significant at the 1% level. While prior research highlights the effectiveness of improved sanitation in reducing child mortality (Tate et al., 2012), these findings indicate that foreign aid tends to be allocated to areas with better existing sanitary infrastructure, which challenges the notion of needs-based targeting in international development programs.

Column (4) incorporates variables for access to the power grid and ownership of basic assets, such as radios and bicycles. The results indicate that a higher share of the population with access to the power grid significantly increases the likelihood of receiving foreign aid projects. This finding aligns with the earlier evidence from Table A3, which highlights the association between aid allocation and areas with greater night-time light intensity. Additionally, a higher proportion of households owning radios is positively associated with aid allocation, whereas the share of households owning bicycles, often used as a mode of transportation, is negatively associated with the probability of receiving aid.

Column (5) integrates demographic variables from the DHS survey locations into the regression model, including average household size, average age of the surveyed population, and the proportion of male-headed households. The findings reveal that locations with a higher proportion of male-headed households and larger household sizes are significantly less likely to receive foreign aid. This suggests that the World Bank may prioritize areas with a lower share of male-headed households, potentially reflecting an emphasis on promoting gender equality objectives. In contrast, the average age of the surveyed population does not exhibit a statistically significant effect.

Finally, column (6) incorporates all DHS variables simultaneously into the regression model. Interestingly, certain coefficients, such as the share of households with rudimentary floor material or access to flush toilets, lose their statistical significance in predicting the likelihood of receiving foreign aid. Similarly, the coefficients for the share of the population with primary education and the average household size also become insignificant. Despite these changes, the overall findings remain consistent, demonstrating the robustness of the results in this comprehensive specification.

Columns (7) to (11) extend the specification with full DHS survey controls by incorporating different combinations and samples of the previously discussed control variables, including bio-geographic factors (Table A2) and socio-economic indicators (Table A3). Reassuringly, the main findings remain largely unchanged, even when restricting the sample in columns (7) and (9) or incorporating additional control variables in columns (8), (10), and (11). Notably, when additional control variables are included, the coefficients for the share of households with rudimentary floor material and flush toilet facilities regain statistical significance. Interestingly, a higher prevalence of flush toilets is now linked to a reduced likelihood of receiving foreign aid, whereas the share of households with rudimentary floor material continues to exhibit a positive association with aid allocation.

5.5 Heterogeneous Effects by Aid Sector

We extend the empirical analysis by considering alternative specifications of the dependent variable, categorized by the sector coding of individual World Bank foreign aid projects. This approach assumes that the DHS individual and household factors influencing aid allocation decisions may exhibit heterogeneous effects depending on the type of project being implemented. The results of this sector-specific analysis are presented in Table A5.

For reference, column (1) reproduces the final specification from Table A4, column (11), using an indicator for the presence of any foreign aid project as the dependent variable.

In column (2), we focus on aid projects aimed at the *education* sector. The results indicate that the likelihood of aid allocation in this sector is positively associated only with the share of the population having secondary educational attainment, while primary and higher education shares show no significant effect. Additionally, locations with a higher proportion of households having processed floor materials are less likely to receive education-related aid, suggesting a preference for areas with intermediate levels of development.

In column (3), we examine foreign aid projects targeting the *health* sector. Unlike the baseline specification, the likelihood of aid allocation in the *health* sector is less influenced by household wealth, as proxied by building materials, and shows weaker dependence on household demographics. Furthermore, health-related projects are more likely to be allocated to areas with higher shares of secondary educational attainment, while higher education levels do not exhibit a significant effect.

In column (4), the analysis focuses on aid projects targeting the improvement of *water supply and sanitation*. The findings reveal that, consistent with the baseline results, these projects are more likely to be allocated to areas with greater access to piped water and electricity. However, the negative and statistically significant coefficient for the share of households with flush toilet facilities suggests some alignment with a needs-based approach in the World Bank's decision-making process. Interestingly, locations with rudimentary floor materials exhibit the highest likelihood of receiving aid, indicating that needs-based targeting may only be effective when a minimum threshold of local development is met.

Columns (5) and (6) examine projects targeting *government and civil society* and *other social infrastructure*. For these sectors, the results highlight that a higher proportion of the population with primary or secondary educational attainment significantly increases the likelihood of foreign aid allocation. This suggests that such development assistance may require a foundational level of education within the population to ensure effective implementation, rather than solely focusing on areas with the greatest need.

Conversely, column (7) focuses on foreign aid projects targeting *economic infrastructure and services*. The results indicate that the spatial allocation of these projects is strongly influenced by higher levels of secondary or tertiary educational attainment in the population, as well as by access to piped water and electricity.

Column (8) examines aid projects directed toward the *production sector*. Interestingly, only the share of the population with secondary educational attainment shows a positive and significant association with the likelihood of receiving foreign aid. This suggests a preference for regions with a workforce possessing intermediate skills, rather than academic qualifications. Additionally, the negative coefficient for the share of households with processed floor material, a proxy for wealth and development, indicates that aid in this sector may target less affluent areas.

In column (9), we analyze aid projects in the *industry, mining, and construction* sector. Contrary to expectations, access to electricity does not exhibit a statistically significant effect on the likelihood of aid allocation. Instead, the results suggest that educational attainment plays a more prominent role, indicating that these projects are directed toward regions with moderate levels of wealth and development, as well as a baseline level of education.

Finally, column (10) focuses on foreign aid projects categorized as *multi-sectoral or cross-cutting* initiatives. These projects address complex development challenges by integrating efforts across multiple sectors, such as gender equality, environmental sustainability, urban and rural development, governance, and education. The results indicate a positive and significant association between the likelihood of aid allocation and the share of the population with secondary or tertiary educational attainment, as well as access to piped water and electricity. This suggests that multi-sectoral projects are more likely to target regions with higher levels of development and education, reflecting the multifaceted nature of these initiatives. Additionally, the positive coefficient for the share of male-headed households may indicate a focus on addressing gender disparities in regions with patriarchal social structures.

5.6 Sensitivity Analysis

To verify the robustness of our primary results, we perform supplementary analyses that assess the sensitivity of the regression model to changes in spatial and temporal matching criteria, as well as to an alternative method for selecting control variables. The results of these robustness tests are presented in Table A6.

Column (1) reproduces the final specification from Table A4, column (11). This specification includes an indicator for the presence of any foreign aid project as the dependent variable, along with comprehensive sets of distance, bio-geographic, and socio-economic controls.

Columns (2), (3), and (4) progressively increase the spatial buffer size for matching procedures from 5 km to 10 km, 15 km, and 20 km, respectively. As the spatial buffer expands, a larger proportion of survey locations are classified as treated, leading to an increase in the mean of the dependent variable from 9.193% in column (1) to 62.23% in column (4). Regardless of the buffer size, the results consistently show that locations with a higher share of households having processed floor material and access to piped water are significantly more likely to receive foreign aid, indicating a preference for relatively wealthier and more developed areas.

In column (5), the analysis is limited to foreign aid project locations with the highest geocoding precision, specifically those classified with accuracy levels of 1 or 2. This restriction reduces the sample size by approximately one-third. Despite the smaller sample, the results align closely with the baseline findings, with some control variables showing enhanced statistical significance.

Columns (6), (7), and (8) investigate the robustness of the results to changes in the temporal matching criteria between survey dates and project implementation dates. The standard analysis considers surveys conducted up to 6 years prior to project implementation. To assess sensitivity, we modify this time window to 3 years (column (6)), 5 years (column (7)), and 10 years (column (8)). Across all alternative time windows, the results remain consistent in both magnitude and statistical significance, indicating that the findings are not sensitive to the choice of temporal matching criteria.

Finally, column (9) employs the post-double selection (PDSLASSO) methodology to address potential biases from manual variable selection in prior specifications. This approach, as proposed by Belloni et al. (2013) and Belloni et al. (2014), identifies control variables with strong predictive power for both the dependent variable and the non-penalized controls.[18] Unlike the baseline specification, which uses contemporaneous distance, bio-geographic, and socio-economic controls, the PDSLASSO method incorporates all available control variables up to five years prior to the DHS survey date.[19] The DHS survey controls, as the primary variables of interest, remain excluded from the selection process. Fixed effects for DHS country-by-region and DHS survey year are

[18]Non-penalized controls include the DHS survey variables, which are excluded from the selection process.

[19]For the conflict variable, we select among the number of conflict events within 10, 20, 30, 40, and 50 km of the DHS survey location.

also included in the regression model. The results from this specification align closely with the main findings, maintaining similar levels of precision. This consistency underscores the robustness of the primary conclusions to alternative methods of control variable selection.

6 Conclusion

This study has examined the determinants of the spatial distribution of World Bank foreign aid projects at a sub-national, project-level scale across a wide range of recipient countries and time periods. By integrating disaggregated household survey data with remote-sensing data, we have conducted an empirical investigation into various factors highlighted in the literature that may influence donor organizations' allocation decisions.

Our findings indicate that the spatial allocation of World Bank foreign aid projects is influenced by a combination of distance-based metrics, bio-geographic characteristics, remote-sensing indicators, and socio-economic variables derived from household survey data. These variables were systematically incorporated into a comprehensive empirical framework with increasing levels of geographic granularity. Overall, the results reveal no consistent pattern of needs-based allocation of aid projects. Instead, locations with relatively better living conditions—such as higher night-time light intensity, improved access to water and sanitation, or higher educational attainment—tend to attract more aid projects. Additionally, our analysis highlights significant heterogeneity in the factors influencing aid allocation across different sectoral classifications.

These findings suggest that the allocation of aid projects is more strongly guided by efficiency considerations than by the needs of local populations. This aligns with existing literature, which posits that donor countries and organizations often base aid allocation on political, economic, and social factors that may not necessarily reflect the needs of the intended beneficiaries.

It is important to note that the factors included in our analysis represent only a subset of the potential determinants of aid allocation, underscoring the exploratory nature of this study. This does not imply that these factors are universally applied as decision-making criteria across all projects and contexts.

Future research should delve deeper into the sequencing and implementation of the project cycle, as well as the dynamics of coordination and collaboration between donor organizations and recipient countries.

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A Regression Tables

Table A1: The Localized Geography of World Bank Foreign Aid Projects – Evaluating the Impact of Distance-Based Controls

	(1) Capital city	(2) Nearest settlement	(3) UNESCO heritage site	(4) Nearest Christian mission	(5) Country border line	(6) River and coast line	(7) Economic infra-structure	(8) Distance controls
	Dependent variable: Presence of foreign aid project (100 = Yes, 0 = No)							
ln Distance to capital city	-14.1846***							-7.8605***
	(0.3361)							(0.3668)
ln Distance to settlement		-11.1666***						-7.1158***
		(0.2617)						(0.2742)
ln Distance to UNESCO heritage site			-6.5200***					-1.5455***
			(0.3785)					(0.3673)
ln Distance to catholic Mission				-7.3681***				-3.0606***
				(0.4666)				(0.3965)
ln Distance to protestant Mission				-8.2705***				-3.0392***
				(0.5407)				(0.4889)
ln Distance to country border line					-2.2111***			-1.4808***
					(0.1678)			(0.1374)
ln Distance to coast						-3.6113***		0.4671*
						(0.2856)		(0.2483)
ln Distance to river						-1.0904***		-0.3696***
						(0.1205)		(0.1085)
ln Distance to railroad							-4.2722***	-1.9938***
							(0.1640)	(0.1450)
ln Distance to road							-1.6461***	-1.3440***
							(0.1059)	(0.1008)
ln Distance to power transmission line							-1.1450***	0.9710***
							(0.1615)	(0.1561)
DHS country×ADM1 region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of foreign aid projects	14446	14446	14446	14446	14446	14446	14446	14446
No. of DHS locations	55377	55377	55377	55377	55377	55377	55377	55377
No. of DHS locations *treated*	14947	14947	14947	14947	14947	14947	14947	14947
Mean of dependent variable	10.38	10.38	10.38	10.38	10.38	10.38	10.38	10.38
Observations	362,036	362,036	362,036	362,036	362,036	362,036	362,036	362,036
Adjusted R^2	0.326	0.350	0.277	0.292	0.274	0.279	0.304	0.378
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Notes: The dependent variable refers to the presence of a World Bank foreign aid project (100 = Yes, 0 = No).
Distance to capital city refers to the distance to the capital city of the aid location's country. *Distance to settlement* refers to the distance to the nearest settlement (with more than 100,000 inhabitants). *Distance to UNESCO heritage site* refers to the distance to the nearest UNESCO heritage site. *Distance to Catholic mission* and *Distance to Protestant mission* refer to the distance to the nearest Catholic or Protestant mission, respectively. *Distance to country border line* refers to the distance to the country's border. *Distance to coast* and *Distance to river* refer to the distance to the coastline or the nearest river, respectively. *Distance to railroad* and *Distance to road* refer to the distance to the nearest railroad or road, respectively. *Distance to power transmission line* refers to the distance to the power grid. Note that for all distance variables, the natural logarithm of the distance is used. See the main text for additional details on data construction and sources. Constant term included but not shown.
Standard errors, clustered at the DHS location level, are reported in parentheses.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table A2: The Localized Geography of World Bank Foreign Aid Projects – Evaluating the Impact of Bio-geographic Controls

	(1) Absolute latitude/ longitude	(2) Elevation	(3) Land type	(4) Tropical region indicator	(5) Mean temper- ature	(6) Mean precipi- tation	(7) Drought indicator	(8) Bio-geo- graphic controls
	Dependent variable: Presence of foreign aid project (100 = Yes, 0 = No)							
Absolute latitude	-0.5767**							-0.6587***
	(0.2437)							(0.2504)
Absolute longitude	0.8709***							0.6669***
	(0.1960)							(0.2015)
Mean of elevation		0.0006						0.0004
		(0.0004)						(0.0005)
Std. Dev. of elevation		0.0024						0.0010
		(0.0018)						(0.0018)
Cropland			-4.7002***					-4.4623***
			(0.6091)					(0.6164)
Pasture land			-4.6296***					-4.4798***
			(0.7213)					(0.7231)
Tropical region				-0.7108*				-0.9554**
				(0.3798)				(0.3812)
Mean temperature					-0.1573***			-0.0300
					(0.0577)			(0.0762)
Mean precipitation						0.0128***		0.0102**
						(0.0048)		(0.0049)
Mean drought index							-0.1340	-0.2104
							(0.2309)	(0.2322)
DHS country×ADM1 region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of foreign aid projects	13852	13852	13852	13852	13852	13852	13852	13852
No. of DHS locations	51134	51134	51134	51134	51134	51134	51134	51134
No. of DHS locations *treated*	12822	12822	12822	12822	12822	12822	12822	12822
Mean of dependent variable	9.168	9.168	9.168	9.168	9.168	9.168	9.168	9.168
Observations	330,459	330,459	330,459	330,459	330,459	330,459	330,459	330,459
Adjusted R^2	0.351	0.351	0.352	0.351	0.351	0.351	0.351	0.352
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Notes: The dependent variable refers to the presence of a World Bank foreign aid project (100 = Yes, 0 = No).
Absolute latitude and *Absolute longitude* refer to the absolute value of the latitude and longitude of the DHS survey location. *Mean of elevation* and *Std. Dev. of elevation* refer to the mean and the standard deviation of the elevation in the DHS survey location, respectively. *Cropland* and *Pasture land* refer to the share of cropland and the share of pasture land area in the DHS survey location, respectively. *Tropical region* is a binary indicator for whether the DHS survey location is located in a tropical region according to the Koeppen-Geiger climate classification. *Mean temperature* refers to the mean annual temperature (in degree Celsius) in the DHS survey location at the year of the survey. *Mean precipitation* refers to mean annual precipitation (in mm) in the DHS survey location at the year of the survey. *Mean drought index* refers to the mean drought index (relative to the pre-12-month period) in the DHS survey location at the year of the survey. All regressions include distance controls. See the main text for additional details on data construction and sources. Constant term included but not shown.
Standard errors, clustered at the DHS location level, are reported in parentheses.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table A3: The Localized Geography of World Bank Foreign Aid Projects – Evaluating the Impact of Socio-economic and Health Conditions

	Socio-economic sample							Malaria ecology sample		
	(1) Lights intensity	(2) Population size	(3) Civil conflicts	(4) Natural disasters	(5) Ethno-linguistic diversity	(6) Political favoritism	(7) Socio-economic controls	(8) Malaria prevalence	(9) Socio-economic controls	(10) Full model
	Dependent Variable: Presence of Foreign Aid Project (100 = Yes, 0 = No)									
ln Lights intensity	0.7353***						0.5065***		0.4307***	0.4254***
	(0.0329)						(0.0343)		(0.0351)	(0.0350)
ln Population size		4.2977***					3.5685***		3.7540***	3.7146***
		(0.2655)					(0.2629)		(0.2773)	(0.2763)
Number of conflict events			0.8172**				0.4945		0.1954	0.1886
within 10 km distance			(0.3316)				(0.3307)		(0.3467)	(0.3465)
Number of natural disasters				-0.5088***			-0.5447***		-0.5136***	-0.5204***
ADM2 region				(0.1734)			(0.1766)		(0.1788)	(0.1789)
Number of ethno-linguistic groups					3.2938***		2.9357**		2.2406*	2.2135*
					(1.1455)		(1.1447)		(1.1478)	(1.1471)
Birthplace of political leader						0.9993**	0.6950*		0.6753*	0.6549
ADM2 region						(0.4119)	(0.4142)		(0.4051)	(0.4050)
Malaria prevalence rate								-10.9705***		-5.0909***
cases per 1,000 population								(1.7522)		(1.7669)
DHS country$\times$ADM1 region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of foreign aid projects	14075	14075	14075	14075	14075	14075	14075	12866	12866	12866
No. of DHS locations	52085	52085	52085	52085	52085	52085	52085	48295	48295	48295
No. of DHS locations *treated*	13440	13440	13440	13440	13440	13440	13440	11933	11933	11933
Mean of dependent variable	9.696	9.696	9.696	9.696	9.696	9.696	9.696	9.029	9.029	9.029
Observations	339,243	339,243	339,243	339,243	339,243	339,243	339,243	319,999	319,999	319,999
Adjusted R^2	0.379	0.383	0.374	0.374	0.374	0.374	0.386	0.350	0.362	0.362
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Notes: The dependent variable refers to the presence of a World Bank foreign aid project (100 = Yes, 0 = No).
ln Lights intensity refers to the natural logarithm of the satellite night-time lights intensity in the DHS survey location. *ln Population size* refers to the natural logarithm of the population size in the DHS survey location. *Number of conflict events* refers to the number of conflict events within a 10 km distance of the DHS survey location. *Number of natural disasters* refers to the number of natural disasters in the DHS survey location's administrative 2 region. *Number of ethno-linguistic groups* refers to the number of ethno-linguistic groups in the DHS survey location. *Birthplace of political leader* takes a value of 1 if the birthplace of a political leader is located in the DHS survey location's administrative 2 region. *Malaria prevalence rate* refers to the mean prevalence rate of *plasmodium falciparum* cases per 1,000 population in the DHS survey location. All regressions include distance controls. See the main text for additional details on data construction and sources. Constant term included but not shown.
Standard errors, clustered at the DHS location level, are reported in parentheses.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table A4: The Localized Geography of World Bank Foreign Aid Projects – Evaluating the Impact of DHS Survey Living Conditions

	(1) Building material	(2) Educational attainment	(3) Water and sanitation	(4) Resources and network	(5) Household demo-graphics	(6) DHS survey controls	(7) Bio-geo-graphic sample	(8) Bio-geo-graphic controls	(9) Socio-economic sample	(10) Socio-economic controls	(11) Full model
	Dependent Variable: Presence of Foreign Aid Project (100 = Yes, 0 = No)										
Floor material: rudimentary	6.4704***					2.5366	2.2535	2.1160	3.5233**	5.2730***	4.3794***
(% of households)	(1.5194)					(1.5752)	(1.6288)	(1.6203)	(1.5969)	(1.6498)	(1.6603)
Floor material: processed	13.2209***					2.5943***	2.8132***	2.6122***	3.2400***	2.1952**	1.8482**
(% of households)	(0.7391)					(0.9351)	(0.8841)	(0.8864)	(0.9367)	(0.9209)	(0.8940)
Primary attainment		8.6452***				2.1186	1.1275	0.5977	0.2719	1.8359	0.9742
(% of population)		(1.5545)				(1.6037)	(1.5501)	(1.5557)	(1.5685)	(1.5597)	(1.5643)
Secondary attainment		28.7021***				13.3977***	12.3976***	11.9911***	13.4154***	11.4671***	10.8792***
(% of population)		(1.7229)				(2.0466)	(1.9985)	(2.0039)	(2.0838)	(2.0880)	(2.0984)
Higher attainment		26.9559***				14.3907***	15.8002***	14.9564***	14.2234***	13.0945***	12.3169***
(% of population)		(2.6305)				(2.9419)	(3.0853)	(3.0953)	(3.1745)	(3.1624)	(3.2397)
Main water source: piped water			11.5185***			8.8459***	8.7194***	8.8338***	8.9109***	8.7338***	8.6968***
(% of households)			(0.5248)			(0.5502)	(0.5387)	(0.5491)	(0.5518)	(0.5528)	(0.5638)
Toilet facility: flush toilet			5.2712***			-1.5833	-1.4533	-1.7008	-2.5713**	-3.5460***	-3.1735***
(% of households)			(0.9311)			(1.0557)	(1.0458)	(1.0498)	(1.0940)	(1.0966)	(1.0917)
Access to electricity				10.6097***		4.1058***	3.2919***	3.4050***	3.6059***	2.8304***	2.5615***
(% of households)				(0.6401)		(0.7470)	(0.7041)	(0.7004)	(0.7297)	(0.7299)	(0.7134)
Possession of a radio				9.2427***		4.6725***	4.5470***	4.9477***	5.6294***	5.8255***	5.6331***
(% of households)				(0.8611)		(0.9095)	(0.8963)	(0.9115)	(0.9141)	(0.9067)	(0.9188)
Possession of a bicycle				-4.9872***		-2.6615***	-2.9090***	-3.4607***	-2.9582***	-2.8297***	-2.4537***
(% of households)				(0.7774)		(0.7924)	(0.7758)	(0.8341)	(0.7892)	(0.7939)	(0.8436)
Mean household size					-0.7495***	-0.0265	0.2065	0.2109	0.0564	0.0160	0.1900
(Average across households)					(0.1788)	(0.1847)	(0.1732)	(0.1733)	(0.1817)	(0.1787)	(0.1748)
Mean age					0.0045	0.0353	0.0363	0.0440	0.0002	0.0430	0.0675*
(Average across population)					(0.0397)	(0.0398)	(0.0388)	(0.0389)	(0.0404)	(0.0404)	(0.0400)
Male household head					-6.5001***	-4.7179***	-4.4051***	-4.4279***	-5.1800***	-4.6741***	-4.5566***
(% of households)					(1.2453)	(1.2739)	(1.2030)	(1.2044)	(1.2743)	(1.2678)	(1.2257)
DHS country×ADM1 region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bio-geographic controls	No	No	No	No	No	No	No	Yes	No	No	Yes
Socio-economic controls	No	No	No	No	No	No	No	No	No	Yes	Yes
No. of foreign aid projects	13779	13779	13779	13779	13779	13779	13203	13203	13407	13407	12862
No. of DHS locations	48504	48504	48504	48504	48504	48504	44709	44709	45403	45403	43227
No. of DHS locations *treated*	13140	13140	13140	13140	13140	13140	11220	11220	11718	11718	10600
Mean of dependent variable	10.43	10.43	10.43	10.43	10.43	10.43	9.271	9.271	9.774	9.774	9.193
Observations	323,533	323,533	323,533	323,533	323,533	323,533	294,526	294,526	301,524	301,524	281,996
Adjusted R^2	0.387	0.390	0.392	0.390	0.381	0.399	0.379	0.381	0.400	0.409	0.395
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Notes: The dependent variable refers to the presence of a World Bank foreign aid project (100 = Yes, 0 = No).

In the following, the DHS survey variables are constructed as share of households or population, respectively, with the specific characteristic in the DHS survey location. *Floor material: rudimentary* refers to the percentage of households with a rudimentary floor material. *Floor material: processed* refers to the percentage of households with a processed floor material. *Primary attainment* refers to the percentage of the population with primary education. *Secondary attainment* refers to the percentage of the population with secondary education. *Higher attainment* refers to the percentage of the population with higher education. *Main water source: piped water* refers to the percentage of households with piped water as the main water source. *Toilet facility: flush toilet* refers to the percentage of households with a flush toilet as the main toilet facility. *Access to electricity* refers to the percentage of households with access to electricity. *Possession of a radio* refers to the percentage of households with a radio. *Possession of a bicycle* refers to the percentage of households with a bicycle. *Mean household size* refers to the average household size in the DHS survey location. *Mean age* refers to the average age of the population in the DHS survey location. *Male household head* refers to the percentage of households where the household head is male. All regressions include distance controls. See the main text for additional details on data construction and sources. Constant term included but not shown.

Standard errors, clustered at the DHS location level, are reported in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table A5: The Localized Geography of World Bank Foreign Aid Projects – Foreign Aid Sector Coding Analysis

	Foreign Aid Sector									
	(1) Any foreign aid project	(2) Education	(3) Health	(4) Water supply and sanitation	(5) Government and civil society	(6) Other social infra-structure and services	(7) Econ. infra-structure and services	(8) Production sectors	(9) Industry, mining and construction	(10) Multi-Sector/ Cross-Cutting
	Dependent Variable: Presence of Foreign Aid Project (100 = Yes, 0 = No)									
Floor material: rudimentary	4.3794***	-0.2679	-0.2794	3.1198***	1.3692	2.0113***	0.9109	-0.6128	1.0197***	0.9569***
(% of households)	(1.6603)	(0.6113)	(0.5130)	(0.8631)	(0.9736)	(0.5441)	(0.9685)	(0.4438)	(0.3668)	(0.2553)
Floor material: processed	1.8482**	-0.6533**	0.2386	0.9354**	1.7755***	1.9061***	0.8721	-0.9337***	-0.0190	-0.7372***
(% of households)	(0.8940)	(0.2667)	(0.2292)	(0.3705)	(0.5354)	(0.3030)	(0.5663)	(0.2099)	(0.2408)	(0.1344)
Primary attainment	0.9742	-0.4622	-0.5481	1.2774*	3.7967***	2.6750***	-1.8514*	-0.0448	1.0692**	-1.7661***
(% of population)	(1.5643)	(0.4679)	(0.4321)	(0.7142)	(0.9845)	(0.5560)	(0.9923)	(0.3971)	(0.5428)	(0.2782)
Secondary attainment	10.8792***	1.5119**	2.2319***	1.7470**	6.1436***	3.6417***	7.2460***	2.6271***	1.8121**	1.0114***
(% of population)	(2.0984)	(0.6165)	(0.4946)	(0.8583)	(1.2023)	(0.6004)	(1.2616)	(0.4630)	(0.7478)	(0.3107)
Higher attainment	12.3169***	0.9088	-1.1500**	1.0538	-0.3289	-1.1779*	5.7362***	0.9183*	3.1009*	2.4734***
(% of population)	(3.2397)	(0.6811)	(0.4942)	(1.2094)	(1.4369)	(0.7105)	(1.6243)	(0.5523)	(1.8405)	(0.4551)
Main water source: piped water	8.6968***	1.6812***	1.0280***	2.5715***	4.5683***	1.1831***	4.7080***	1.4002***	1.1315***	0.1329*
(% of households)	(0.5638)	(0.1649)	(0.1427)	(0.2457)	(0.3343)	(0.1762)	(0.3469)	(0.1325)	(0.1509)	(0.0802)
Toilet facility: flush toilet	-3.1735***	-0.7805**	-1.0974***	-1.5807***	-3.0446***	-0.9513***	-1.6813**	0.1028	-0.3312	0.4098**
(% of households)	(1.0917)	(0.3145)	(0.2522)	(0.4578)	(0.6092)	(0.3203)	(0.6861)	(0.2539)	(0.3362)	(0.1956)
Access to electricity	2.5615***	1.9187***	1.4341***	2.2213***	2.8549***	1.0797***	1.4624***	1.0082***	-0.3000	0.4358***
(% of households)	(0.7134)	(0.2172)	(0.1936)	(0.3039)	(0.4585)	(0.2390)	(0.4504)	(0.1765)	(0.1952)	(0.1137)
Possession of a radio	5.6331***	0.9016***	1.9651***	2.0610***	5.7668***	2.3164***	3.8419***	1.1191***	-0.3613	-0.0448
(% of households)	(0.9188)	(0.2720)	(0.2406)	(0.3989)	(0.5526)	(0.3106)	(0.5530)	(0.2155)	(0.3180)	(0.1453)
Possession of a bicycle	-2.4537***	-0.5689**	-0.3219	-2.1550***	-0.1169	-0.6086**	-1.7043***	-0.4910**	-0.8154***	-0.5201***
(% of households)	(0.8436)	(0.2350)	(0.2131)	(0.4009)	(0.4933)	(0.3102)	(0.5107)	(0.2046)	(0.2387)	(0.1200)
Mean household size	0.1900	0.1405***	-0.0097	0.2173***	0.0231	0.0075	-0.1096	-0.0453	0.0399	-0.0906***
(Average across households)	(0.1748)	(0.0459)	(0.0412)	(0.0759)	(0.1064)	(0.0595)	(0.1110)	(0.0382)	(0.0611)	(0.0285)
Mean age	0.0675*	0.0083	0.0161*	0.0270	0.0189	-0.0009	-0.0561**	-0.0087	0.0547***	-0.0096*
(Average across population)	(0.0400)	(0.0105)	(0.0088)	(0.0169)	(0.0212)	(0.0111)	(0.0240)	(0.0086)	(0.0155)	(0.0055)
Male Head	-4.5566***	-1.2293***	-0.3759	-1.2546**	-2.8171***	-0.6262	-3.3698***	-0.8667***	-0.0837	0.3516*
(% of households)	(1.2257)	(0.3594)	(0.3188)	(0.5518)	(0.7138)	(0.3960)	(0.7693)	(0.2850)	(0.4282)	(0.2063)
DHS country×ADM1 region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bio-geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of foreign aid projects	12862	12862	12862	12862	12862	12862	12862	12862	12862	12862
No. of DHS locations	43227	43227	43227	43227	43227	43227	43227	43227	43227	43227
No. of DHS locations *treated*	10600	10600	10600	10600	10600	10600	10600	10600	10600	10600
Mean of dependent variable	9.193	9.193	9.193	9.193	9.193	9.193	9.193	9.193	9.193	9.193
Observations	281,996	281,996	281,996	281,996	281,996	281,996	281,996	281,996	281,996	281,996
Adjusted R^2	0.395	0.0882	0.0869	0.145	0.294	0.120	0.256	0.0641	0.191	0.176
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Notes: The dependent variable refers to the presence of a World Bank foreign aid project (100 = Yes, 0 = No).
In the following, the DHS survey variables are constructed as share of households or population, respectively, with the specific characteristic in the DHS survey location. *Floor material: rudimentary* refers to the percentage of households with a rudimentary floor material. *Floor material: processed* refers to the percentage of households with a processed floor material. *Primary attainment* refers to the percentage of the population with primary education. *Secondary attainment* refers to the percentage of the population with secondary education. *Higher attainment* refers to the percentage of the population with higher education. *Main water source: piped water* refers to the percentage of households with piped water as the main water source. *Toilet facility: flush toilet* refers to the percentage of households with a flush toilet as the main toilet facility. *Access to electricity* refers to the percentage of households with access to electricity. *Possession of a radio* refers to the percentage of households with a radio. *Possession of a bicycle* refers to the percentage of households with a bicycle. *Mean household size* refers to the average household size in the DHS survey location. *Mean age* refers to the average age of the population in the DHS survey location. *Male household head* refers to the percentage of households where the household head is male. All regressions include distance, bio-geographic, and socio-economic controls. See the main text for additional details on data construction and sources. Constant term included but not shown.
Standard errors, clustered at the DHS location level, are reported in parentheses.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table A6: The Localized Geography of World Bank Foreign Aid Projects – Additional Robustness Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Inner Buffer Size				AidData-DHS Time Difference: ΔT_{ai}			
	Baseline Results	$Dist_{ia} \leq 10$ km	$Dist_{ia} \leq 15$ km	$Dist_{ia} \leq 20$ km	AidData Precision Code ≤ 2	≤ 3 years	≤ 5 years	≤ 10 years	PDSLASSO selected controls
	Dependent variable: Presence of foreign aid project (100 = Yes, 0 = No)								
Floor material: rudimentary	4.3794***	3.3986*	0.5792	-2.9003	7.1480***	-0.2619	4.2776**	4.3794***	4.9787***
(% of households)	(1.6603)	(1.9025)	(2.5032)	(3.0371)	(1.8644)	(1.7119)	(1.6782)	(1.6603)	(1.6710)
Floor material: processed	1.8482**	5.3328***	5.1662***	3.6042**	2.7270**	1.2767	1.4724	1.8482**	1.0238
(% of households)	(0.8940)	(1.2317)	(1.5928)	(1.6292)	(1.1095)	(0.9446)	(0.9060)	(0.8940)	(0.9120)
Primary attainment	0.9742	1.6948	-1.2364	-0.0590	2.2124	1.0524	2.0344	0.9742	-0.4981
(% of population)	(1.5643)	(2.3001)	(3.2335)	(3.2911)	(1.9214)	(1.6799)	(1.5906)	(1.5643)	(1.6091)
Secondary attainment	10.8792***	7.9726***	5.8979*	3.5648	16.5116***	8.6034***	11.2564***	10.8792***	10.5598***
(% of population)	(2.0984)	(2.7447)	(3.4349)	(3.3648)	(2.4926)	(2.1754)	(2.1405)	(2.0984)	(2.1372)
Higher attainment	12.3169***	11.8854***	1.0430	-2.6412	14.0230***	7.6654**	11.9491***	12.3169***	12.3663***
(% of population)	(3.2397)	(3.4139)	(3.7759)	(3.5193)	(3.7477)	(3.4299)	(3.3483)	(3.2397)	(3.2466)
Main water source: piped water	8.6968***	10.3019***	6.4419***	4.5442***	10.3244***	8.7610***	8.8618***	8.6968***	8.2145***
(% of households)	(0.5638)	(0.8003)	(1.0289)	(1.0823)	(0.6905)	(0.5820)	(0.5678)	(0.5638)	(0.5686)
Toilet facility: flush toilet	-3.1735***	-3.1062**	-4.8289***	-2.1630	-4.5595***	-3.8164***	-3.4609***	-3.1735***	-3.3465***
(% of households)	(1.0917)	(1.2316)	(1.4629)	(1.4949)	(1.2242)	(1.1201)	(1.1027)	(1.0917)	(1.0992)
Access to electricity	2.5615***	0.3237	-2.9935*	-2.9319*	2.4225***	3.5142***	3.0347***	2.5615***	2.6544***
(% of households)	(0.7134)	(1.1639)	(1.5305)	(1.6157)	(0.8574)	(0.7271)	(0.7197)	(0.7134)	(0.7298)
Possession of a radio	5.6331***	6.7612***	5.7634***	3.6045*	5.9328***	6.7424***	5.6977***	5.6331***	5.6133***
(% of households)	(0.9188)	(1.3746)	(1.8588)	(1.9515)	(1.1107)	(0.9906)	(0.9441)	(0.9188)	(0.9447)
Possession of a bicycle	-2.4537***	-7.0073***	-8.2661***	-6.5387***	-4.0269***	-1.9384**	-2.1773**	-2.4537***	-2.7209***
(% of households)	(0.8436)	(1.3367)	(1.7008)	(1.8728)	(1.0524)	(0.8920)	(0.8626)	(0.8436)	(0.8509)
Mean household size	0.1900	-0.3482	0.0653	0.1630	0.1829	0.2272	0.1399	0.1900	0.3275*
(Average across households)	(0.1748)	(0.2208)	(0.2771)	(0.2849)	(0.2143)	(0.1904)	(0.1779)	(0.1748)	(0.1788)
Mean age	0.0675*	-0.0893*	0.0401	-0.0380	0.0758	0.1112***	0.0934**	0.0675*	0.0856**
(Average across population)	(0.0400)	(0.0508)	(0.0672)	(0.0673)	(0.0494)	(0.0396)	(0.0401)	(0.0400)	(0.0399)
Male Head	-4.5566***	3.8649**	1.4291	-5.0622**	-5.0655***	-4.4282***	-4.6304***	-4.5566***	-4.4914***
(% of households)	(1.2257)	(1.6643)	(2.2163)	(2.1440)	(1.4838)	(1.2966)	(1.2476)	(1.2257)	(1.2323)
DHS country×ADM1 region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bio-geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LASSO-selected controls	No	No	No	No	No	No	No	No	Yes
No. of foreign aid projects	12862	12473	11934	11811	8511	10979	12494	12862	12362
No. of DHS locations	43227	42239	41860	41817	35105	38257	42024	43227	41190
No. of DHS locations *treated*	10600	17554	23001	27310	8943	8514	10122	10600	9772
Mean of dependent variable	9.193	21.83	41.49	62.23	11.52	8.975	9.239	9.193	8.847
Observations	281,996	182,574	138,101	126,989	183,125	200,009	254,646	281,996	273,708
Adjusted R^2	0.395	0.485	0.499	0.489	0.459	0.390	0.394	0.395	NA
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	PDSLASSO

Notes: The dependent variable refers to the presence of a World Bank foreign aid project (100 = Yes, 0 = No).

In the following, the DHS survey variables are constructed as share of households or population, respectively, with the specific characteristic in the DHS survey location. *Floor material: rudimentary* refers to the percentage of households with a rudimentary floor material. *Floor material: processed* refers to the percentage of households with a processed floor material. *Primary attainment* refers to the percentage of the population with primary education. *Secondary attainment* refers to the percentage of the population with secondary education. *Higher attainment* refers to the percentage of the population with higher education. *Main water source: piped water* refers to the percentage of households with piped water as the main water source. *Toilet facility: flush toilet* refers to the percentage of households with a flush toilet as the main toilet facility. *Access to electricity* refers to the percentage of households with access to electricity. *Possession of a radio* refers to the percentage of households with a radio. *Possession of a bicycle* refers to the percentage of households with a bicycle. *Mean household size* refers to the average household size in the DHS survey location. *Mean age* refers to the average age of the population in the DHS survey location. *Male household head* refers to the percentage of households where the household head is male. All regressions include distance, bio-geographic, and socio-economic controls. See the main text for additional details on data construction and sources. Constant term included but not shown.

Standard errors, clustered at the DHS location level, are reported in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

B Figures

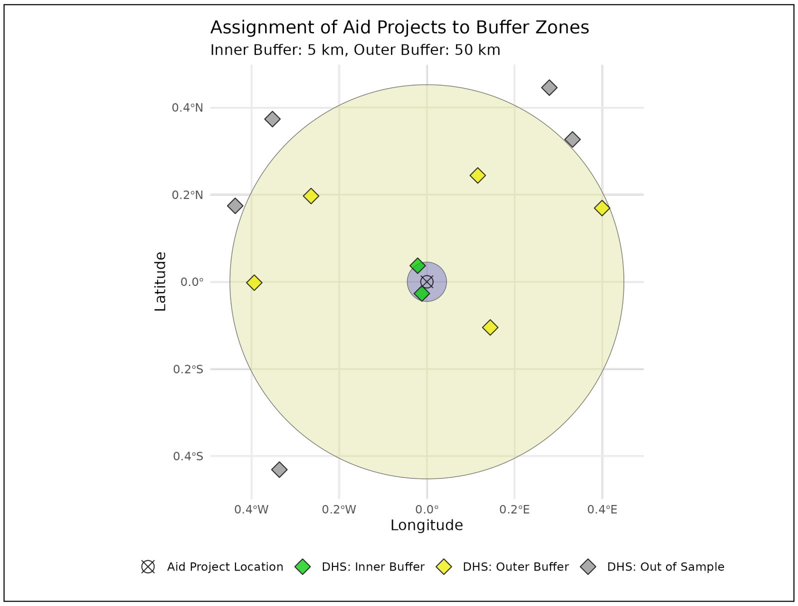

Figure B1: Buffer Approach Visualized

Notes: The figure visualizes the buffer approach employed in the empirical analysis. The inner buffer (blue shading) is the area within 5 km of the foreign aid project location. The outer buffer (green shading) is the area between 5 km and 50 km from the foreign aid project location. The points are randomly chosen as an illustration of the concept and are not part of the regression sample. Diamonds with green fill represent DHS locations inside the inner buffer, while diamonds with yellow fill represent DHS locations inside the outer buffer. The temporal dimension is not shown in the figure. See the main text for additional details regarding the data construction.

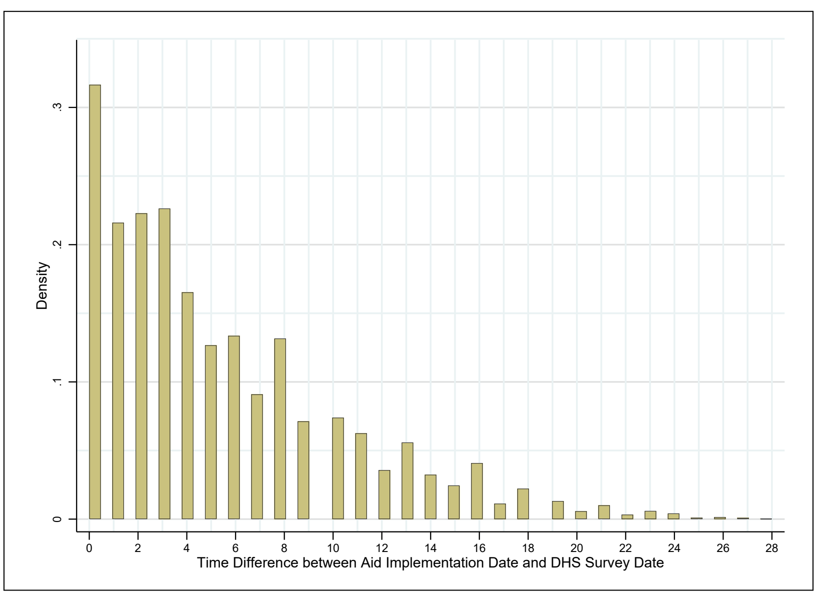

Figure B2: Distribution between Aid implementation Date and DHS Survey Date

Notes: This figure plots the distribution of the time difference between the implementation date of foreign aid projects and the survey date of the DHS locations. The data originate from AidData (2017b) and the Demographic and Health Survey (DHS).

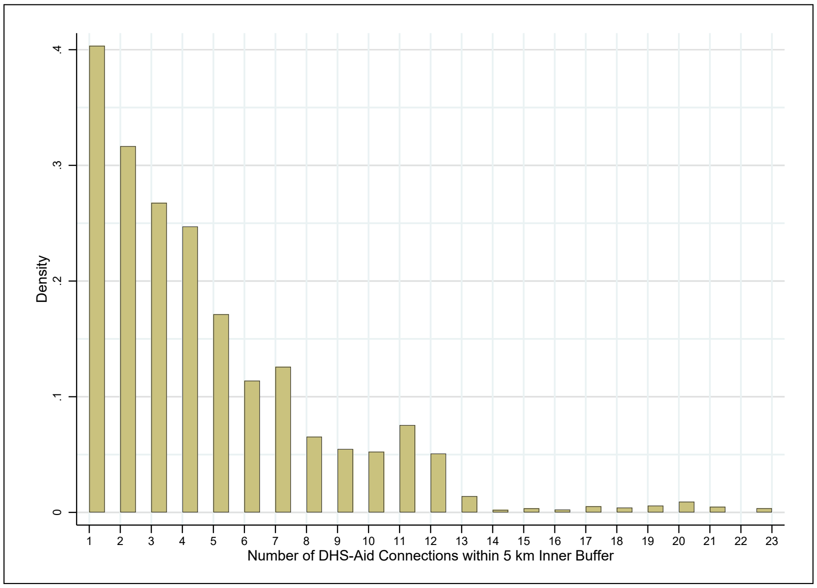

Figure B3: Distribution of DHS-Aid Connections within 5 km Inner Buffer Area

Notes: This figure plots the distribution of DHS-Aid connections within the 5 km inner buffer area. The data originate from AidData (2017b) and the Demographic and Health Survey (DHS). The connections are based on the spatial proximity of the DHS locations to the foreign aid projects.

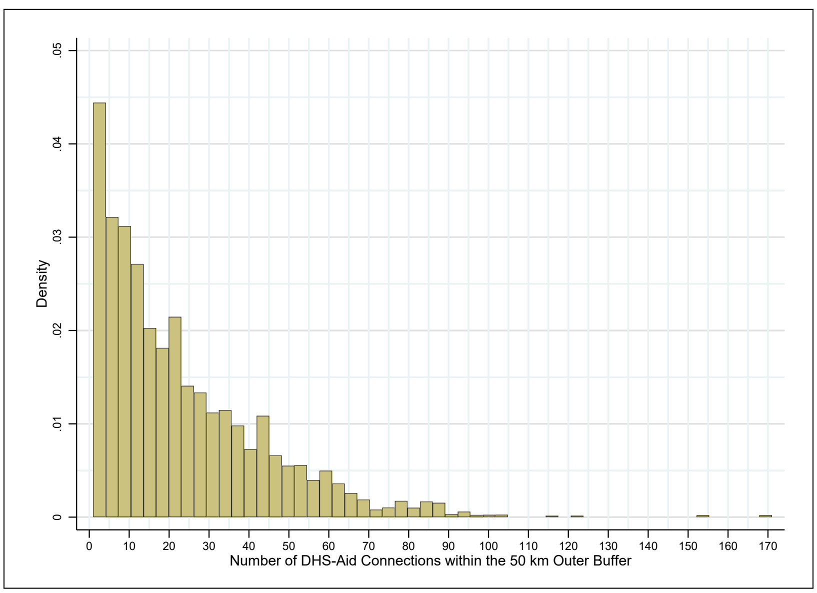

Figure B4: Distribution of DHS-Aid Connections within 50 km Outer Buffer Area

Notes: This figure plots the distribution of DHS-Aid connections within the 50 km outer buffer area. The data originate from AidData (2017b) and the Demographic and Health Survey (DHS). The connections are based on the spatial proximity of the DHS locations to the foreign aid projects.

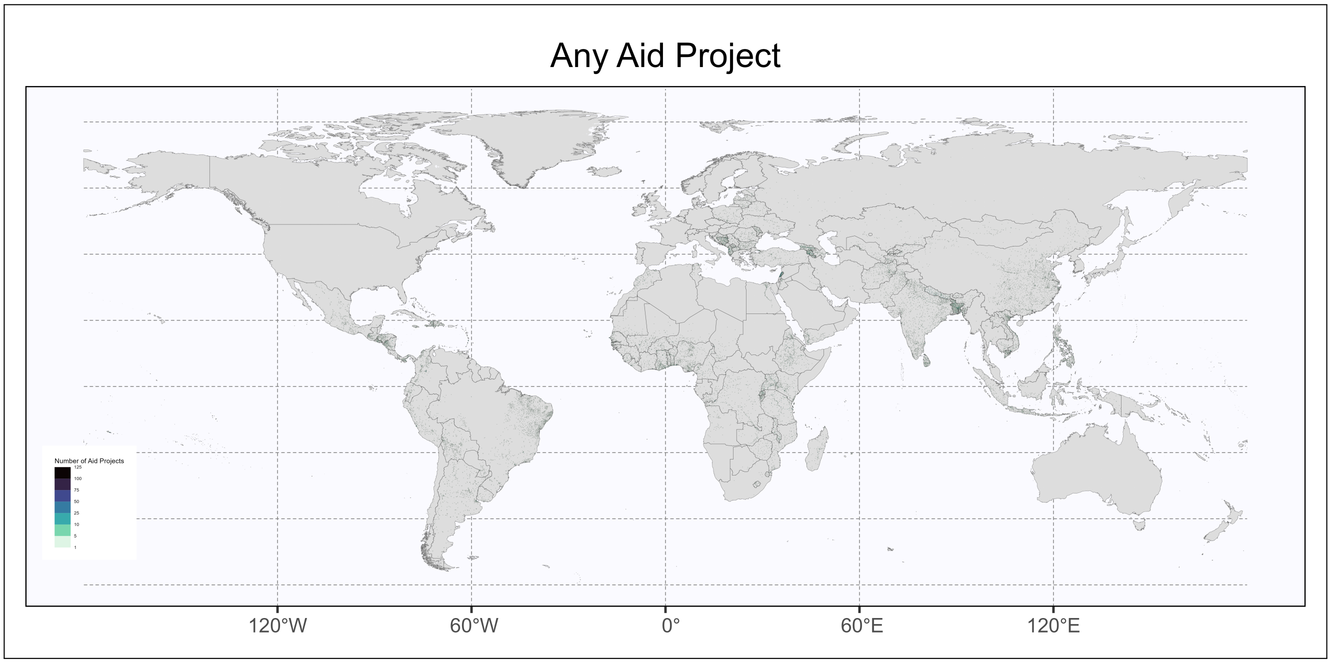

Figure B5: Distribution of Aid Projects Across Grid Cells

Notes: This figure plots the distribution of foreign aid projects (precision code 1, 2, or 3) across 0.1 Decimal Degrees (DD) grid cells (see Section 3). The color indicates the number of any projects in a given cell. The data originate from AidData (2017b) and cover the period from 1995 to 2014.

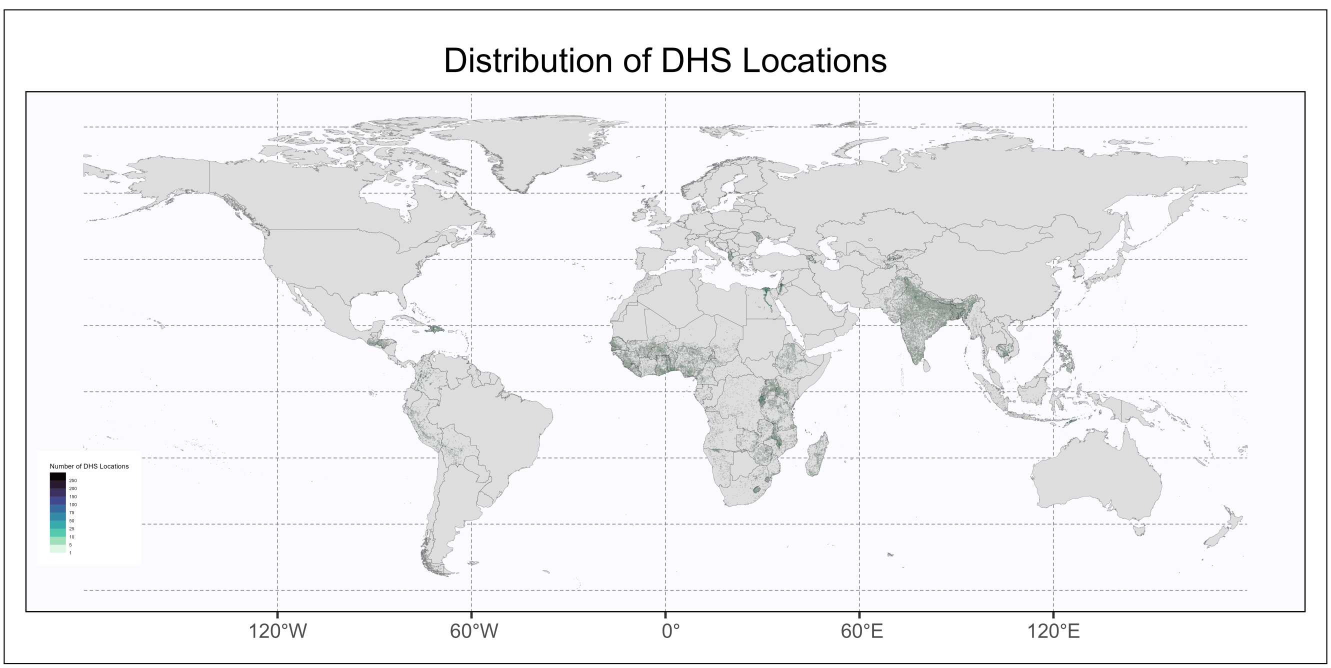

Figure B6: Distribution of DHS Locations Across Grid Cells

Notes: This figure plots the distribution of DHS locations across 0.1 Decimal Degrees (DD) grid cells (see Section 3). The color indicates the number of geocoded DHS locations in a given cell. The raw data originate from the Demographic and Health Survey (DHS) and cover the period from 1986 to 2019.

C Descriptive Statistics

Table C1: Descriptive Statistics for the Main Regression Variables by Treatment and Control Status

	Total Sample				Treated Sample				Control Sample			
Variables	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
	Panel A: DHS Controls											
Aid Indicator: $AID_{i(a)s}$	9.1927	28.8923	0	100	100	0	100	100	0	0	0	0
Floor material: rudimentary (% of households)	0.0349	0.1362	0	1	0.0322	0.1123	0	1	0.0351	0.1384	0	1
Floor material: processed (% of households)	0.4687	0.391	0	1	0.7798	0.2948	0	1	0.4372	0.3857	0	1
Primary attainment (% of population)	0.3531	0.1601	0	0.9238	0.2966	0.1391	0	0.8786	0.3588	0.161	0	0.9238
Secondary attainment (% of population)	0.2091	0.1535	0	1	0.3043	0.1454	0	1	0.1994	0.151	0	1
Higher attainment (% of population)	0.0575	0.0974	0	1	0.1207	0.1435	0	1	0.0511	0.0889	0	1
Main water source: piped water (% of households)	0.3711	0.406	0	1	0.7259	0.3619	0	1	0.3352	0.3928	0	1
Toilet facility: flush toilet (% of households)	0.287	0.3919	0	1	0.4394	0.4199	0	1	0.2715	0.3856	0	1
Access to electricity (% of households)	0.4697	0.434	0	1	0.7436	0.3363	0	1	0.4419	0.4331	0	1
Possession of a radio (% of households)	0.5458	0.2699	0	1	0.7026	0.2447	0	1	0.5299	0.2673	0	1
Possession of a bicycle (% of households)	0.2465	0.2419	0	1	0.1828	0.1991	0	1	0.253	0.2449	0	1
Mean household size (average across households)	4.9008	1.2677	1	24.1667	4.7173	1.3033	1.25	18.5	4.9193	1.2625	1	24.1667
Mean age (average across population)	27.134	5.0442	12.9464	85	27.3144	5.5319	12.9464	63.5	27.1158	4.9918	14.3333	85
Male household head (% of households)	0.7714	0.1531	0	1	0.7561	0.1541	0	1	0.7729	0.1529	0	1
	Panel B: Distance Controls											
ln Distance to capital city	4.6318	1.3861	-4.2907	7.6907	3.3411	2.3233	-4.2907	7.5053	4.7624	1.1763	-2.2609	7.6907
ln Distance to settlement	3.3575	1.2525	-4.3056	6.4798	1.9165	1.6526	-4.3048	6.4798	3.5034	1.1044	-4.3056	6.461
ln Distance to UNESCO heritage site	4.5307	0.9373	-1.9365	6.8088	4.1837	1.4704	-1.9365	6.7744	4.5658	0.8575	-1.3574	6.8088
ln Distance to catholic mission	5.4681	2.393	-1.8147	9.0194	4.6045	2.5491	-1.8147	9.0138	5.5555	2.3591	-.9256	9.0194
ln Distance to protestant mission	5.9271	2.4251	-1.5717	9.082	5.1585	2.6768	-1.2423	9.0796	6.0049	2.3844	-1.5717	9.082
ln Distance to country border line	3.4188	1.37	-4.5461	6.2975	3.6036	1.5959	-4.5461	6.2975	3.4001	1.3436	-4.4617	6.2096
ln Distance to coast	4.8	1.785	-4.5461	7.3629	4.6486	2.0265	-4.5461	7.3372	4.8153	1.758	-4.4617	7.3629
ln Distance to river	2.5088	1.3522	-4.5726	6.5225	2.3166	1.4825	-4.4878	6.4849	2.5283	1.3368	-4.5726	6.5225
ln Distance to railroad	2.74	1.8785	-4.5891	6.7748	1.4911	2.138	-4.5372	6.5722	2.8665	1.8026	-4.5891	6.7748
ln Distance to road	0.9195	1.51	-4.6037	5.6743	0.1609	1.2748	-4.5851	5.2129	0.9963	1.5107	-4.6037	5.6743
ln Distance to power transmission line	2.9417	1.8232	-4.5895	6.9031	2.2849	2.0874	-4.3632	6.8578	3.0081	1.7809	-4.5895	6.9031
	Panel C: Bio-geographic and Climatic Controls											
Absolute latitude	15.3837	10.5875	0.0003	48.0438	13.807	10.2304	0.0093	47.1867	15.5433	10.6099	0.0003	48.0438
Absolute longitude	48.1958	35.84	0.0027	126.4055	39.327	33.1466	0.0027	126.1791	49.0936	35.9799	0.0027	126.4055
Mean of elevation	592.4862	749.1734	-42.9097	5313.729	585.2878	729.3811	-36.0764	4497.493	593.2149	751.1455	-42.9097	5313.729
Std. Dev. of elevation	69.3725	100.3021	0.1661	892.303	55.1267	73.2858	0.3818	735.3344	70.8146	102.5313	0.1661	892.303
Cropland	0.3663	0.2964	0	1	0.1982	0.2455	0	1	0.3834	0.2958	0	1
Pasture land	0.1176	0.1896	0	1	0.0868	0.1565	0	1	0.1207	0.1923	0	1
Tropical region indicator	0.6222	0.4848	0	1	0.5542	0.4971	0	1	0.6291	0.4831	0	1
Mean temperature	23.7972	4.0052	-3.85	31.825	23.7401	4.109	4.0833	31.6167	23.803	3.9946	-3.85	31.825
Mean precipitation	128.6527	86.9317	0	589.7584	112.8338	84.5117	0	562.7417	130.254	87.013	0	589.7584
Mean drought index	-0.0256	0.8206	-2.4524	2.4831	0.0132	0.8056	-2.4524	2.3438	-0.0296	0.822	-2.4524	2.4831
	Panel D: Socio-economic and Health Controls											
ln Lights intensity	2.7774	5.5625	-4.6052	9.1842	7.3232	2.9221	-4.6052	9.1842	2.3172	5.5593	-4.6052	9.1842
ln Population size	11.0423	1.5737	-4.6052	15.4704	12.4248	1.7645	3.0354	15.3666	10.9024	1.4829	-4.6052	15.4704
Number of conflict events within 10 km distance	0.1023	0.7818	0	31	0.3466	1.2938	0	20	0.0776	0.705	0	31
Number of natural disasters (adm2 region)	0.0937	0.3473	0	4	0.0507	0.2374	0	3	0.0981	0.3562	0	4
Number of ethno-linguistic groups	1.475	0.8684	0	9	1.4544	0.9466	0	9	1.4771	0.86	0	9
Birthplace of political leader (adm2 region)	0.0383	0.1919	0	1	0.1059	0.3077	0	1	0.0314	0.1745	0	1
	Obs.: 281,996				Obs.: 25,923				Obs.: 256,073			

Notes: This table provides descriptive statistics for all DHS locations in the dataset, distinguishing between treated and non-treated DHS locations.

Table C2: Time Difference between Start of Aid Project and Year of DHS survey

$T_{ai} = \text{date}_a - \text{date}_i$	Frequency	Percent	Cumulative
0	135,327	15.02	15.02
1	92,353	10.25	25.27
2	95,275	10.58	35.85
3	96,792	10.74	46.59
4	70,660	7.84	54.44
5	54,165	6.01	60.45
6	57,123	6.34	66.79
7	38,870	4.31	71.10
8	56,287	6.25	77.35
9	30,456	3.38	80.73
10	31,630	3.51	84.24
11	26,744	2.97	87.21
12	15,279	1.70	88.91
13	23,898	2.65	91.56
14	13,853	1.54	93.10
15	10,510	1.17	94.27
16	17,471	1.94	96.21
17	4,839	0.54	96.74
18	9,512	1.06	97.80
19	5,646	0.63	98.43
20	2,481	0.28	98.70
21	4,302	0.48	99.18
22	1,417	0.16	99.34
23	2,570	0.29	99.62
24	1,789	0.20	99.82
25	458	0.05	99.87
26	640	0.07	99.94
27	400	0.04	99.99
28	125	0.01	100.00
Total	900,872	100.00	

Notes: This table presents the distribution of the time differences between the initiation of aid projects and the year of the DHS survey. It includes the frequency, percentage, and cumulative percentage of these differences. Further details on data construction can be found in the main text.

D Data Description and Sources

D.1 Foreign Aid Data

We employ data on development aid projects from the AidData database (AidData, 2017b). The data are restricted to projects with a start date between 1992 and 2014. The data are further restricted to projects with a reported precision code of 3 or less, which corresponds to locations *near*, *in the area of*, or up to 25 km away from the given coordinates. Further, we include projects that are reported to be located in one of the nine main sectors of the World Bank, that is, *Education*, *Health*, *Water Supply and Sanitation*, *Government and Civil Society*, *Other Social Infrastructure*, *Economic Infrastructure and Services*, *Production Sectors*, *Industry, Mining and Construction*, as well as *Multi-Sector/Cross-Cutting*.

D.2 Geocoded Distance Variables

Capital City. This variable refers to the minimum geodesic distance (in kilometers) from the DHS location to the country's capital city. The corresponding country's capital city latitude and longitude coordinates are obtained from the CIA's *The World Factbook*, available at https://www.cia.gov/the-world-factbook/.

Settlement Points. This variable refers to the minimum geodesic distance (in kilometers) from the DHS location to the nearest large settlement with an estimated population size of at least 100,000 in the year 2000. Information on geocoded settlement points is provided by the Global Rural-Urban Mapping Project, Version 1 (GRUMPv1) database. The raw data is distributed by the NASA Socioeconomic Data and Applications Center (SEDAC) (Center For International Earth Science Information Network-CIESIN-Columbia University et al., 2011). Data access is granted through the NASA Earth Science website at https://www.earthdata.nasa.gov/data/catalog/sedac-ciesin-sedac-grumpv1-stlmnt-1.00.

UNESCO World Heritage Site. This variable refers to the minimum geodesic distance (in kilometers) from the DHS location to the nearest UNESCO World Heritage Site. The data on UNESCO World Heritage Sites is obtained from the UNESCO World Heritage Centre at https://whc.unesco.org/en/list/.

Catholic and/or Protestant Mission. This variable measures the minimum geodesic distance (in kilometers) from the DHS location to the closest Catholic or Protestant mission established in Africa during the late 19th and early 20th centuries. The data on Catholic missions is sourced from Cagé and Rueda (2016), while the data on Protestant missions is derived from Cagé and Rueda (2020).

Country Border. This variable refers to the minimum geodesic distance (in kilometers) from the DHS location to the country's national border. The data on country borders is obtained from the *Seamless Digital Chart of the World* (DCW) Base Map Version 10.5 at https://worldgeodatasets.com/basemaps/index.html.

Coastline. This variable refers to the minimum geodesic distance (in kilometers) from the DHS location to the coastline. The coastline feature data is obtained from the *Seamless Digital Chart of the World* (DCW) Base Map Version 10.5 at https://worldgeodatasets.com/basemaps/index.html.

River. This variable measures the minimum geodesic distance (in kilometers) from the DHS location to the nearest major sea-navigable river. The geo-spatial data on rivers and lakes is sourced from the Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG), which is maintained and distributed by the National Oceanic and Atmospheric Administration (NOAA). The dataset is accessible at https://www.ngdc.noaa.gov/mgg/shorelines/gshhs.html.

Railroads. This variable measures the minimum geodesic distance (in kilometers) from the DHS location to the closest railroad. The geo-spatial data on railroads is sourced from the *Seamless Digital Chart of the World* (DCW) Base Map Version 10.5, accessible at https://worldgeodatasets.com/basemaps/index.html.

Roads. This variable refers to the minimum geodesic distance (in kilometers) from the DHS location to the closest road. Geocoded data on the location of roads is provided by the *Seamless Digital Chart of the World* (DCW) Base Map Version 10.5 at https://worldgeodatasets.com/basemaps/index.html.

Power Transmission Lines. This variable refers to the minimum geodesic distance (in kilometers) from the DHS location to the closest power transmission line. Geocoded data on the location of power transmission lines is provided by the *Seamless Digital Chart of the World* (DCW) Base Map Version 10.5 at https://worldgeodatasets.com/basemaps/index.html.

D.3 Bio-geographic and Climatic Variables

Absolute Latitude. The absolute latitude of the DHS location is calculated as the absolute value of the latitude in decimal degrees.

Absolute Longitude. The absolute longitude of the DHS location is calculated as the absolute value of the longitude in decimal degrees.

Elevation. The elevation of the DHS location is calculated as the mean elevation in meters above sea level within a 0.1 decimal degree grid cell around the DHS location. The elevation data is obtained from the NASA Shuttle Radar Topography Mission (SRTM) digital topographic data. The raw data has a spatial resolution of 1 arc-second latitude and longitude (approximately 30 meters at the equator). The data is distributed by the United States Geological Survey (USGS) at https://earthexplorer.usgs.gov/.

Cropland and Pasture Area. The cropland and pasture area at the DHS location is determined as the average proportion (ranging from 0 indicating no coverage to 1 indicating full coverage) of cropland and pasture within a 0.1 decimal degree grid cell surrounding the DHS location. The cropland and pasture area data is obtained from the EarthStat database at http://www.earthstat.org/.

Climatic Variables. Climatic variables, including temperature (in degrees Celsius) and precipitation (in millimeters per month), are provided by the Climatic Research Unit (CRU) at the University of East Anglia. The dataset, known as CRU TS v4.05, offers gridded data with a spatial resolution of 0.5 decimal degrees latitude and longitude, covering the period from 1901 to 2020. The data is accessible at https://crudata.uea.ac.uk/cru/data/hrg/.

The Standardized Precipitation Evapotranspiration Index (SPEI) is a drought index that evaluates the balance between precipitation and potential evapotranspiration over various time scales (e.g., 12, 18, or 24 months) to determine drought severity. The Global SPEI database offers gridded data on drought conditions with a spatial resolution of 0.5 decimal degrees latitude and longitude, spanning the period from January 1901 to December 2018 (SPEIbase v2.6). The dataset is accessible at https://spei.csic.es/database.html.

D.4 Additional Geo-spatial Indicators: Socio-economic and Health Variables

Night-Time Light Intensity. To measure night-time light emissions, we employ two series of satellite imagery. For the period 1992 to 2013, we use the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) from the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Centre (NGDC) (NOAA-NGDC, 2015). For the period 2014 to 2019, we use the Visible Infrared Imaging Radiometer Suite (VIIRS) data set from NASA's Earth Observation Group (Ghosh et al., 2021). Note that pixel-level values of night-time light images from the different DMSP-OLS satellite-by-year observations are not comparable across time and even within the same satellite F-series due to a lack of in-flight calibration and technical degradation of optical sensors over time (Elvidge et al., 2014). We apply an inter-annual calibration method to ensure comparability of pixel level brightness values across the different satellite-by-year observations (Elvidge et al., 2009; Hsu et al., 2015). This implies calibrating all satellite-by-year night-time light images to match the range of brightness values of satellite series F12 from the year 1999 as the reference year and Los Angeles, USA as the reference area. The raw night-time light data is distributed by the Earth Observation Group, Payne Institute for Public Policy, and available at https://payneinstitute.mines.edu/eog/nighttime-lights/.

Population. The population data is obtained from the Gridded Population of the World (GPW) versions 3 and 4. The population grid data consists of population estimates of worldwide population counts for the years 1990, 1995, 2000, 2005, 2010, 2015, and 2020. We use the input rasters to interpolate the population count for the years in between. The raw data is distributed by the NASA Socioeconomic Data and Applications Center (SEDAC) at https://www.earthdata.nasa.gov/centers/sedac-daac.

Civil Conflicts. The conflict data employed in Table A3 are based on the UCDP/PRIO Georeferenced Event Dataset (Sundberg and Melander, 2013). We use the count of all conflict events that are reported with a date between 1992 and 2014 and are located within 10 km of the DHS survey location.

Ethnic Fractionalization. The spatial distribution of ethno-linguistic groups is derived from the World Language Mapping System (Global Mapping International, 2016). Using this data, we compute the count of ethno-linguistic groups within the 0.1 decimal degree grid cell encompassing the survey location.

Political Leader's Birthplace. Information on the birthplaces of political leaders is sourced from the Political Leader's Affiliation Database (PLAD), available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/YUS575. The dataset provides geocoded birthplaces of political leaders, which are matched to ADM2 regions within their respective countries. This data is utilized to identify whether a survey location corresponds to the birthplace of a political leader. See Dreher et al. (2020) for further details on the construction of the variable.

Natural Disasters. The Geocoded Disasters (GDIS) Dataset provides information on the worldwide occurrence of eight different types of natural disasters, including earthquakes, floods, landslides, storms, volcanic eruptions, droughts, wildfires, and extreme temperatures for the period from 1960 to 2018. The highest spatial resolution in the dataset corresponds to ADM3 level, while the vast majority of the disaster locations are geocoded at ADM1 level. The input data is used to calculate the total number of natural disasters at the ADM2 level. The raw data is distributed by Socioeconomic Data and Applications Center (SEDAC) and available at https://www.earthdata.nasa.gov/data/catalog/sedac-ciesin-sedac-pend-gdis-1.00.

Malaria Prevalence Rate. The Malaria Atlas Project (MAP) provides data on the prevalence of malaria *plasmodium falciparum* cases (per 1,000 people) for the years 2000 to 2019. The spatial resolution of the input data are 5 km grid cells and are available at https://malariaatlas.org/. The input rasters are used to calculate the mean malaria prevalence rate within 0.1 decimal degree grid cells. These values are then spatially matched to the DHS survey locations.

D.5 DHS Survey Variables

For our analysis, we rely on the Demographic and Health Surveys (DHS) program to obtain data on household characteristics. The sample includes all available combinations of countries and waves, for which GPS coordinates are available. We use the variables `hv000`, `hv001`, and `hhid` to identify countries, DHS survey locations, and households and calculate the following characteristics. For our analysis, the variables are aggregated to the survey location level by calculating, where applicable, the mean of the respective variable for all households in the survey location, using the household sample weights provided in the DHS data (`hv005`).

Building Material. The floor building material (`hv213`) is used as a proxy for household resources. This variable is employed in the calculation of the DHS wealth index and has been administered across all waves. The variable is recoded to the three major categories of floor types mentioned in the DHS recode manuals, that is, *"natural"*, *"rudimentary"*, or *"finished"* floor material, which are standard across all waves and countries. For example, the answer *"natural floor material"* encompasses all country-specific building materials that are categorized as natural, for example, *"earth/sand"*, *"dung"*, or *"mud and hay"* for Afghanistan.

Educational Attainment. The educational attainment of household members (`hv106`) is used as a human capital proxy. We calculate the shares of individuals in a survey location that have completed either primary, secondary, or higher education, or have no education at all, respectively.

Water Source. The source of drinking water (`hv201`) is used as a proxy for the quality of the dwelling's sanitation. The variable is recoded to the major categories of water sources mentioned in the DHS recode manuals, that is, *"piped water"*, *"tube well water"*, *"dug well water"*, *"surface from spring"*, *"rainwater"*, *"tanker truck"*, or *"bottled water"*, which are standard across all waves and countries. We employ an indicator variable whether a household has access to piped water or not.

Type of Toilet Facility. The type of toilet facility (`hv205`) is used as a proxy for the quality of the dwelling's sanitation. The variable is recoded to the major categories of toilet facility mentioned in the DHS recode manuals, that is, *"flush toilet"*, *"pit toilet latrine"*, *"No Facility"*, or *"composting toilet / bucket"*, which are standard across all waves and countries. We employ an indicator variable whether a household has access to a flush toilet or not.

Resources Owned. Indicator variables whether a household owns certain resources that are used as a proxy for wealth and possessions, as well as access to basic infrastructure. We calculate the shares of households in a survey location that own a radio, a bicycle, or have access to electricity, respectively. These variables are based on the question, whether the household owns the respective item (*"Bicycle"* (`hv210`), *"Radio"* (`hv207`)) or has access to the respective infrastructure (*"Electricity"*, `hv206`).

Household Demographics. Based on responses from the individual household members, we calculate the average size of the household, the mean age of the survey respondents, as well as the share of households that report the household head to be male.

Household size is calculated as the total number of household members. *Mean age* is calculated as the average of the age of all household members (`hv105`). *Male head* is an indicator variable that is set to 1 if the household head (`hv101=1`) is reported as male (`hv104=1`).

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