# Lighting the path: The influence of historical Christian missions on modern-day development aid allocation in Africa*

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December 21, 2017

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**Abstract**

Recent studies suggest that development aid is not always directed toward the poorest areas within countries, contrary to what we would expect if the objective is to end poverty. In this paper, we document a positive correlation between the location of historical Christian missions and the within-country allocation of World Bank and Chinese financed development projects in Africa. The correlation is conditioned on observable geographical and historical factors that have shaped missionaries' settlement decisions. Christian missions often included health and education facilities, and we consider them to be ancestors of modern micro-development projects. We interpret our finding as evidence of historical path dependence in the spatial distribution of aid, which can be rationalized by assuming decreasing unit cost of implementing aid at the local level. We do not find evidence that the results are driven by donor preference for Christian or westernized areas.

**Keywords:** development aid; christian missions; historical path dependence; africa
**JEL-codes:** F35; I3; N37; N77; O19

*We are grateful to Valeria Rueda and Julia Cagé for sharing their data with us. We also thank Axel Dreher, Martin Flatø, Nicola Gennaioli, Rune Jansen Hagen, Andreas Kotsadam, Eliana La Ferrara, Edwin Leuven, Jo Thori Lind, Silvia Marchesi, Halvor Mehlum, Anirban Mitra, Kalle Moene, Alexander Moradi, Andreas Müller, Ola Olsson, Anna Tompsett, Gaute Torsvik, Nina Bruvik Westberg, participants at the 2016 Conference on Development Economics and Policy, the 2016 Nordic Conference on Development Economics, the 2016 Frisch-PRIO Workshop on Foreign Aid, the 2016 African Economic History Network Conference, the 2017 CSAE Conference, and the 2017 Royal Economic Society meeting for helpful comments and suggestions. This project was supported by the Centre of Equality, Social Organization and Performance (ESOP). ESOP is supported by the Research Council of Norway through its Centres of Excellence funding scheme, project number 179552.

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# 1 Introduction

Where does foreign development aid go? This question is of central importance in the aid effectiveness debate. The World Bank has the explicit goal to end extreme poverty, and to focus on the poorest segment of the population (World Bank Group, 2013). This strategy would suggest that aid allocation should be targeted to the poorest regions first, but several empirical studies seem to suggest that it is instead biased by political and strategic considerations. For example, Alesina and Dollar (2000) find colonial history and co-voting in the UN to be major predictors of donor-recipient foreign aid flows. Along the same lines, Dreher, Sturm, and Vreeland (2009) show that the World Bank allocates disproportionately more development projects to countries during their tenure as temporary members of the UN Security Council. Most of the early research on this subject has focused on the cross-country and across-time dimensions; however, the more recent literature on the determinants of within-country aid allocation has come to similar conclusions: various kinds of favoritism are important in explaining the spatial distribution of development aid (Dreher et al., 2016; Jablonski, 2014; Masaki, forthcoming).

We add to this literature by studying the role of historical accidents in shaping the present-day within-country allocation of aid. In particular, we argue that the development efforts initiated by 19th and 20th century Christian missionaries laid the foundation for future development aid in Africa, by decreasing the cost of implementing additional aid projects in the same location. Consequently, the post-war emergence of the aid industry has disproportionately benefited areas with a missionary history.

In the empirical analysis, we compare a georeferenced snapshot of all mission stations in Africa in 1903 to the precise locations of World Bank-funded projects in 1995–2014. The unit of analysis is derived from a grid of $55 \times 55$ km square cells covering the African mainland and Madagascar.[1] The results imply that the presence of (at least) one mission station increases the probability that an area is allocated a development project by approximately 50 %. We take several empirical measures to alleviate concerns of omitted variables bias. First, we control for country dummies in all specifications, because the first step of aid allocation is at the country level. Second, we address the non-random selection of missionaries into specific locations. To this end, we always exclude areas covered by desert or dense forest, and control for historical and geographical factors that guided the missionaries' settlement decisions according to historical sources. Con-

[1] The main results are robust to collapsing the data to administrative levels 1 and 2 (regions and districts, respectively), as well as to ethnic homelands, as defined in Murdock (1959). Results available on request.

trols capture cultivation potential, accessibility, 19th century Western contact, historical settlement patterns and the pre-colonial presence of Islam. Third, we show that the correlation is robust when restricting the sample to areas that are more likely to be similar: areas that intersect the ocean coastline or one of the main rivers, and subsamples obtained by propensity score matching. Fourth, we show that the link between historical missions and aid survives also when controlling flexibly for present-day population density. Finally, the test developed by Oster (forthcoming) to assess the extent of omitted variable bias suggests that only a small part of the estimated correlation is likely to be driven by unobservable factors.

We interpret these findings as evidence of path dependence, i.e. long-term persistence in the location of specific activities. Although development aid in its present form is a relatively recent phenomenon, similar activities implemented by Westerners in developing countries began much earlier.[2] In particular, they can be traced back to the work by Christian missionaries, who were particularly active at the end of the 19th century. The first wave of Christian missionaries reached Africa before the European colonization of the continent, and established a permanent presence in the form of mission stations, which was expanded during the scramble for Africa.

The missionary effort was primarily driven by proselytism motives, but it was not restricted to conversion. Missions provided the locals with a wide range of education and health services, primarily to boost the odds of conversion. Missionaries were quite explicit about the instrumental role of these investments. For example Robinson (1915), in his *History of Christian missions*, devotes a whole chapter to how building schools and hospitals is by far the most effective way to convert locals to Christianity. The belief in the instrumental role of medicine led to the establishment of special medical schools designed to provide missionaries with medical training (R. Johnson, 2010). Many missionaries served as teachers in missionary schools, where they taught not only the Bible, but also secular subjects, and provided job training. All in all, we believe that mission stations can be considered as the ancestors of modern micro-development projects. Our interpretation is consistent with the recent literature in economics which has found positive long-term effect of missionary interventions on a variety of development outcomes (discussed in section 2.2).

Evidence of path dependence in the spatial distribution of development aid parallels the well-known evidence of path dependence in the location of production activities (e.g.

[2]The beginning of modern development aid coincides with the establishment of the World Bank in 1944, and the launch of the U.S.-sponsored Marshall Plan in 1948, aimed at reconstructing European economies after WWII.

the Manufacturing Belt in the U.S.). The new economic geography theory explains path dependence in the location of manufacturing firms by assuming increasing returns to scale at the firm level (Krugman, 1991b). Economies of scale force firms to produce in a limited number of locations. When choosing their preferred production location, firms would like to establish in high-demand regions, and serve the rest of the market from there in order to minimize transportation costs. In turn, high-demand regions are exactly those where other firms chose to locate. In this set-up, history matters and the initial spatial distribution of firms perpetuates over time.[3]

A similar pattern of geographical path dependence would equivalently be generated by decreasing unit costs. There are reasons to believe that the implementation of development aid is indeed subject to decreasing unit costs at the local level, for example due to the presence of initial fixed costs. Setting up a development project in a village where others have been implemented in the past is likely to be substantially cheaper than doing so in a "greenfield" village. First, returning to the same location allows for exploiting existing material infrastructures (wells, roads, buildings, etc.) built during previous interventions. Second, continued interaction between locals and aid workers (missionaries or not) is also likely to enhance mutual trust and effective cooperation. Third, and along the same lines, continued investment in the same location enables the accumulation of region-specific knowledge, which is likely to decrease information costs. Finally, complex development projects may require that the target population has already acquired particular skills during previous interventions. In this framework, the presence of Christian missions is likely to have permanently shifted downwards the cost of implementing development projects in the regions where missionaries first settled. We provide some indirect evidence of the presence of decreasing unit costs by showing that development projects closer to historical missions are able to unlock subsequent payments earlier compared to projects elsewhere. This finding suggests that projects close to missions proceed faster, which indicates that these areas have higher absorption capacities for aid.

We contrast the path dependence hypothesis with the most likely competing explanation: that the allocation of aid is shaped by favoritism and strategic considerations. The most influent World Bank members are Western and predominantly Christian countries. As such, World Bank aid may favor locations close to Christian missions because of their cultural proximity to Western values, and their higher Christian share of population, as

[3]For example Krugman (1991a) uses this type of model to illustrates the case of the U.S. Manufacturing belt. The first bulk of U.S. manufacturing firms located in the Midwest region stretching from New York to the Great Lakes when this area was the main agriculture center, but this production cluster remained in the same location for decades after farming activities shifted elsewhere.

shaped by the missionary work. In contrast to this hypothesis, we find the same robust correlation when analyzing the distribution of Chinese-financed aid, which is unlikely to be prone to Christian and Western biases. Furthermore, the spatial correlation between aid projects and historical missions is robust when controlling for the Christian share of population in the area, which in itself is a predictor of aid location.

# 2 Literature

Our paper connects the literature on determinants of development aid allocation with studies on the long-term effects of missionary activity, both relatively new branches of development economics. The following review substantiates our argument for path dependence in aid, by presenting evidence that existing conditions and some level of development are prerequisites for receiving aid, and by describing some ways in which the presence of missions has influenced long-term development, and thereby contributed to fulfilling these prerequisites. A secondary objective is to give the reader some knowledge of the observed consequences of Christian missionary activity, in order to contextualize our empirical results. To the best of our knowledge, we are the first to provide evidence that historical events affect present day aid allocation.

## 2.1 Determinants of aid allocation

Most research on aid allocation falls within two categories; papers that investigate whether poverty targeting is successful, and those that explicitly examine whether political targeting occurs. Our preferred mechanism relates to the first category, in that existing conditions reduce the cost of implementing aid projects. Evidence of political targeting supports an alternative hypothesis, in which mission stations play a political (or religious) role in attracting aid projects. This literature has largely pivoted toward within-country studies, thanks to the availability of new granular data at the subnational level.

Several studies explore whether aid is directed to poor areas, as we should expect if poverty alleviation is the primary objective. Francken, Minten, and Swinnen (2012) study relief aid following a cyclone in Madagascar. They find that, while some effort is devoted to the affected areas, some NGO and foreign funded projects are located in less affected, but more accessible areas. Importantly, their findings on the importance of accessibility are consistent with aid displaying decreasing unit costs at the local level. Nunnenkamp, Öhler, and Andrés (2017) provide evidence from India that health, water and transportation aid does target poor areas, whereas aid within energy and agriculture is not related to poverty. They further show that World Bank infrastructure projects are located in areas with higher foreign direct investment, at the cost of not reaching the poorest areas. Briggs (2017) investigates the localization of African Development Bank (AfDB) and World Bank (WB) projects in Africa. The evidence shows a near monotonic relationship between wealth percentiles and the share of total aid allocation. The results from these papers are consistent with our hypothesis about a path dependence in aid, in that more developed areas are likely to provide better conditions for efficient project implementation.

The recent literature also provides evidence that domestic political considerations have considerable weight in the within-country allocation of aid. Dreher et al. (2016) find that Chinese aid is disproportionately allocated to the birth region of African presidents, while there is no such effect for World Bank-funded projects. Jablonski (2014) shows that AfDB and WB aid to Kenya in the period 1992–2010 was diverted away from areas with strong support for the opposition, and Briggs (2014) confirms this pattern, using data on project aid from individual donors in 1989–1995. The opposite pattern emerges in Zambia, however; Masaki (forthcoming) shows that Zambian political elites have funneled AfDB and WB aid away from their political base and toward areas where the opposition has been strong. The apparent inconsistencies between these results can likely be explained by the importance of clientelistic ethnic politics in Kenya (Chabal & Daloz, 1999). These findings raise the possibility that a correlation between missionary activity and development aid may be a result of a political or religious bias.

### 2.2 Long-term effects of missionary activity

Economists are becoming increasingly aware of the long-term effects of historical Christian missions. Nunn (2010) shows that Christian missionaries have been successful in converting people to Christianity, arguably their primary target. Using Afrobarometer survey data and the location of historical missions, he documents that individuals whose ethnic group has been in contact with missions are more likely to be Christian today. There is also ubiquitous evidence that historical Christian missions have had a positive impact on the current level of education of people in the surrounding areas. Nunn (2014) finds that the location of Catholic and Protestant missions in Africa is associated with higher average educational attainment, but that the effect from Catholic missions only appears in males. Using historical records from Uganda on women born between 1880 and 1945, Meier zu Selhausen (2014) finds that Protestant mission education improved female literacy, and that being employed at a mission station had a significant positive impact on women's position within the household. Okoye and Pongou (2017) exploits the fact that missionary activity in Nigeria was partly aimed at ending the slave trade, and finds that although slave trade had a total negative effect on schooling, it had a positive indirect effect through attracting missionaries.

Mantovanelli (2014) documents the educational legacy of Protestant missionary work in India. He finds that districts that had at least one Protestant mission at the beginning of the 20th century have a more literate population today. The effect is not present in districts with Catholic missions. Using the same data, Castelló-Climent, Chaudhary, and Mukhopadhyay (forthcoming) use Catholic missions as an instrumental variable for tertiary education in a regression on nighttime luminosity. Their first stage displays a positive and significant correlation. Interestingly, the same first-stage relationship does not appear for Protestant missions, which seems inconsistent with previous findings. Castelló-Climent et al. (forthcoming) reconcile the results by pointing to the Protestant concern for basic literacy. Similarly, Chen, Wang, and Yan (2014) document a positive effect of protestant missions on subnational GDP in China, working partly through education and health. Using historical floods and droughts to instrument for the likelihood of attracting missionaries, they estimate the elasticity of current GDP with respect the 1920 convert share of population to be between 0.1 and 0.2. In a recent paper, Waldinger (2017) exploits the fact that the missionary expansion from Mexico City followed the direction of initial missionaries, giving plausibly exogenous variation in missionary activity. She shows that the historical presence of Mendicant missions has led to persistent increases in current educational attainment and literacy.

In the literature reviewed so far there seems to be consistent denominational differences in the long-term effects of missionary activity. Gallego and Woodberry (2010) argues that part of this differential can be explained by differences in competition; whereas Catholic missions in Africa were protected from competitors, Protestant missions faced competitive pressure, leading them to increase the provision of education.

There is also evidence that missions have improved health outcomes. Calvi and Mantovanelli (2016) investigate the long-term effects of missionary health investments in India, comparing missions with and without hospitals. They find persistent positive effects on current individuals' body mass index. Their findings are not explained by persistence of physical infrastructure, but rather by improved health practices.

Furthermore, several papers have investigated the effects of missions on attitudes and behavioral outcomes. Caicedo (2017) looks at the effect of the Jesuit expansion and subsequent expulsion in southern parts of Latin America. Through surveys and behavioral experiments, he finds that people in these areas exert substantially higher collaborative behavior today. The effect seems to be context dependent, however. Using data from Nigeria, Okoye (2017) presents evidence of a negative relationship of missionary activity on collaborative behavior. He argues that the erosion of traditional institutions that missionaries deemed incompatible with Christian values led to societies with lower levels of trust.

There is also evidence that the introduction of Christian values have changed particular traditional behaviors. For example, Kudo (2017) finds that missionary-educated women marry later, and are less likely to get married with a polygamous husband. Cagé and Rueda (2017) and Mantovanelli (2014) find that individuals living close to historical missions more often have negative attitudes toward condom use, and that this explains higher HIV prevalence in these areas. Finally, Cagé and Rueda (2016) focus on missionary investments in a specific technology, rather than in education or health. They find that the printing press, imported by Protestant missionaries to print Bibles, facilitated the birth of newspapers, and is still important in explaining newspaper diffusion today, which in turn results in higher social capital.

# 3 Empirical strategy and data

## 3.1 Empirical strategy

Our empirical strategy exploits spatial variation in historical mission stations and present-day aid allocation across Africa. Since the location of missions is predetermined and does not vary over time, we collapse the temporal dimension of aid allocation to get a cross-sectional dataset. The unit of observation is contiguous grid cells at a resolution of $0.5 \times 0.5$ degrees, which at the equator roughly corresponds to $55 \times 55$ kilometers. We intersect the grid with the African continent, and keep the part of the grid covering continental Africa and Madagascar. Cells are split by borders, in order to make sure that aid projects are geographically assigned to the correct country. We further assign cells to the first two within-country administrative levels from the GADM database of Global Administrative Areas (region and district), by matching the centroid of each cell with the ADM in which it falls. The baseline specification to be estimated by OLS is

$$EverAid_{ik} = \beta \cdot Mission_{ik} + \delta_k + \mathbf{X}_{ik}\gamma + \varepsilon_{ik} \ , \tag{1}$$

where $i$ and $k$ are indexes for cell and country, respectively. $EverAid_{ik}$ is binary variable equal to one if cell $i$ had at least one active aid project in the period of study, and zero otherwise. $Mission_{ik}$ is an indicator equal to one if at least one historical mission was located in cell $i$, and zero otherwise.

The baseline estimation exploits within-country variation only. The inclusion of country dummies $\delta_k$ is important, because the first step of the aid allocation procedure is at the country level.[4] The vector $\mathbf{X}_{ik}$ contains control variables at the grid cell level, including a number of historical and geographical factors, described in section 3.2.2. The error term $\varepsilon_{ik}$ is allowed to be spatially correlated within a radius of 220 kilometers from the centroid of each cell. We use the standard error estimator developed by Conley (1999).[5]

Coefficient $\beta$ has a causal interpretation if $\mathbf{X}$ and $\delta_k$ contain all relevant determinants of mission locations that are also correlated with present-day aid allocation. Failure to include important controls will bias the size of the coefficient. In the following, we discuss possible sources of bias, and how we deal with them.

The most obvious threat to a causal interpretation of $\beta$ is non-random selection of mission stations. Missions are predetermined with respect to present-day aid, but they may have located in areas that were more suitable for missionary work, and areas where missionaries could survive and be self-sustained. If these areas for some reason, other than mission station presence, are more or less likely to be selected for aid projects today, $\beta$ will be biased, or the correlation may be entirely spurious. For example, we may believe that missionaries were more likely to establish in relatively more populated areas, in order to convert as much people as possible. If these areas are more populated also today, we would expect them to be large recipients of aid, for reasons unrelated to the presence of missionaries. We have quite detailed information about the determinants of the location of mission stations from historical sources, notably from H. B. Johnson (1967) and Robinson (1915). Moreover, there is an increasing amount of detailed and spatially disaggregated historical data available, so we are able to plausibly control for most of these determinants by using existing data sources. Section 3.2.2 discusses in detail the data we use to deal with this source of bias.

A second source of bias is the lack of common support in the distribution of the control variables. Even if our set of controls $\mathbf{X}_{ik}$ fully accounts for the selection problem, the simple OLS estimator will still be biased if the cells hosting a historical mission (the treated observations) are very different in their covariates compared to cells without a historical mission (the control observations), and if the control function is misspeci-

[4]For example, to be eligible for IDA (International Development Association) funds from the World Bank, a country must be below a threshold level of GNP per capita (Galiani, Knack, Xu, & Zou, 2017).

[5]The standard errors are calculated using the Stata program *x_ols*, written by Jean-Pierre Dube, available at http://economics.uwo.ca/faculty/conley/.

fied (Imbens & Rubin, 2015). The African continent is geographically and historically diverse, and so are single African countries. Although we use only within-country variation, i.e. cells within a country as control groups for treated cells within the same country, the risk of non-common support remains. We have a number of strategies to tackle this problem.

First, the sample always excludes cells covered by more than 90 % barren land and cells that are more than 90 % covered by forest from our sample. These cells are likely special with respect to both aid allocation and the potential for sustaining a permanent missionary presence.[6]

Second, we experiment with restricting the sample to coastal cells, to those that intersect one of the main African rivers,[7] and both. There is evidence that areas close to the coast and to navigable rivers are more developed and more densely populated (Gallup, Sachs, & Mellinger, 1999), so these cells are likely to form a more homogeneous sample. At the same time, these areas were the most accessible for the missionaries, who came predominantly by sea, and often penetrated inland by navigating rivers upstream (H. B. Johnson, 1967). In addition to consolidating the distributions of observed covariates, these subsamples likely make mission and non-mission cells more comparable in *unobserved* covariates, reducing the potential for selection bias.

Third, we restrict the analysis to subsamples obtained using propensity score matching. Specifically, we construct three different balanced subsamples of our data, one where the matching has no geographical restrictions and two where we match within countries to account for the country-level nature of World Bank aid. To obtain the first, we estimate a logit model on the full sample using $Mission_{ik}$ as the dependent variable, and $\mathbf{X}_{ik}$, its interactions, its squared terms, and country dummies as predictors.[8] We then match mission cells with their nearest (statistical) neighbor without replacement using the predicted values as propensity scores. For the second sample, we re-estimate propensity scores separately country by country (using the logit model but without interactions and squared terms, because the individual country samples are small), and restrict the pool of possible matches to cells that belong to the same country. For the third sample, we re-estimate propensity scores with the same logit model as for the first sample, but without country dummies. We then perform the same matching procedure, but we again match country by country. Imbens (2015) stresses that different matching strategies are equally valid as long as they tackle the lack of common support in the

[6]The specific choice of threshold at 90 % is chosen to exclude a significant mass in the right tail of the distributions.

[7]Nile, Niger, Senegal, Zambezi, Congo and its attributes Ubangi and Kasai.

[8]We do not include ethnic dummies, because this prevents the logit model from converging.

covariate distribution. He suggests a procedure similar to ours for studies where the number of control observations is way higher than the number of treated ones, which is the case in our application.

Finally, a third source of bias derives from the spatial nature of our data. If mission stations are clustered, we may be overestimating the impact of a single mission station on aid allocation in a given cell, since the density of missions in nearby cells may be similarly important. We assess robustness to spatial correlation by constructing spatial lags of mission stations, and adding them to the regression model.

## 3.2 Data

### 3.2.1 Aid

Data on foreign aid is based on World Bank projects in the period 1995–2014, geocoded by AidData, and Chinese-financed aid projects in the period 2000–2012, geocoded by A. Strange, Dreher, Fuchs, Parks, and Tierney (2015) and Dreher et al. (2016).[9] These are the only geocoded datasets covering the whole African continent (and beyond) over a substantial time period. Although we collapse the data to a cross-section, wide temporal coverage ensures that results are not driven by aid in a given year.

The World Bank dataset contains projects from both the International Bank for Reconstruction and Development (IBRD) and the International Development Association (IDA), in total 1,092 projects in Africa, split across 5,079 different locations. The IBRD provides low or zero interest rate loans to sufficiently credit-worthy countries, whereas the IDA gives loans to poorer and less credit-worthy countries. 12 % of IDA funds are given as grants not to be paid back. Both types of lending is accompanied by technical assistance from the Bank, and projects are monitored by Bank agents.

The information available at the project level includes the original World Bank identifier, project title, date of approval, expected date of completion, total net disbursement, sector (e.g. Finance, Transportation, Health, etc.), lending instrument, implementing agency, and total committed amount (in U.S. dollars). The Chinese-financed aid dataset contains 1,952 projects in Africa, split across 1,308 different locations, and the information at the project level is similar to that available for the World Bank dataset.

The data contains information on all sites in which a given project has been implemented. The geocoding of the World Bank data is based on the same methodology as the UCDP Georeferenced Event Dataset.[10] The source of location information is

[9] Detailed information about public data sources is given in Appendix A, Table A.2.
[10] Described in detail in Strandow, Findley, Nielson, and Powell (2011).

World Bank project documents, and personal communication with project managers if additional detail is required. If locations cannot be retrieved from donor documents, AidData checks recipient country documents and aid management systems, or information from implementing agency websites. Locations may be towns, hills, farms, or other geographical features. The coders then search for coordinates in geographical databases like Geonames and Google Earth. If the name of a specific location cannot be matched with a set of coordinates, coders look for nearby towns or other identifiable features. The Chinese aid data is similarly geocoded, but the underlying project information is collected based on the "Tracking Underreported Financial Flows" methodology, due to a low degree of transparency for Chinese aid. Coders identify projects using media reports, and supporting information is then collected via aid information management systems operated by recipients, Chinese donor institution websites, web scraping and journal article searches.[11]

Each location is categorized according to the precision of its coordinates: precision 1 locations correspond to a specific place (e.g. village, hill, bridge, railroad station, etc.) and precision 2 locations are identified within a 25 kilometer distance from the reported coordinates. The remaining precision codes (3–8) include aid that is either not successfully geocoded, too imprecise, or given to municipalities, provinces or the entire country. These project locations are too coarse to be useful in our grid-level analysis, so we drop them from the sample. Table 1 shows the distribution of location precision codes. On average, a World Bank project is split across 46 locations, while the median project is split across 28 locations.

Table 1: Precision of aid locations

| | World Bank (%) | China (%) |
|---|---|---|
| Precision 1 – specific place | 41 | 39 |
| Precision 2 – within 25km of specific place | 2 | 4 |
| Precision 3 – municipality (ADM1) | 26 | 8 |
| Precision 4 – province (ADM2) | 20 | 11 |
| Precision 5 – imprecise | 2 | 2 |
| Precision 6 – country-wide projects | 4 | 19 |
| Precision 8 – state or national capitals | 5 | 17 |

### 3.2.2 Mission stations

We rely on two different historical sources to retrieve information on the location of Christian mission stations. Our preferred source is the *Geography and Atlas of Christian*

[11] Detailed information in A. M. Strange, Parks, Perla, and Desai (2015).

*Missions* (Beach, 1903), digitized by Cagé and Rueda (2016). It includes the location of Protestant mission stations in Africa as of 1903, coupled with information on the investment of each mission (school, dispensary, hospital, etc.). In Appendix C, we replicate the entire analysis using mission stations identified in *Ethnographic Survey of Africa: Showing the Tribes and Languages* by Roome (1924), and digitized by Nunn (2010). This source reports locations of both Protestant and Catholic foreign mission stations in Africa as of 1924. The results of virtually all the analyses are quantitatively similar, and qualitatively identical, using either one of these sources to construct $Mission_{ik}$.

The reason to rely on two different sources is twofold. First, historical sources are likely to be subject to measurement error in the precise location of missions, and we cannot rule out that some stations are not reported. The two sources are independent from each other, which means that any non-random measurement error affecting one is not likely to affect the other as well. Second, both sources report locations at a specific point in time; however, new missions are likely to be founded afterwards, and some of the early stations abandoned. It is less likely that our results are driven by the location of missions in one specific year if we can replicate the analysis using sources recorded twenty years apart. Figure 1 shows the location of mission stations in the two sources, along with main rivers. The period between the two sources saw a massive expansion of missionary activity in Africa, due to the colonization of the continent. Therefore, the cell-level correlation between protestant missions from Beach (1903) and Roome (1924) is only 0.31. One specific reason for the low correlation is that missionaries started penetrating the African inland after first settling on the coast. Hence, the 1924 data has a higher concentration further from the coast, which is evident in Figure 1.

#### 3.2.3 Selection of missions and historical controls

Missionary activity in Africa was not randomly assigned across the continent, as illustrated by the case studies in H. B. Johnson (1967). If the factors that determine the selection of mission station location correlate with present-day aid allocation, coefficient $\beta$ in equation (1) will be biased.

The first factor to consider is accessibility. Missionaries came by sea, and inland penetration was difficult, so missionaries followed the tracks of early European explorers, some of whom were missionaries themselves.[12] The early explorer routes partly correspond to the course of the main rivers, for two reasons. First, upstream navigation was the most effective means of transportation, and would ensure water supply all

[12] For example, David Livingstone was a missionary at the London Missionary Society (Shepperson, n.d.).

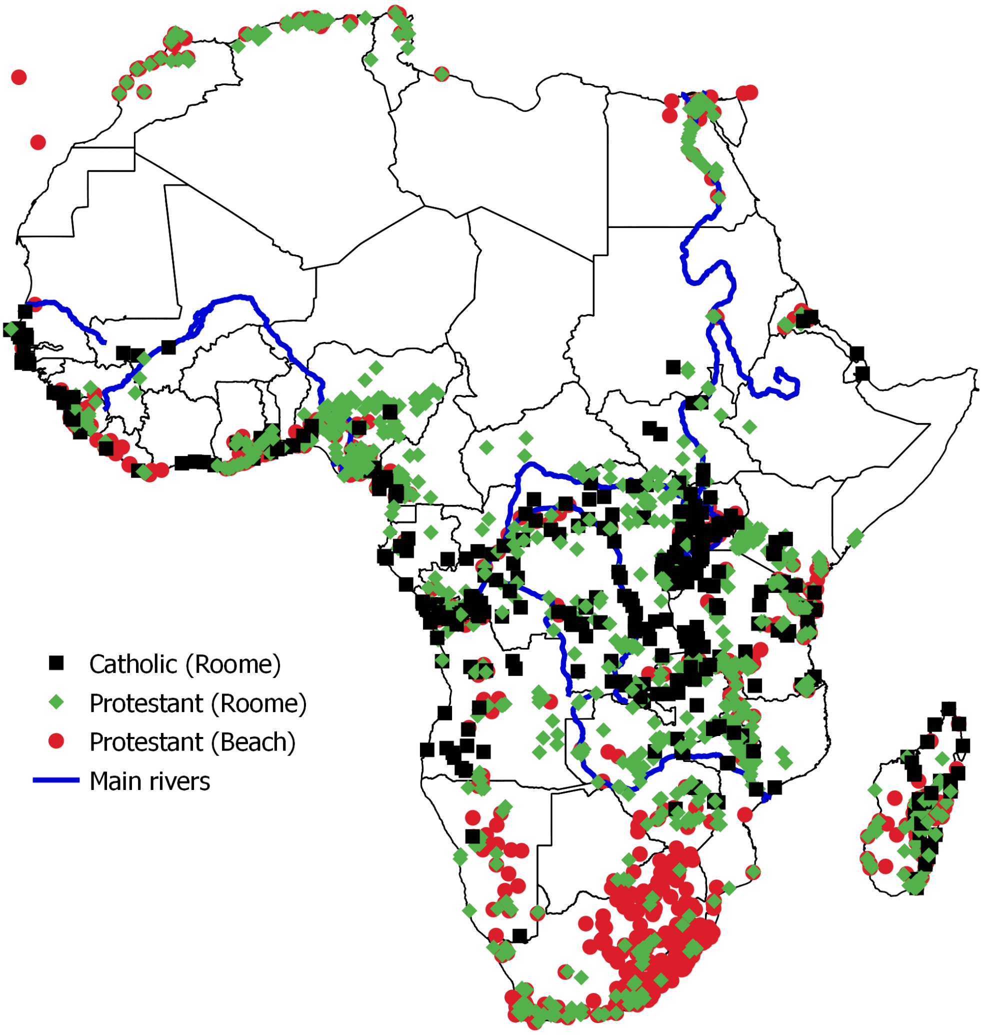


Figure 1: Location of mission stations and main rivers

along the trip. Second, one of the main goals of explorers was to map the geography of Africa, and in particular track rivers from mouth to spring.[13] As there is evidence that areas along coast and rivers have an advantage in development, and are more densely populated (Gallup et al., 1999), we control for the (log) kilometer distance from the closest point on the coast and from the closest main river. We use distances in logs of because the marginal effect of a unit of proximity is likely to approach zero as distance increases.[14] The data on coastlines and rivers is from Natural Earth. We include rivers with importance ranking 1–3, as defined by the source. The resulting main rivers are the Senegal, the Nile, the Niger, the Zambezi, the Congo and its attributes the Ubangi and the Kasai.

We also control for the (log) distance to the closest explorer route, using data from the Century Company Atlas, digitized by Nunn (2010). Colonial railways built by European powers provided an alternative way of transportation inland. As recent research has documented long-lasting effects of colonial railways on urbanization and growth in Africa (Jedwab & Moradi, 2016; Jedwab, Kerby, & Moradi, 2017), we control for the (log) kilometer distance from these using data from the Century Company Atlas. Finally, as a (inverse) measure of accessibility, we also include terrain ruggedness.[15] Ruggedness has been found to have both positive and negative effects on development in Africa. Rugged landscape makes it easier to hide, which provided protection from slave traders (Nunn & Puga, 2012), but it also enables rebel warfare (Fearon & Laitin, 2003).

The second factor to consider is the capacity to keep the settlement self-sustained for a long period of time. Self-sustainability crucially depended on access to water and land cultivation suitability, which are likely to be important for present-day outcomes as well. Land cultivation suitability is proxied by the *Caloric Suitability Index* (CSI) (Galor & Özak, 2016). The CSI builds on information from FAO about the land suitability for a number of crops over the world and computes from this the maximum caloric potential of crops in 5 by 5 arcminute cells, from which we take averages at a 0.5 degree resolution.[16] We control for the access to water by the share of cell area that is within 10 kilometers of a water source, using data from the Seamless Digital Chart of the World.[17] Missions

[13] In a famous expedition, Henry Morton Stanley discovered first the source of the Nile. Then he established that the Lualaba was not part of the Nile, by navigating it downstream until was clear that was instead connected with the Congo (Encyclopædia Britannica, n.d.).

[14] More precisely, we use the log of 1 + the distance measured in kilometers, to avoid losing the cells at zero distance. The average distance is large, so the addition of 1 is analytically inconsequential.

[15] Calculated with the QGIS raster analysis plug-in, based on USGS GMTED2010 elevation data.

[16] One arcminute is 1/6th of a degree.

[17] 10 kilometers is considered to be the maximum distance that cattle can travel without stress (Mati, Muchiri, Njenga, de Vries, & Merrey, 2006).

were also more likely to establish in high altitudes, partly to avoid diseases like malaria, but also because of a more comfortable climate (H. B. Johnson, 1967). We therefore control for average elevation, calculated at the 0.5 degree cell level from the GMTED2010 map by the USGS, and for its interaction with a dummy for the tropics (between $-23.5$ and 23.5 degrees latitude). As a further control for disease environment, we include a measure of malaria prevalence, the *Malaria Ecology Index* from Kiszewski et al. (2004).

Finally, we also need to account for the main missionary purpose, namely conversion of Africans to Christianity. Whether missionaries considered conversion more likely in densely populated areas than sparsely populated areas is not clear. Different missionary societies likely had different strategies. Some may have preferred sparsely populated areas to convert peoples that would not otherwise have been reached, and others may have targeted large populations in order to maximize the number of converts. In any case, some minimum level of settlement was likely a prerequisite for establishing a missionary presence. Ideally, we would like to control for population in 18th century, prior to most missionary activity on the African continent. There are no spatially disaggregated censuses from this time, but there have been some attempts to produce population estimates. We employ the population data from the History Database of the Global Environment (HYDE), which provides estimates of population density for the whole world at a resolution of 5 arcminutes for every decade in the 18th century. We take the 0.5 degree average of these estimates, and average the result across the 18th century. The population data is included as a fourth order polynomial to allow for non-linearities.

Furthermore, we also employ data on the location of historical cities collected by Chandler (1987). We assign a dummy equal to one to cells that hosted a city any time before 1800. In addition, the existence of different ethnic groups may have played an important role in the missionaries' settlement decisions. Some groups may have been more open to missionaries and foreigners in general, while others were more hostile. Alternatively, some groups may have been particularly poorly developed, thus offering a higher potential for selling the Gospel along with educational and health services. We are concerned that unobserved variables at the ethnicity level may introduce biases, in light of research showing that pre-colonial ethnic institutions had long-lasting effects on development and public good provision in Africa (Gennaioli & Rainer, 2007; Michalopoulos & Papaioannou, 2013). We tackle this concern by including a separate dummy for each of the more than 800 pre-colonial ethnic homelands, whose boundaries are from Murdock's (1959) ethnolinguistic map. We assign cells to the ethnic polygon that covers the highest percentage of its surface. Regressions therefore only exploit within-ethnicity variation, and results cannot be driven by factors varying across ethnicities.

According to Robinson (1915), competition with Islam was a deterring factor, in that spreading the Gospel in predominantly Muslim areas was more complicated. Although speculative, Muslim populations may receive less development aid today for political and religious reasons, so we would like to control for a measure of Muslim penetration at the time of early exploration of Africa. Michalopoulos, Naghavi, and Prarolo (forthcoming) show that medieval trade routes to the Arab world had a strong impact on adherence to Islam, which has persisted until today. We digitize and georeference maps on Arab trade routes and ports from Kennedy (2001), and include as controls the (log) kilometer distance from the closest of these routes. Finally, some missions were set up for the purpose of ending slave trade (H. B. Johnson, 1967), a practice that was especially prevalent along the coast of West Africa, and had long-lasting detrimental effects on development and social capital (Nunn, 2008; Nunn & Wantchekon, 2011). Although we are not aware of georeferenced measures of slave trade that are precise enough for our application, we are already controlling for many of its correlates, e.g. distance to the coast, terrain ruggedness, distance to Arab trade routes, and for ethnic-level dummies.

Table 2 shows the unconditional average values of all historical controls in cells without missions, and cells with at least one mission, respectively. All variables but elevation are significantly different between mission and non-mission cells. The difference in means of distance to main river and distance to explorer route do not have the expected sign. Note, however, that these are unconditional correlations, and the distance variables are all correlated.[18]

#### 3.2.4 Present-day control variables

We also collect data from more recent years. We do not control for these variables in the baseline estimation, because they may be endogenous to our variable of interest, $Mission_{ik}$, and hence constitute bad controls that may cause a bias (Angrist & Pischke, 2008). However, we do use these variables to probe for mechanisms.

We collect estimates of grid level population data in 1995 from Gridded Population of the World at 2.5 arcminute resolution (CIESIN, 2016), and we aggregate it to the 0.5 degree resolution. The data contains estimates based on official censuses, and may therefore be noisy at the local level.[19] To complement the gridded data, we get the location and population of populated places from WorldGeoDatasets. The data contains information about 16,207 places in Africa, from which we construct dummies for populated places of different sizes, as well as province and national capitals.

[18] The conditional correlations have the correct sign.

[19] The results are unchanged if we use population data from the ISAM-HYDE project for 2000.

Table 2: Difference in means of control variables

| | No mission | Mission | Difference |
|---|---|---|---|
| Log(Distance to coast) | 5.76 | 4.01 | 1.76*** |
| Log(Distance to main river) | 5.29 | 5.89 | −0.60*** |
| % area within 10 km of water | 0.07 | 0.10 | −0.03*** |
| Malaria Ecology Index | 11.64 | 6.82 | 4.83*** |
| Caloric mean index / 1000 | 1.33 | 1.57 | −0.24*** |
| Terrain Ruggedness Index | 17.18 | 26.42 | −9.25*** |
| Mean elevation | 714.05 | 750.26 | −36.22 |
| Tropical dummy | 0.86 | 0.56 | 0.31*** |
| Log(Distance to explorer route) | 3.62 | 4.20 | −0.58*** |
| Log(Distance to colonial railway) | 5.28 | 3.59 | 1.68*** |
| 18th cent. population | 11.46 | 23.48 | −12.02*** |
| Precolonial city | 0.01 | 0.04 | −0.04*** |
| Log(Distance to Arab trade) | 5.44 | 6.09 | −0.64*** |
| No. observations | 6512 | 380 | |

*Notes:* Mission data from Beach (1903). Each row represents an unconditional mean. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

To test if there is a Christian bias, we collect information on religion from the USAID Demographic and Health Surveys (DHS). The DHS is extensive in both spatial and temporal coverage, and we exploit the fact that the survey relocates geographically between waves to attain a large spatial coverage, approximately 40 % of the cells in main sample. We make the assumption that religious affiliation is fairly stable over the period, or at least that changes in religion is not related to the other variables in the regression models. We use the individual recode of the DHS, which includes women of reproductive age (15–49), as it has the highest country coverage (in some countries, DHS only surveys women). The variable of interest is the cell-level population share of Christians, which we calculate using respondents' stated religion.[20]

# 4 Results

## 4.1 Missions and World Bank aid

We estimate equation (1) by least squares, and the results are reported in Table 3. The dependent variable is an indicator equal to one if the cell ever received a World Bank project between 1995 and 2014. All regressions include the full set of historical and geographical controls described in section 3.2.2. In the first column, the mission data is from Roome (1924), and we separate missions into Protestant and Catholic.

[20]See Appendix A for information on how we map survey responses to each major religion.

In the second column, we use only missions from Beach (1903), which only includes Protestant stations. In the third column, we use Catholic missions from Roome (1924) and Protestant from Beach (1903). Finally, in column 4, we define $Mission_{ik}$ equal to one if the cell hosted at least one mission, either Catholic or Protestant, from any of the two sources.

The correlation between historical mission presence and Word Bank aid location is positive and significant across the columns of Table 3. The estimated coefficients imply that cells with missions are approximately 46 % to 80 % more likely to host a World Bank project, compared to the sample mean. In order to assess the bias from unobservables, we draw on the procedure constructed by Oster (forthcoming) to get a lower bound for $\beta$.[21] The methodology is not suitable for models with more than one treatment, so we consider only columns 2 and 4. Under the assumption that selection on observables is equal to selection on unobservables, the test produces lower bound coefficients close to 0.1, corresponding to mission cells having a 40 % higher likelihood of aid allocation.[22]

The estimated correlation is higher for Catholic missions, but we have no way to address differences in geographical selection of different confessions, so it is difficult to interpret the difference between the two coefficients. If we drop Congo DRC from the sample, the difference between the two is lower than 2 percentage points, and not significant. Congo DRC covers 509 cells, making it the largest country in the sample, and has a high concentration of Catholic missions. Hence, the differential in the coefficient size seems to be driven by this heavyweight outlier.

In the remaining parts of the paper we only report results on the mission data from Beach (1903). The reason is partly to simplify the exposition, and partly because the base map from which the missions were georeferenced is of much higher resolution than the one in Roome (1924), so there is likely less measurement error coming from inaccurate georeferencing. Nonetheless, in Appendix C we report all tables that appear in the paper using data from Roome (1924), to ensure that results are not sensitive to the data source.

**Subsample analysis** As a first robustness test, we restrict the sample to cells on the coast or on one of the main rivers. As discussed in section 3, this subsample is likely more

[21]This test is a refinement of Altonji, Elder, and Taber (2005), in that it takes into account the effect of the observable selection on the R-squared.

[22]In the configuration of the procedure we set the R-squared from the hypothetical regression on $Mission_{ik}$ and both observed and unobserved controls equal to 1.3 times the R-squared from the actual regression on $Mission_{ik}$ and observed controls, as suggested by Oster (forthcoming). The calculation is based on the assumption that observables and unobservables correlate with $Mission_{ik}$ in the same direction.

Table 3: WB aid and missions from Beach (1903) and Roome (1924)

| | World Bank aid 1995–2014 | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Catholic mission (Roome) | 0.18*** | | 0.20*** | |
| | (0.03) | | (0.03) | |
| Protestant mission (Roome) | 0.14*** | | | |
| | (0.02) | | | |
| Protestant mission (Beach) | | 0.13*** | 0.12*** | |
| | | (0.03) | (0.03) | |
| Any mission | | | | 0.16*** |
| | | | | (0.02) |
| Ethnic dummies | Yes | Yes | Yes | Yes |
| Mean dep. var. | 0.25 | 0.25 | 0.25 | 0.25 |
| Oster bound | | 0.10 | | 0.11 |
| R-sq. | 0.40 | 0.39 | 0.40 | 0.40 |
| N | 6876 | 6876 | 6876 | 6876 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables include log distance to: coast, explorer route, colonial railway, Arab trade route; a third order polynomial in 18th century population; presence of a city as of 1800; country dummies; pre-colonial ethnic dummies; average altitude; terrain ruggedness index; percentage area within 10 kilometers from a water source; the caloric suitability index; malaria ecology; tropics dummy (also interacted with mean altitude). Cells that are more than 90 % covered by barren land or more than 90 % covered by forest are excluded from the sample. The lower bound on the coefficient of interest is calculated as in Oster (forthcoming): we set the R-squared from the hypothetical regression on $Mission_{ik}$ and both observed and unobserved controls equal to 1.3 times the R-squared from the actual regression on $Mission_{ik}$ and observed control. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

homogeneous and enhances the credibility of our selection on observables strategy, that relies on mission and non-mission cells having the same covariate distributions (Imbens & Rubin, 2015). We present estimates both with and without pre-colonial ethnic dummies, because the within-ethnicity variation is very small for the subsamples. The results are reported in Table 4, where the sample is restricted to coastal cells in 1 and 2, river cells in 3 and 4, and to the union of the two in 5 and 6.

The subsample analysis yields a correlation similar in sign and magnitude to that estimated in the baseline Table 3. When ethnic dummies are included, the point estimate is smaller and marginally insignificant at conventional levels in the coastal subsample, and slightly higher in the river subsample. However, even the most conservative specification suggests that mission cells are approximately 20 % more likely to receive World Bank aid projects.

Table 4: WB aid and missions (Beach, 1903): Coastal and river samples

| | Coast | | River | | Coast or river | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mission | $0.15^{***}$ | 0.11 | $0.19^{**}$ | $0.18^{*}$ | $0.18^{***}$ | $0.12^{**}$ |
| | (0.06) | (0.07) | (0.09) | (0.10) | (0.05) | (0.05) |
| Ethnic dummies | No | Yes | No | Yes | No | Yes |
| Mean dep. var. | 0.45 | 0.46 | 0.41 | 0.41 | 0.42 | 0.43 |
| R-sq. | 0.39 | 0.59 | 0.29 | 0.51 | 0.31 | 0.52 |
| N | 367 | 363 | 494 | 491 | 851 | 844 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables are the same as in table 3. Rivers include: Nile, Niger, Senegal, Zambezi, Congo and its attributes Ubangi and Kasai. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.

The next test is again aimed at restricting estimation to a subsample that is more likely to exhibit common support in the covariate distribution. Here, we proceed in a more structured way by constructing three subsamples where observations are balanced on propensity scores, using three different strategies. The first strategy has no geographical restrictions in estimation of propensity scores or matching between treatment and control groups (column 1–2 in Table 5). In the second, we estimate propensity scores separately within each country, and include treatment-control pairs that are statistical neighbors in the same country (columns 3–4). In the third, we estimate propensity scores on the full sample, but include only treatment-control pairs that are neighbors within the same country (columns 5–6). We then estimate equation (1) on each of the balanced subsamples, with and without ethnic dummies. Across the different subsamples, the coefficient of interest is always positive, significant, and very similar in size to those estimated on the full sample. The coefficients are slightly smaller when ethnic dummies are included, as in Table 4, but still significant at conventional levels, and sizable (30 % of the sample mean in the most conservative specification).

Table 5: WB aid and missions (Beach, 1903): Propensity score matched samples

| | Simple | | Within 1 | | Within 2 | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mission | $0.17^{***}$ | $0.11^{***}$ | $0.11^{***}$ | $0.08^{***}$ | $0.13^{***}$ | $0.09^{**}$ |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| Ethnic dummies | No | Yes | No | Yes | No | Yes |
| Mean dep. var. | 0.34 | 0.34 | 0.28 | 0.28 | 0.35 | 0.35 |
| R-sq. | 0.47 | 0.68 | 0.46 | 0.67 | 0.47 | 0.69 |
| N | 790 | 787 | 593 | 592 | 800 | 797 |

*Notes:* Robust standard errors in parentheses. OLS on matched subsamples. The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables are the same as in table 3. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.

**Controlling for present-day population** In all the regressions estimated so far, we have only included controls that are pre-determined with respect to the variable of interest, $Mission_{ik}$. This approach is the most appropriate to attempt a causal interpretation of $\beta$. However, it forces us to rely heavily on historical controls, some of which are likely to be measured with error, in particular population density. If the measurement error in the historical variables is severe, we may fail to control credibly for the selection of missions.[23] Furthermore, there is reason to believe that the presence of mission stations and the activities of missionaries has influenced settlement patterns. In that case, the coefficient on $Mission_{ik}$ partly captures a correlation between current population and aid allocation.

To tackle these concerns, we introduce in the control set different measures of present-day population. Under the assumption that population density is positively auto correlated, the present-day measures may serve as proxy controls for historical population. Under the additional assumptions that selection on population is positive, and that the presence of missions stations increase population, we can interpret the coefficients on $Mission_{ik}$ from these regressions as a lower bound on the true causal effect.[24] The

[23] In the most extreme scenario, we are just controlling for random variables.

[24] See Angrist and Pischke (2008) for a discussion of this point, and Michalopoulos and Papaioannou (2013, footnote 13) for an example.

results from these regressions are reported in Table 6.

Table 6: WB aid and missions (Beach, 1903): Present-day population controls

| | All cells | All cells | Pop. place | | Prov. capital | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mission | 0.10*** | 0.07*** | 0.07 | 0.10** | 0.19*** | 0.22*** |
| | (0.03) | (0.03) | (0.04) | (0.04) | (0.05) | (0.04) |
| Population (1995) | 0.01*** | 0.01*** | | | | |
| | (0.00) | (0.00) | | | | |
| Pop. place dummy | No | Yes | No | No | No | No |
| Ethnic dummies | Yes | Yes | Yes | No | Yes | No |
| Mean dep. var. | 0.25 | 0.25 | 0.49 | 0.49 | 0.62 | 0.62 |
| R-sq. | 0.40 | 0.43 | 0.59 | 0.33 | 0.64 | 0.32 |
| N | 6876 | 6876 | 1168 | 1168 | 698 | 698 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). Estimation by ordinary least squares. The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables are the same as in table 3. The estimation samples in columns 3–4 and 5–6 are restricted by the presence of a populated place with at least 10,000 inhabitants, and a provincial capital, respectively. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

In column 1 we include fourth order polynomial terms in population in 1995.[25] The coefficient on $Mission_{ik}$ is slightly smaller than the baseline, but still highly significant. In column 2 we add dummies for populated places of different size.[26] The coefficient drops to about half of the baseline, but stays highly significant. In column 3 we restrict the sample to cells that contain at least one populated place with more than 10,000 inhabitants. The coefficient stays positive, but drops a bit and loses significance. Note, however, that the inclusion of both country and ethnic dummies in this reduced sample is a demanding test. Dropping the ethnic dummies in column 4 gives a coefficient and standard error closer to the baseline. Column 5 and 6 is estimated on the sample of cells that contain a provincial capital, with and without ethnic dummies, respectively. The coefficient increases sharply compared to the baseline, but the effect relative to the mean of the dependent variable is very similar.

[25] To preserve space, I show only the coefficients on the mission dummy and the linear term. The coefficients on the higher order terms are shown in appendix Table B.3.

[26] Dummies for each for the presence of at least one: a) national capital; b) province capital; c) urban agglomeration of at least one million people, or city with at least 500,000 people; d) urban agglomeration of at least 250,000 people, or city with at least 100,000 people; d) urban agglomeration of at least 100,000 people, or city with at least 50,000 people; e) places with at least 10,000 people; f) places with at least 1,000 people.

**Sensitivity tests** The results in the baseline estimation in Table 3 are largely robust to various sensitivity tests. First, we check if the estimated relationships are stable over time. The Paris Declaration signed at the "Second High Level Forum on Aid Effectiveness" organized by the OECD in 2005 was aimed at transferring more management and discretion to recipient countries (although casual observation suggests that it has not had much effect).[27] In appendix Table B.1 we therefore test if we see the same pattern for aid committed in two different ten year periods, 1995–2004 and 2005–2014. The coefficients are slightly higher for the second period, but so is the total number of cells receiving aid, so in relative terms the coefficients are virtually unchanged.

Next, we check if our use of binary treatment and outcomes is important for the results. In column 1 and 2 of appendix Table B.2, we use the number of missions and the log number of missions + 1 as treatment variables, with results very similar to the baseline. We also investigate whether the relationship between aid and missions is also at work at the intensive margin. We estimate equation (1), replacing the dependent variable with the number of World Bank aid projects, and report the results in columns 3–6 of Table B.2. In column 3–4 we use OLS, but in column 4 we additionally restrict the sample to cells that received at least one project in the period. In the last two columns, the estimates are based on theoretically more appropriate count models: Poisson regression in column 5, and a Negative Binomial regression in column 6.[28] All models deliver a similar result, namely that mission cells host a higher number of aid projects, compared to non-mission cells.

**Spatial spillovers** Missions are highly clustered in our data, as apparent from Figure 1. This leaves open the possibility that we are overestimating the effect of missions on aid. For two neighboring cells that both have missions, but where only one gets aid, it may be argued that we should be accounting for the presence of that neighbor mission. Failure to do so may induce omitted variable bias.

To alleviate concerns of spillover bias from neighboring cells, we include spatial lags of missions into the regression. The lag variables for cell $i$ are constructed by multiplying the value of the dummy $Mission_{ik}$ for a given neighbor $j$ with a binary indicator variable for whether the neighbor is within a given cutoff distance from cell $i$, and summing these products for all $j \neq i$.[29] We include spatial lags for both the inner ring of surrounding 8

[27]See http://www.oecd.org/dac/effectiveness/parisdeclarationandaccraagendaforaction.htm

[28]The last two models are estimated without ethnic dummies to ensure convergence.

[29]There are different ways of incorporating spatial lags of independent variables, including inverse distance weighting matrices. The choice of a binary contiguity is one of convenience, because it makes calculations less intensive and more natural since the cell-structure of the data implies non-continuous

neighbors (cutoff distance $\approx$ 70 kilometers) and for the outer ring of 16 next neighbors (cutoff distance $\approx$ 140 kilometers).

Since the location of World Bank-funded projects is likely determined by each country's government, they are probably not correlated across country borders. Allowing for cross-border correlations would bias the results, since zero correlations between border cells would pull down the overall estimate.[30] Therefore, we construct the spatial weighting matrix so that it gives zero weight to all neighbors that are not in the same country. Define the $N_k \times N_k$ weighting matrix $W_k^r$ for country $k$ and neighbor ring $r \in \{inner, outer\}$, and let $Mission_k$ be the $1 \times N_k$ column vector, with elements indicating the presence of missions in each cell in country $k$. The equation to be estimated is then:

$$EverAid_{ik} = \beta \cdot Mission_{ik} + \sum_r \zeta_r W_{ik}^r \cdot Mission_k + \delta_k + \mathbf{X}_{ik}\gamma + \varepsilon_{ik} \ , \qquad (2)$$

where $W_{ik}^r$ is row $i$ of the weighting matrix for neighbors in ring $r$. The estimates, reported in Table 7, reveal that the coefficient of interest is not affected by the inclusion of the spatial lags. Furthermore, there is no evidence of spatial spillovers across cells, suggesting that our estimated correlation holds at a very local level. The results are reassuring, given the high degree of spatial clustering in the data.

## 4.2 Christian religion and Western culture

There is extensive evidence that strategic and political considerations are key factors behind aid allocation, so it is natural consider these as potential mechanisms behind the results in section 4.1.[31] Western and predominantly Christian countries stand out as the largest shareholders of the World Bank: the U.S. is the largest (holding respectively 10 % in the IDA, and 16 % in the IBRD), and, although Japan is second (with respectively 8 % and 7 %), and Western European countries together form a sizable group.[32] If shareholders for some reason prefer to allocate more aid to areas that are culturally similar to their own countries, we should expect to find disproportionately more World

distances. Results are robust to using an inverse distance weighting matrix.

[30] Cross-border spatial correlation could be relevant if missions had persistent effects on surrounding areas, especially before current borders were put in place. The inclusion of cross border cells in the weighting matrix has virtually no impact on the results, and we present only our preferred specification here.

[31] In this section we consider mechanisms that to some extent relies on the assumption that donors have significant control over the location of specific projects, which may not be the case.

[32] For example, UK, France and Germany together account for 15 % and 12 % of IDA and IBRD funds, respectively. Figure available at https://www.worldbank.org/en/about/leadership/votingpowers/.

Table 7: WB aid and missions (Beach, 1903): Spatial lags

| | World Bank aid 1995–2014 | |
|---|---|---|
| | (1) | (2) |
| Mission | 0.17*** | 0.17*** |
| | (0.03) | (0.03) |
| Mission spatial lag, inner ring | | 0.03 |
| | | (0.02) |
| Mission spatial lag, outer ring | | -0.01 |
| | | (0.02) |
| Ethnic dummies | Yes | Yes |
| Mean dep. var. | 0.26 | 0.26 |
| R-sq. | 0.40 | 0.40 |
| N | 6102 | 6102 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Inner ring refers to the 8 neighbors adjacent to each cell. Outer ring refers to the next 16 closest outer neighbors. Control variables are the same as in table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Bank projects in African regions with a large Christian population, and in areas that have strong ties with Western countries. In both respects, cells with a history of Christian missionary activity are likely to stand out, as the presence of missions increased both Christian and Western footprints.

We explore this channel by replicating our analysis using aid data for China, a donor that is not likely to be biased toward Christian and Western areas. If cultural or religious bias is the main explanation behind our results, then we should find no relationship between the presence of a historical mission and present-day Chinese-financed aid. Chinese culture is markedly distinct from Western culture, and the Chinese government is unlikely to give preferential treatment to Christians of any confession. On the other hand, existing research has found China to be roughly comparable to other Western donors in terms of political and economic considerations behind aid allocation (Dreher & Fuchs, 2015; Dreher, Fuchs, Parks, Strange, & Tierney, forthcoming). We estimate the baseline equation (1) on an indicator for presence of at least one Chinese aid project over the period 2000–2012, and report the coefficient on $Mission_{ik}$ in column 1 of Table 8. The coefficient is smaller relative to the baseline (0.04), but the share of cells in the sample that is allocated Chinese aid is roughly one third of the share for World Bank aid. This means that in relative terms, the estimates are comparable to the main results on World Bank aid, with the mean of Chinese aid in mission cells about 60 % higher than the sample mean.

The similarity of the results may not be surprising if Chinese aid simply co-locates with World Bank aid; for example, the presence of World Bank aid may provide a signal of the quality of project locations. Although we are not aware of any evidence in this respect, the unconditional correlation between the two outcome variables is non-negligible at 0.25. We tackle this concern by introducing World Bank aid as a control in the regression on Chinese aid, which becomes:

$$EverAidfromChina_{ik} = \beta \cdot Mission_{ik} + \theta \cdot EverAidfromWB_{ik} + \delta_k + \mathbf{X}_{ik}\gamma + \varepsilon_{ik}. \quad (3)$$

However, $EverAidfromWB_{ik}$ is not predetermined with respect to $Mission_{ik}$, and therefore the interpretation of $\beta$ requires additional caution. In particular, the coefficient $\beta$ now captures the difference in the outcome between mission and non-mission cells, conditional on having ever received World Bank aid. The cells that never received World Bank aid despite having a mission could be less suitable for aid due to other unobservable characteristics, and vice versa for cells that received World Bank aid despite not having a mission. In other words, conditional on $EverAidfromWB_{ik} = 0$, equation (3) compares "bad" mission cells to regular non-mission cells; conditional on $EverAidfromWB_{ik} = 1$, equation (3) compares "good" non-mission cells to regular mission cells. Thus, controlling for $EverAidfromWB_{ik}$ is likely to bias the estimate of $\beta$ downward.

Consistent with this logic, the estimate of $\beta$ (reported in column 2 of Table 8) is 1 percentage point smaller than the coefficient in column 1. However, it is still positive and significant, suggesting that missions do predict Chinese aid, even when the selection on unobservables (introduced by controlling for $EverAidfromWB_{ik}$) is working against finding any effect. Overall, we interpret the results in Table 8 as evidence against the Christian and Western bias hypothesis discussed above.

As a second and more direct attempt to test the Christian bias channel, we add a control for the Christian share of population to the model. There is no comprehensive georeferenced data on religion, so we estimate it using geocoded surveys from the DHS. More specifically, our measure of cell-level Christian population share is equal to the share of DHS respondents in the cell who self-identify as Christians. We can construct this variable for about 3,000 cells. This measure is not likely to be representative at the cell level, and thus subject to (non-systematic) measurement error, which will attenuate coefficients toward zero. If the measurement error is severe, the variable is not particularly useful in controlling for religion. In column 1 and column 4 of Table 9 we examine whether the Christian share is correlated with aid allocation. Failing to find a

Table 8: Chinese aid and missions (Beach, 1903)

| | Chinese aid 2000–2012 | |
|---|---|---|
| | (1) | (2) |
| Mission | 0.04** | 0.03* |
| | (0.02) | (0.02) |
| World Bank aid | | 0.09*** |
| | | (0.01) |
| Ethnic dummies | Yes | Yes |
| Mean dep. var. | 0.07 | 0.07 |
| R-sq. | 0.31 | 0.32 |
| N | 7911 | 7911 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees (≊ 200 km). Estimation by OLS. The dependent variable is a dummy for whether the grid cell had at least one active Chinese aid project in the period 2000–2012. Control variables are the same as in table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

significant correlation would be cause for concern, given the hypothesis of a Christian bias. In both cases, however, the correlation is positive, significant and large.

Next, we re-estimate our equations (1) and (3), and we find that our coefficient of interest remains virtually the same with or without controlling for the Christian share (Table 9).[33] To conclude, we do not find any evidence that the association between missions and aid is motivated by religious or cultural bias on the donor side.

### 4.3 Speed of disbursement

Having found no evidence that the relationship between missions and aid is driven by biased preferences on the donor side, we turn to investigating whether mission cells are somehow more suitable to host aid projects, for example due to the possibility of exploiting preexisting material and immaterial infrastructure. Evidence in this direction would provide support for our path dependence hypothesis. Although we do not have measures of "suitability" at the cell level, we test this indirectly using data on financial flows at the project level.

[33] Also in this case the interpretation of the coefficient is not trivial due to the endogeneity of the Christian share. The coefficients on $Mission_{ik}$ in column 3 and 6 can be interpreted as a lower bound in light of existing evidence that missions increased conversion (Nunn, 2010). The coefficients on $Mission_{ik}$ are not significant in column 5 and 6, but this is a heavily reduced sample, and the coefficient is the same as in the full sample (see Table 8).

Table 9: WB aid and missions (Beach, 1903): Christian share of population

| | World Bank aid 1995–2014 | | | Chinese aid 2000–2012 | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share Christian | $0.12^{**}$ | | $0.11^{**}$ | $0.11^{***}$ | | $0.11^{***}$ |
| | (0.05) | | (0.05) | (0.03) | | (0.03) |
| Mission | | $0.10^{**}$ | $0.10^{**}$ | | 0.04 | 0.04 |
| | | (0.04) | (0.04) | | (0.03) | (0.03) |
| Ethnic dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean dep. var. | 0.41 | 0.41 | 0.41 | 0.13 | 0.13 | 0.13 |
| R-sq. | 0.41 | 0.41 | 0.41 | 0.41 | 0.37 | 0.41 |
| N | 2895 | 2895 | 2895 | 2792 | 2792 | 2792 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). Estimation by ordinary least squares. The dependent variable is a dummy for at least one aid project in the indicated period. Control variables are the same as in table 3. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.

Initially committed project funds are not disbursed up-front as a lump sum, but in successive tranches over the course of several years. The structure of disbursements varies between projects, but are usually linked to the successful implementation of some steps in the project. For example, borrowers can ask for reimbursements of eligible expenditures that they have anticipated, or the World Bank can pay third parties (suppliers, NGOs, etc.) directly for implementing specific activities.[34] As such, a high speed of disbursement can be taken as an indication that the project is proceeding fast and efficiently toward its goals. In order to test if projects implemented in mission cells display a higher speed of disbursement, we collect financial data for each project from the World Bank website. This data records the date and type of all financial transactions over the project lifetime and during the repayment phase.

We adopt the methodology in Kersting and Kilby (2016), who investigate how the speed of disbursements depends on recipient countries' political alignment with the U.S. Disbursement speed is measured by tracking the number of months until 25 % of commitments have been disbursed. We use only initial commitments and disbursements linked to those committed funds.[35] The reason for using the 25 % threshold is that most projects cross it during the sample period, giving a larger sample, but we also report results using 50 % and 75 % thresholds.

Since disbursement data is at the project, rather than location level, we collapse the data to the project level. We also depart from the grid-cell structure, since we want

[34]See siteresources.worldbank.org/PROJECTS/Resources/DisGuideEng.pdf.

[35]Some projects receive additional commitments several years after the initial commitment.

information about specific projects, and there may be several projects in the same cell. We thus match missions to aid by identifying mission stations within a 25-kilometer buffer around each aid location. This distance corresponds approximately to the extent of the $0.5 \times 0.5$ degree cells in the baseline. Our explanatory variable of interest is the project's fraction of precision 1 and 2 locations that are within 25 kilometers of a mission station. Since the speed of disbursement may depend on the size of the initial commitment, we include it as a control in the regression. We also include dummies for country and year of commitment.

Table 10 shows that having more project locations in the proximity of Christian missions is positively correlated with speed of disbursement (negatively correlated with months until X % disbursed). The sign is invariably negative no matter what threshold we use, and it is marginally insignificant only for the highest threshold (75 %), which is estimated on the smallest sample. The coefficients are small, but non-negligible. When the fraction of locations close to a mission increases with one standard deviation, projects reach the 25 % threshold about 2 months, or 6 %, earlier than the sample mean.

The analysis of disbursement speed indicates that projects with a high fraction of locations near mission stations tend to receive money slightly faster. We interpret this as evidence that mission cells have higher absorption capacity, due to favorable conditions on the ground. However, World Bank staff does have some degrees of discretion over the timing of the tranches, and Kersting and Kilby (2016) show that disbursement is sometimes sped up or slowed down in response to political pressure. As such, the results in Table 10 could also be consistent with favoritism. However, in light of the fact that we have not found any other evidence in this direction, we regard the path dependence hypothesis as the most convincing explanation for the findings in this paper.

Table 10: WB aid and missions (Beach, 1903): Project speed of disbursement

| | Mos. until X % disbursed | | | Log(mos.) |
|---|---|---|---|---|
| | 25% | 50% | 75% | 25% |
| Fraction of locations with mission | -6.14*** | -6.96* | -8.46 | -0.28** |
| | (2.03) | (3.61) | (5.30) | (0.12) |
| Log initial commitment | 0.01 | 0.84 | 2.21 | -0.07 |
| | (1.04) | (1.34) | (1.46) | (0.05) |
| Country FE | Yes | Yes | Yes | Yes |
| Year of committment FE | Yes | Yes | Yes | Yes |
| Mean dep. var. | 33.21 | 47.48 | 60.62 | 3.37 |
| R-sq. | 0.18 | 0.19 | 0.28 | 0.17 |
| N | 524 | 477 | 404 | 521 |

*Notes:* Standard errors clustered at country level in parentheses. Estimation by OLS. The dependent variable is the number of months until X % of initial commitments have been disbursed. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

## 5 Conclusion

This paper has documented that 19th and 20th century Christian missionary activity in Africa predicts the location of present-day aid allocation. We find that the probability of receiving World Bank development projects is about 50 % higher in areas that contain a historical Christian mission station. In light of the importance of education and health facilities in the missionary effort, we consider mission stations as the ancestors of present-day development projects. We therefore interpret these findings as evidence of historical path dependence in the spatial distribution of aid. The missionary presence is likely to have caused a permanent downward shift in the cost of implementing development projects in the same locations, due to the possibility of exploiting existing material and immaterial infrastructure. Consistent with this hypothesis, we find that projects implemented in the proximity of mission stations manage to unlock successive disbursements faster than the average project, which suggests a higher absorption capacity. We show that this mechanism is able to compete with the most likely alternative explanations, which is that the results are caused by biased donor preferences toward Christian or westernized areas. Chinese aid projects show a similar spatial allocation pattern as World Bank aid, and although the Christian share of the population does predict aid allocation, it does not affect the role of mission stations.

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# Appendix A Data sources

The construction of the religion variables from DHS survey responses requires parsing and categorization of a wide range of spellings and different denominations, and we proceed as follows: "Protestant" is assigned to respondents who state one of the following (all sic): protestant, protestantism, anglican, sda, Evangelical, anglican church, presbyterian, pentecotist, pentecostal/charismatic, pentecostal, baptist, anglican/protestant, prostestant, salvation army, other christian, armé de salut, evangelical, other christians, ccap, anglican, seventh day advent./baptist, united faith, kimbanguist, kimbanguiste, kibanguist, evangelical/pentecostal, evangelical presbyterian, evangelical, evangelist, evangelica (crente), evangelic. "Catholic" is one of: Catholic, Roman Catholic, catholic, catholique, catolica romana. "Muslim" is one of: muslim, moslem, mulsim, muslem, muslim - alawi, muslim - sunni, muslum, muslman, musulman, musulmane, islam, muslim/islam, islamic, Muslim. Summary statistics for the final categorization are shown in Table A.1.

Table A.1: Religion of DHS respondents

| Religion | N | Mean | SD |
|---|---|---|---|
| Christian | 909,621 | 0.52 | 0.50 |
| Catholic | 909,621 | 0.18 | 0.38 |
| Protestant | 909,621 | 0.29 | 0.46 |
| Muslim | 909,621 | 0.40 | 0.49 |
| No religion | 909,621 | 0.02 | 0.15 |
| Other religion | 909,621 | 0.06 | 0.22 |

*Notes:* The categories are not mutually exclusive, since "Christian" contains both "Catholic" and "Protestant".

Table A.2: Data sources

| Data | Source | Link | Access date |
|---|---|---|---|
| World Bank projects | AidData | www.aiddata.org/ | 2016-06-22 |
| World Bank project documents | World Bank | projects.worldbank.org/ | 2016-06-22 |
| Chinese projects | AidData | www.aiddata.org/ | 2016-12-12 |
| Missions in 1924 | Roome (1924), Nunn (2010) | scholar.harvard.edu/nunn/ | 2016-06-15 |
| Country borders | GADM | www.gadm.org/ | 2016-12-22 |
| Coast line | Natural Earth | www.naturalearthdata.com/ | 2017-02-20 |
| Rivers | Natural Earth | www.naturalearthdata.com/ | 2017-02-20 |
| Explorer routes | Century Company, Nunn (2010) | scholar.harvard.edu/nunn/ | 2016-12-13 |
| Colonial railways | Century Company, Nunn (2010) | scholar.harvard.edu/nunn/ | 2016-12-13 |
| Gridded elevation data | United States Geological Survey | topotools.cr.usgs.gov/ | 2016-05-23 |
| Caloric Suitability Index | Galor and Özak (2016) | www.omerozak.com/ | 2016-10-05 |
| Water sources | WorldGeoDatasets (fee) | www.worldgeodatasets.com/ | 2016-05-20 |
| Malaria Ecology Index | Kiszewski et al. (2004) | www.gordonmccord.com/ | 2016-12-13 |
| 18th century population | HYDE | www.pbl.nl/hyde/ | 2016-03-08 |
| Historical cities | Chandler (1987) | www.worldcitypop.com/ | 2016-04-05 |
| Ethnic groups | Murdock (1959), Nunn (2008) | scholar.harvard.edu/nunn/ | 2016-03-14 |
| Arab trade routes | Kennedy (2001) | referenceworks.brillonline.com/ | 2016-09-03 |
| Population in 1995 | SEDAC | sedac.ciesin.columbia.edu | 2016-02-06 |
| Populated places | WorldGeoDatasets (fee) | www.worldgeodatasets.com/ | 2016-06-15 |
| Religious affiliation | USAID DHS Program | www.dhsprogram.com/ | 2016-04-08 |

# Appendix B Supplementary material

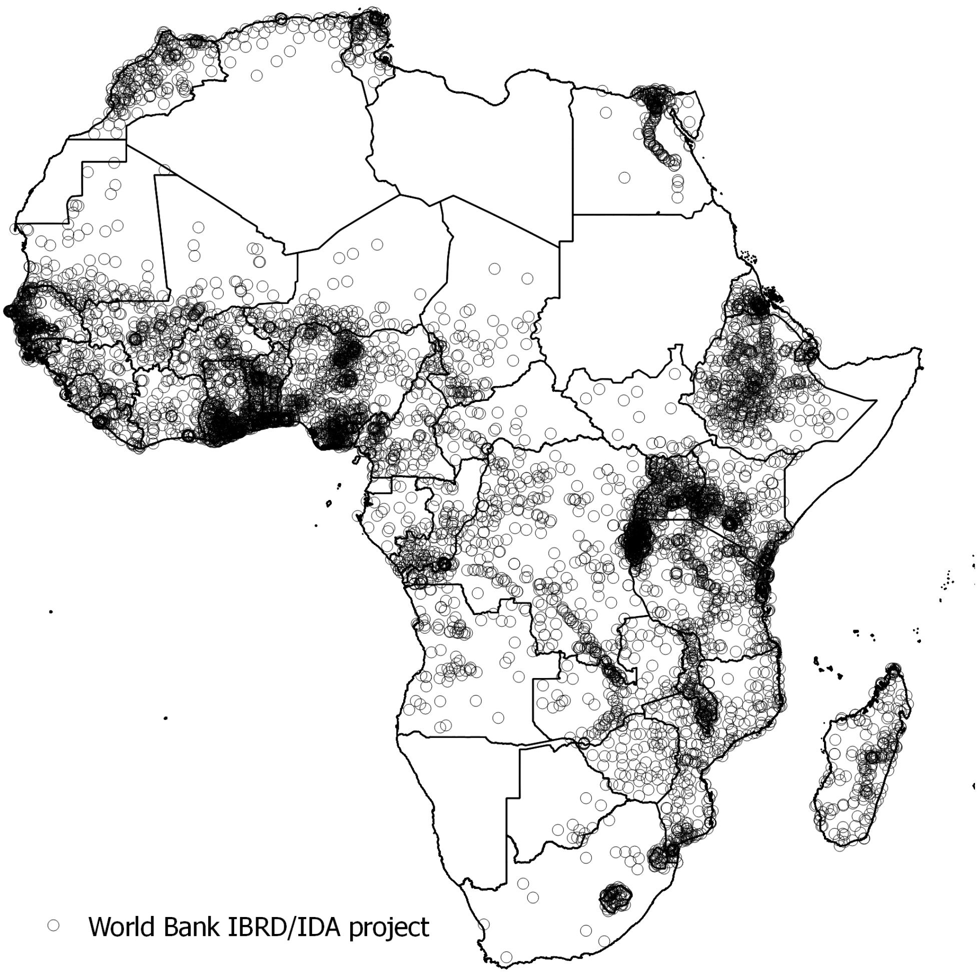


Figure B.1: Location of World Bank IBRD/IDA projects

Table B.1: WB aid and missions (Beach, 1903) in two decades

| | Ever World Bank aid in period | |
|---|---|---|
| | 1995-2004 | 2005-2014 |
| Mission | $0.09^{***}$ | $0.13^{***}$ |
| | (0.02) | (0.03) |
| Ethnic dummies | Yes | Yes |
| Mean dep. var. | 0.15 | 0.19 |
| R-sq. | 0.39 | 0.36 |
| N | 6876 | 6876 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees (≊ 200 km). Estimation by ordinary least squares. The dependent variable is a dummy for at least one World Bank project commitment in each period. Control variables are the same as in table 3. $^{*}$ p < 0.1; $^{**}$ p < 0.05; $^{***}$ p < 0.01.

Table B.2: WB aid and missions (Beach, 1903): Non-binary treatment and outcome

| | Ever WB aid | | Number of WB projects | | | |
|---|---|---|---|---|---|---|
| | OLS | OLS | OLS | OLS | Poisson | NB |
| No. of missions | $0.05^{***}$ | | | | | |
| | (0.01) | | | | | |
| Ln(No. of missions) | | $0.13^{***}$ | | | | |
| | | (0.03) | | | | |
| Mission dummy | | | $1.39^{***}$ | $2.34^{***}$ | $0.83^{***}$ | $0.73^{***}$ |
| | | | (0.33) | (0.75) | (0.11) | (0.07) |
| Ethnic dummies | Yes | Yes | Yes | Yes | No | No |
| Mean dep. var. | 0.25 | 0.25 | 0.92 | 3.63 | 0.92 | 0.92 |
| R-sq. | 0.39 | 0.39 | 0.48 | 0.51 | | |
| N | 6876 | 6876 | 6876 | 1737 | 6884 | 6884 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees (≊ 200 km) in columns 1–4. Robust standard errors in column 5 and 6. In columns 1 and 2 the dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. In columns 3 to 6 the dependent variable is the number of aid commitments. In column 4 the sample is restricted to cells with at least one project commitment. Control variables are the same as in table 3, but without ethnic dummies in columns 5 and 6. $^{*}$ p < 0.1; $^{**}$ p < 0.05; $^{***}$ p < 0.01.

Table B.3: WB aid and missions (Beach, 1903): Present-day population controls

| | All cells | All cells | Pop. place | | Prov. capital | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mission | 0.10*** | 0.07*** | 0.07 | 0.10** | 0.19*** | 0.22*** |
| | (0.03) | (0.03) | (0.04) | (0.04) | (0.05) | (0.04) |
| Population (1995) | 0.01*** | 0.01*** | | | | |
| | (0.00) | (0.00) | | | | |
| Population$^2$ | -0.80*** | -0.52*** | | | | |
| | (0.11) | (0.10) | | | | |
| Population$^3$ | 0.00*** | 0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Population$^4$ | -0.00*** | -0.00*** | | | | |
| | (0.00) | (0.00) | | | | |
| Pop. place dummy | No | Yes | No | No | No | No |
| Ethnic dummies | Yes | Yes | Yes | No | Yes | No |
| Mean dep. var. | 0.25 | 0.25 | 0.49 | 0.49 | 0.62 | 0.62 |
| R-sq. | 0.40 | 0.43 | 0.59 | 0.33 | 0.64 | 0.32 |
| N | 6876 | 6876 | 1168 | 1168 | 698 | 698 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). Estimation by ordinary least squares. The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables are the same as in table 3. The estimation samples in columns 3–4 and 5–6 are restricted by the presence of a populated place with at least 10,000 inhabitants, and a provincial capital, respectively. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.

# Appendix C Results with an alternative data source

The tables in this section is a replication of all tables in the paper, using the mission station data by Roome (1924) in place of Beach (1903). The former contains information on missionary denomination, so we report separate dummy variables for Protestant and Catholic, except in table C.2, where we collapse the two.

Table C.1: WB aid and missions (Roome, 1924): Coastal and river samples

| | Coast | | River | | Coast or river | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Catholic mission | 0.263*** | 0.284*** | 0.088 | 0.147 | 0.171*** | 0.159** |
| | (0.074) | (0.085) | (0.095) | (0.121) | (0.058) | (0.071) |
| Protestant mission | 0.141** | 0.116* | 0.181** | 0.172** | 0.180*** | 0.155*** |
| | (0.058) | (0.063) | (0.081) | (0.080) | (0.051) | (0.053) |
| Ethnic dummies | No | Yes | No | Yes | No | Yes |
| Mean dep. var. | 0.452 | 0.457 | 0.407 | 0.409 | 0.422 | 0.425 |
| R-sq. | 0.417 | 0.604 | 0.303 | 0.514 | 0.323 | 0.530 |
| N | 367 | 363 | 494 | 491 | 851 | 844 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees (≈ 200 km). The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables are the same as in table 3. Rivers include: Nile, Niger, Senegal, Zambezi, Congo and its attributes Ubangi and Kasai. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.2: WB aid and missions (Roome, 1924): Propensity score matched samples

| | Simple | | Within 1 | | Within 2 | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mission | 0.196*** | 0.212*** | 0.212*** | 0.216*** | 0.190*** | 0.186*** |
| | (0.021) | (0.026) | (0.023) | (0.028) | (0.021) | (0.027) |
| Ethnic dummies | No | Yes | No | Yes | No | Yes |
| Mean dep. var. | 0.385 | 0.385 | 0.332 | 0.332 | 0.379 | 0.379 |
| R-sq. | 0.328 | 0.528 | 0.284 | 0.515 | 0.345 | 0.537 |
| N | 1532 | 1532 | 1222 | 1222 | 1521 | 1521 |

*Notes:* OLS on matched subsamples. Robust standard errors in parentheses. The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables are the same as in table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.3: WB aid and missions (Roome, 1924): Split in two periods

| | Ever world bank aid in period | |
|---|---|---|
| | (1) | (2) |
| Catholic mission | 0.167*** | 0.199*** |
| | (0.030) | (0.030) |
| Protestant mission | 0.132*** | 0.135*** |
| | (0.019) | (0.022) |
| Ethnic dummies | Yes | Yes |
| Mean dep. var. | 0.154 | 0.187 |
| R-sq. | 0.403 | 0.374 |
| N | 6876 | 6876 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). The dependent variable is a dummy for at least one World Bank project in each period. Control variables are the same as in table 3. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.

Table C.4: Chinese aid and missions (Roome, 1924)

| | Chinese aid 2000–2012 | |
|---|---|---|
| | (1) | (2) |
| Catholic mission | 0.131*** | 0.116*** |
| | (0.030) | (0.030) |
| Protestant mission | 0.060*** | 0.049*** |
| | (0.016) | (0.016) |
| World Bank aid | | 0.083*** |
| | | (0.011) |
| Ethnic dummies | Yes | Yes |
| Mean dep. var. | 0.071 | 0.071 |
| R-sq. | 0.320 | 0.330 |
| N | 7911 | 7911 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 km). Estimation by OLS. The dependent variable is a dummy for at least one Chinese aid project in 1995–2014. Control variables are the same as in table 3. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.

Table C.5: WB aid and missions (Roome, 1924): Present-day population controls

| | All cells | All cells | Pop. place | | Prov. capital | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Catholic mission | 0.165*** | 0.124*** | 0.079 | 0.056 | 0.127** | 0.127*** |
| | (0.033) | (0.034) | (0.076) | (0.054) | (0.064) | (0.046) |
| Protestant mission | 0.114*** | 0.085*** | 0.112*** | 0.106*** | 0.180*** | 0.214*** |
| | (0.022) | (0.021) | (0.042) | (0.037) | (0.059) | (0.043) |
| Population (1995) | 0.011*** | 0.006*** | | | | |
| | (0.001) | (0.001) | | | | |
| Population$^2$ | -0.765*** | -0.503*** | | | | |
| | (0.113) | (0.102) | | | | |
| Population$^3$ | 0.002*** | 0.001*** | | | | |
| | (0.000) | (0.000) | | | | |
| Population$^4$ | -0.000*** | -0.000*** | | | | |
| | (0.000) | (0.000) | | | | |
| Pop. place dummy | No | Yes | No | No | No | No |
| Ethnic dummies | Yes | Yes | Yes | No | Yes | No |
| Mean dep. var. | 0.253 | 0.253 | 0.492 | 0.492 | 0.617 | 0.617 |
| R-sq. | 0.409 | 0.437 | 0.591 | 0.336 | 0.645 | 0.324 |
| N | 6876 | 6876 | 1168 | 1168 | 698 | 698 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees (≈ 200 km). Estimation by ordinary least squares. The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. The estimation samples in columns 3–4 and 5–6 are restricted by the presence of a populated place with at least 10,000 inhabitants, and a provincial capital, respectively. Control variables are the same as in table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.6: WB aid and missions (Roome, 1924): Non-binary treatment and outcome

| | Ever WB aid | | Number of WB projects | | | |
|---|---|---|---|---|---|---|
| | OLS | OLS | OLS | OLS | Poisson | NB2 |
| No. of Catholic | 0.123*** | | | | | |
| | (0.024) | | | | | |
| No. of Protestant | 0.079*** | | | | | |
| | (0.014) | | | | | |
| Ln(No. of Cath.) | | 0.156*** | | | | |
| | | (0.029) | | | | |
| Ln(No. of Prot.) | | 0.171*** | | | | |
| | | (0.026) | | | | |
| Catholic dummy | | | 2.572*** | 2.833*** | 0.687*** | 0.668*** |
| | | | (0.443) | (0.732) | (0.099) | (0.076) |
| Protestant dummy | | | 1.279*** | 2.274*** | 0.700*** | 0.624*** |
| | | | (0.210) | (0.499) | (0.074) | (0.063) |
| Ethnic dummies | Yes | Yes | Yes | Yes | No | No |
| Mean dep. var. | 0.253 | 0.253 | 0.916 | 3.626 | 0.915 | 0.915 |
| R-sq. | 0.398 | 0.400 | 0.499 | 0.533 | | |
| N | 6876 | 6876 | 6876 | 1737 | 6884 | 6884 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees ($\approxeq$ 200 Km) in columns 1 to 4. Robust standard errors in column 5 and 6. In columns 1 and 2 the dependent variable is a dummy for at least one World Bank project in 1995–2014. In columns 3 to 6 the dependent variable is the number of active projects in 1995–2014. In column 4 the sample is restricted to cells that received at least one aid project. Control variables are the same as in table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.7: WB aid and missions (Roome, 1924): Spatial lags

| | World Bank aid 1995–2014 | |
|---|---|---|
| | (1) | (2) |
| Catholic mission | 0.204*** | 0.205*** |
| | (0.034) | (0.034) |
| Protestant mission | 0.131*** | 0.128*** |
| | (0.024) | (0.024) |
| Protestant spatial lag - inner ring | | 0.025* |
| | | (0.015) |
| Protestant spatial lag - outer ring | | -0.013 |
| | | (0.014) |
| Catholic spatial lag - inner ring | | 0.025 |
| | | (0.020) |
| Catholic spatial lag - outer ring | | 0.016 |
| | | (0.020) |
| Ethnic dummies | Yes | Yes |
| Mean dep. var. | 0.257 | 0.257 |
| R-sq. | 0.435 | 0.436 |
| N | 6102 | 6102 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees (≊ 200 Km). The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Inner ring refers to the 8 neighbors adjacent to each cell. Outer ring refers to the next 16 closest outer neighbors. Control variables are the same as in table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.8: WB aid and missions (Roome, 1924): Christian share of population

| | World Bank aid 1995–2014 | | | Chinese aid 2000–2012 | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Christian share | 0.117** | | 0.108** | 0.113*** | | 0.104*** |
| | (0.054) | | (0.053) | (0.035) | | (0.034) |
| Catholic mission | | 0.153*** | 0.152*** | | 0.162*** | 0.161*** |
| | | (0.036) | (0.035) | | (0.039) | (0.039) |
| Protestant mission | | 0.088*** | 0.087*** | | 0.073*** | 0.071*** |
| | | (0.029) | (0.029) | | (0.022) | (0.022) |
| Ethnic dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean dep. var. | 0.413 | 0.413 | 0.413 | 0.131 | 0.131 | 0.131 |
| R-squared | 0.409 | 0.414 | 0.415 | 0.371 | 0.383 | 0.384 |
| N | 2895 | 2895 | 2895 | 2792 | 2792 | 2792 |

*Notes:* Conley (1999) standard errors in parentheses, with cutoff at 2 degrees (≊ 200 km). Estimation by ordinary least squares. The dependent variable is a dummy for at least one World Bank project commitment in 1995–2014. Control variables are the same as in table 3. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.9: WB aid and missions (Roome, 1924): Project speed of disbursement

| | Months until disbursement reached | | | Log(months) |
|---|---|---|---|---|
| | 25% | 50% | 75% | 25% |
| Fraction of locations with mission | -4.69** | -5.32* | -8.36* | -0.19* |
| | (1.76) | (2.91) | (4.86) | (0.11) |
| Log initial commitment | 0.09 | 0.50 | 2.23 | -0.05 |
| | (0.98) | (1.31) | (1.38) | (0.04) |
| Country FE | Yes | Yes | Yes | Yes |
| Year of committment FE | Yes | Yes | Yes | Yes |
| Mean dep. var. | 33 | 47 | 61 | 3 |
| R-sq. | 0.247 | 0.251 | 0.348 | 0.201 |
| N | 524 | 477 | 404 | 521 |

*Notes:* Standard errors clustered at country level in parentheses. Estimation by OLS. The dependent variable is the number of months until X % (on top of each column) of initial commitments have been disbursed. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.