2020 N° 32 | ECONOMIE INTERNATIONALE | INTERNATIONAL ECONOMICS

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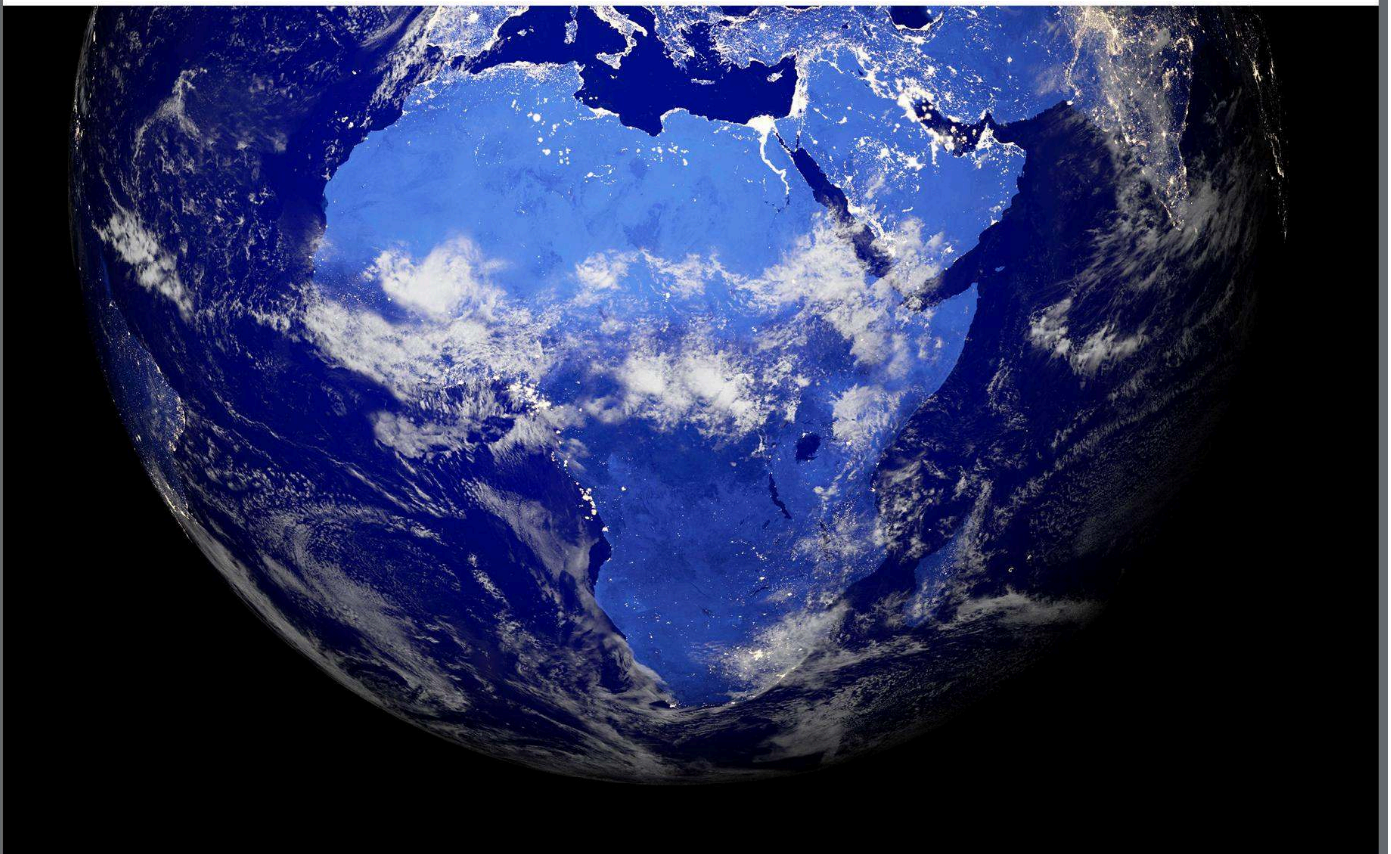

# The Effect of Foreign Aid on Sub-national Development: A Quantile Regression Approach

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Graduate Institute Publications

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DOI: 10.4000/books.iheid.7797
Publisher: Graduate Institute Publications
Place of publication: Genève
Year of publication: 2020
Publication date: 7 septembre 2020
Series: eCahiers de l'Institut
Digital ISBN: 978-2-940600-20-5



## DIGITAL REFERENCE

Ochem, Dumebi. *The Effect of Foreign Aid on Sub-National Development*. Graduate Institute Publications, 2020, https://doi.org/10.4000/books.iheid.7797.

**Cover metadata**
**Caption**
Nasa
**Credits**
Shutterstock
This text was automatically generated on 5 mai 2025.

## ABSTRACT

This ePaper investigates the non-linear effects of geo-referenced World Bank aid projects on economic development at the sub-national level, measured as night-time luminosity. The data framework is based on a grid cell structure at a 0.5 x 0.5 decimal degree resolution, covering approximately 10,600 grid cells across 54 African countries, over the period of 1992 to 2014. This approach addresses endogeneity concerns associated with sample selection and reverse causality. Using a fixed effects quantile regression approach, I estimate the impact of foreign aid at distinct levels of development within countries. Overall, the results suggest a positive and statistically significant effect of aid on night-time luminosity, with the largest impact observed within relatively poorer grid cells. In addition, there is evidence of spill-over aid effects from neighbouring grid cells. These findings are however sensitive to different model specifications and variable transformations.

*We extend our heartfelt thanks to the Vahabzadeh Foundation for financially supporting the publication of best works by young researchers of the Graduate Institute, giving a priority to those who have been awarded academic prizes for their master's dissertations.*

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# Acknowledgments

1 I wish to thank my supervisor, Prof. Jean-Louis Arcand, for his invaluable help and guidance throughout the writing of this thesis. I am grateful to Professors Ugo Panizza and Lore Vandewalle for their constructive feedback. I would also like to thank my peers – Julien Christen, Carolina Lemos and Sofia Schroeter – for their helpful comments. Finally, I thank my family – Alex, Irene and Ekene Ochem – and Todd Jelinek for their love and support.

# 1. Introduction

1 The question of whether official development assistance is effective in promoting economic development is one that has been heavily discussed over the past decades. This debate is particularly relevant in the context of Africa, which is one of the largest recipients of development aid. According to Aiddata (2017), the World Bank disbursed over 75 billion US dollars towards 1,907 geo-referenced aid projects in African countries between 1995 and 2014, with the explicit mission to "end extreme poverty by 2030".

2 However, no consensus has been reached on whether foreign aid is actually effective, due to endogeneity concerns in the allocation of aid. This impediment has led researchers to pay more attention to the effects of aid at the sub-national level, which still represents a clear knowledge gap in the literature. In addition, existing studies generally assume the effects of foreign aid to be linear, when in reality it is very likely that these effects would vary at different levels of development within countries.

3 In this paper, I analyse the heterogeneous effects of geo-referenced World Bank aid projects on economic development within African countries, at the disaggregated sub-national level. The data framework is based on a standardized grid cell structure, where the unit of analysis is a single grid cell at a 0.5 x 0.5 decimal degree resolution. This unique approach effectively addresses endogeneity issues related to reverse causality or sample selection, as aid donors are unlikely to allocate funds according to socio-economic conditions within arbitrarily constructed grid cells.

4 Using a fixed effects quantile regression approach, I estimate the impact of foreign aid at different levels of development across 10,674 grid cells, over the period of 1992 to 2014. As a supplementary strategy, I also adopt an instrumental variable approach, following the methodology developed by Dreher & Lohmann (2015), which exploits a plausible quasi-experiment created by an eligibility threshold set by the International Development Association (IDA).

5 The baseline results suggest a positive and statistically significant effect of foreign aid on development, measured as night-time luminosity. For instance, looking at the $75^{th}$ percentile, the presence of an aid project would lead to a 15.9% increase in night-time luminosity in subsequent periods. In addition, this marginal effect is largest within relatively poorer grid cells, suggesting that World Bank aid is in fact achieving its

primary objective. Moreover, the estimations show clear evidence of spill-over effects of aid from neighbouring grid cells, which may even dominate the within-cell treatment.

6 These findings are however quite sensitive to different specifications and variable transformations, specifically the inclusion of year fixed effects and the use of the inverse hyperbolic sine transformation. Indeed, the coefficients become significantly smaller in both cases. The 2SLS results also diverge from the baseline estimates, showing a negative effect of foreign aid on night-time lights. Given all the findings above, I conclude that foreign aid is generally effective in fostering development at the grid cell level, but the economic impact may be smaller than initially predicted.

7 The remainder of the paper is structured as follows. Section 2 provides an overview of the literature regarding the effectiveness of aid and the main empirical limitations. Section 3 describes the sample data and its construction. Section 4 discusses the identification strategy. Section 5 presents the empirical results and additional robustness checks. Section 6 concludes.

# 2. Literature Review

1 The literature on the effectiveness of foreign aid has predominantly revolved around cross-country analyses of the impact on national-level outcomes, particularly economic growth. Despite this being a long-standing debate, no consensus has been reached on whether foreign aid actually has any impact on aggregate development outcomes, and if so, to what extent. Some studies have found that foreign aid has a robust and positive effect on economic growth in recipient countries, while others obtained a significant effect only in countries with certain characteristics, such as good governance and institutions.

2 Clemens *et al.* (2012) argue that the main reasons behind the large divergence in the literature are contingent on the timing of the aid effects and the methodology used. They suggest that many studies erroneously measured the contemporaneous effect of aid on growth, when in fact most aid-funded projects would only have a discernible impact after a time lag. Such results would therefore suffer from simultaneity bias. With regards to the methodology, the majority of research papers have relied on instrumental variables as an identification strategy for foreign aid. These instruments have consisted of some measure of political ties to donors, lagged aid flows, or population size of recipient countries, all of which could arguably pose concerns about both their relevance and validity.[1]

3 In order to address these endogeneity issues, Clemens *et al.* (2012) re-analyse the results from three of the most influential studies in the aid-growth literature, namely Boone (1996), Burnside and Dollar (2000; 2004), and Rajan and Subramanian (2008). The authors adapt the methodologies in each of the papers by including a time lag in the specification and by first-differencing to remove time-invariant omitted variables. In addition, they only consider those portions of aid that would be most expected to influence growth in receiving countries (e.g. budget support and project aid for real sector investments in infrastructure).

4 Their findings demonstrate aid flows to be systematically associated with modest but positive growth, with evidence of a non-linear relationship indicating potential limits to the aggregate aid effects. However, a replication of this study by Roodman (2015) raises further questions, as he finds that the two strategies relating to lagging and first-differencing fail to remove contemporaneous endogeneity. In fact, once aid is lagged by

two periods, the results suggest a zero or negative Granger causation flowing from aid to growth.

5 On a different note, researchers are now paying more attention to the effects of foreign aid at the sub-national level, thanks to the increased availability of georeferenced data on aid and relevant outcome variables. Many argue that the non-robust results in the macro literature are dependent on the spatial unit of investigation, as the effects of aid would be too small and localized to have an impact on aggregate outcomes (Kotsadam *et al.*, 2018; Bitzer and Gören, 2018). In addition, the lack of suitable country-level controls, sample selection bias and measurement error in both the outcome and aid variables all aggravate concerns of endogeneity.

6 The work by Dreher & Lohmann (2015) introduced a new identification strategy to estimate the causal effects of aid on growth at the sub-national level, which has grown more popular in subsequent research. Using a sample of 478 first-order and circa 8,400 second-order administrative regions (ADM1 and ADM2, respectively) from 21 countries between 2000 and 2011, the authors instrument aid flows with a binary variable indicating whether a country has crossed the income threshold for eligibility to the World Bank's concessional aid, interacted with a region's probability of receiving aid. When controlling for the levels of the interacted variables, the authors argue that this instrument satisfies the exclusion restriction, and is akin to a difference-in-differences estimator.

7 Overall, their baseline OLS results show that growth increases with aid in ADM2 regions, but once endogeneity is accounted for, the effects become completely insignificant. However, this strategy poses some concerns towards external validity, as the analysis is only limited to countries that have crossed the IDA income threshold during the sample period.

8 Bitzer & Gören (2018) also study the effects of aid on growth of night-time lights, but instead use equally sized and arbitrarily constructed grid cells as the spatial unit of observation. One of the main advantages of using such an approach is the ability to create potential counterfactual observations, allowing one to identify a causal relationship between aid and growth.

9 Using a full-set of grid and country-year fixed effects, the authors estimate a night-time lights logarithmic growth model using four different estimators: pooled OLS, Fixed Effects, difference GMM and system GMM. Their baseline estimates suggest a positive and significant relationship between foreign aid and economic activity, which remains robust across different specifications. They also find that projects targeted towards water and sanitation, health and infrastructure have the strongest effect on nightlight growth, and that short-term projects are more effective than long-term projects. However, all estimation strategies raise doubts concerning the reliability of these results, due to the obvious inconsistency issues in estimating a dynamic model using OLS, and the poor performance of the GMM instruments revealed by various diagnostic tests.

10 Moving away from economic growth, Kotsadam *et al.* (2018) is arguably the first systematic attempt to study the effects of official development assistance on infant mortality at the sub-national level. Using a difference-in-differences analysis, the authors compare infant mortality rates in regions in close proximity to aid projects before and after implementation, to regions located further away. The results support

their hypothesis that children born in areas close to aid projects have a higher probability of survival, with an even stronger relationship within less privileged groups.

11 On the other hand, several studies remain critical of foreign aid, particularly from multilateral donors, with regards to whether or not it actually achieves its principal objective of helping the poorest. Briggs (2018, p. 134) reasons that “aid cannot help the poor unless it both works and reaches where the poor live”, a point all the more relevant when one considers the high degree of sub-national geographical inequality in Africa. Using a spatially gridded dataset, the author examines whether aid from the World Bank and African Development Bank is targeted towards relatively poorer areas within African countries, for the period between 2009 and 2010.

12 Briggs (2018) stresses the fundamentally descriptive nature of the paper’s research question, and thus only includes a poverty measure and grid cell-level population as covariates in all estimations, to avoid obscuring the spatial relationship between aid and poverty. He operationalises the dependent variable using three indicators for grid cell-level aid, and uses five separate proxies to describe the poverty level. These are: night-time luminosity, travel time to nearest city with at least 50,000 inhabitants, distance to the national capital, prevalence of child malnutrition and the infant mortality rate. The results suggest an anti-poverty bias in the within-country allocation of aid, as grid cells with more nightlight intensity, shorter distances to the capital and shorter travel times receive a greater amount of aid. These findings are consistent with previous work in the literature (Dreher *et al.*, 2015; Nunnenkamp *et al.*, 2017), and remain robust across different specifications and estimation strategies.[2]

13 Nevertheless, there are several limitations to the paper’s methodology that may challenge the strength of the results. For instance, the author does not attempt to identify any causal mechanism in the model and only estimates correlations between aid and poverty at the sub-national level, therefore making his conclusions of anti-poor targeting somewhat reductive. In addition, the time period of observation is very small and does not account for already existing projects, thus potentially biasing the results. In fact, the dataset would suggest that Cape Verde, Somalia and Zimbabwe receive absolutely no aid, which is highly unlikely given that all three are eligible for World Bank borrowing.

14 Furthermore, the investigation fails to acknowledge potential spill-overs from neighbouring regions within the same country. For instance, this mechanism would apply in the case of aid projects financing the construction of “connective infrastructure”, such as roads, bridges and railways, which are believed to disperse economic activity (Bluhm *et al.*, 2018). Therefore, it is worth considering that a given grid cell may indirectly benefit from a project implemented in a neighbouring grid.

15 This paper aims to expand on the sub-national strand of the aid effectiveness literature and address the aforementioned challenges through two empirical contributions. First, it examines the effects of aid at a high degree of spatial resolution, across 10,600 grid cells over a sample period of almost 20 years. This approach, which has not been used in the literature, should tackle endogeneity concerns more effectively. Second, it highlights the heterogeneous effects of foreign aid at different levels of development within countries. This concept has often been touched upon in previous studies, but to the best of my knowledge, it is yet to be investigated in this context.

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**1.** Examples of these include: binary variables indicating whether a recipient country is a "friend" of the US or OPEC (i.e. receiving more than 1% of the donor's total aid budget); indicators for common language and/or former colonial relationship; lagged arms imports as a share of total imports; interaction terms between an initial level of income or population and a policy measure (e.g. indices of inflation, budget balance, openness to trade etc.).
**2.** The author used a linear probability and a logistic model for the regressions involving a binary aid indicator; for the count analysis (number of projects), the negative binomial and Poisson models were used; finally, OLS was used for the analysis using the total value of aid.

# 3. Data

1 The data framework employed in this paper is derived from the PRIO-GRID 2.0 dataset, which is based on a standardized quadratic grid cell structure covering all terrestrial areas of the world (Tollefsen *et al.*, 2012). The spatial unit of analysis is a single grid cell at a 0.5 x 0.5 decimal degree resolution, which corresponds to a cell size of approximately 55 x 55 kilometres at the equator. Each grid cell then contains cell-specific information on socio-economic conditions, climate characteristics, local conflict events and foreign aid, where the latter is spatially linked to the grid cell structure.[1]

2 The main advantage of this approach consists in its ability to mitigate some of the endogeneity issues faced in the aid effectiveness literature. Contrary to administrative regions such as provinces and municipalities, grid cells are insensitive to political influences, and are completely exogenous to the variables in my analysis. As such, it is unlikely that aid donors would allocate funds according to economic conditions within grid cells, addressing concerns related to reverse causality or sample selection. In addition, the high degree of spatial resolution allows for a more accurate analysis of the impact of aid projects, as one should be able to separate the effect within a particular grid from an unrelated effect in a more distance cell.

3 Given that this investigation focuses solely on African countries, the panel covers a cross-section of 10,674 grid cells representing all 54 fully recognised sovereign states, over the period 1992-2014.[2] Table 1 provides descriptive statistics for the relevant variables used in the estimation.

## 3.1 Outcome variable

4 Night-time luminosity data at the grid cell-level is derived from the DMSP-OLS Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, & Cloud Free Coverages), for the period of 1992 to 2012.[3] The data are calibrated to account for inter-satellite differences and inter-annual sensor decay, as per the methodology in Elvidge *et al.* (2014), rendering it suitable for time-series analysis. Values are standardized between 0 and 1, where 1 indicates the highest observed nightlight intensity in the time-series, and 0 represents the lowest. This approach allows the indicator to be

comparable across grids, countries and time, as opposed to other sources such as income data obtained from household surveys.

5 The use of satellite data as a proxy for economic activity and development has become widespread in recent years. In fact, night-time lights have been shown to be a suitable alternative for sub-national measures of real GDP, particularly in low-income countries where such information is seldom available or accurate. In addition, many studies have estimated an "exchange rate" between night-time lights and real GDP, allowing one to make interpretations on the effects of foreign aid in economic terms.

6 For instance, Henderson *et al.* (2012) and Hodler & Raschky (2014) argue for a linear relationship between nightlights and GDP at the country and regional levels respectively, and calculated an elasticity of approximately 0.3. Hu & Yao (2019) instead found the relationship to be non-linear and dependent upon geographic location.

7 It is important to note that the nightlight distribution across grid cells and time exhibits a high degree of positive skewness, as a result of over 70% of the sample displaying very low night-time light activity. I account for this issue by applying a logarithmic transformation to the data, to which I also add a small number of 0.01 to retain all zero values.

8 In Section 5.2, I instead employ an inverse hyperbolic sine (IHS) transformation, which has been argued to be a more desirable alternative to the natural log (Friedline *et al.*, 2015).

## 3.2 Treatment variable

9 Data on the foreign aid projects is obtained from the World Bank Geocoded Research Release (Version 1.4.2) published by AidData. This geo-referenced dataset includes all World Bank projects from both the International Bank of Reconstruction and Development (IBRD) and International Development Association (IDA) lending lines (AidData, 2017).[4] It covers a total of 5,881 projects, of which 5,684 are geocoded, approved between 1995 and 2014 and distributed across 61,243 project locations. The AidData dataset provides information on the coordinates of each project location, recipient countries, main sector, duration, as well as commitment and disbursement flows.

10 In addition, each geocoded location is assigned a location class code and a geographic exactness code according to the IATI standard to describe the level of granularity (AidData Research and Evaluation Unit, 2017). The location class specification comprises of 4 discrete categories to differentiate geographic features; these include: administrative regions (e.g. state, province, independent political entity), populated place (e.g. village, city), structure (e.g. building, road, bridge), and other topographical features (e.g. national park, river). The binary geographic exactness specification describes whether the coordinates correspond to an exact location, or an approximation.

11 For the main empirical analysis, I restrict the sample to only include project locations classified as either a populated place or structure (location code 2 and 3), which reduces the sample to 47% of its original size. Using AidData's original eight-point precision code geocoding methodology, this corresponds to locations that are exactly geocoded (precision code 1) or within 25km of an exact location (precision code 2).

12 One problem with using this dataset is the incidence of missing observations, particularly for the disbursements and project end date variables.

13 To address the first issue, I refer to a separate AidData document outlining project- and year-specific transactions. I argue that for those project locations for which there is a recorded total commitment amount but missing disbursements, it actually signifies that there were no disbursements made, and should therefore correspond to zero values.[5]

14 For the second issue, I assume that projects that have a start date but no recorded end date represent projects that were dropped by the respective governments, or were never implemented. This hypothesis is supported by the fact that all such projects received no disbursements. I therefore re-classify their project status as “Dropped”, and set the end date equal to the start date. Those projects would therefore be considered as active only for the year coinciding with the time a commitment was made – which may itself have an economic effect.[6]

15 Using the projects’ start and end years, I then spatially overlay each project location on the PRIO-GRID grid cells by means of Geographic Information Systems (GIS) techniques, in order to obtain a panel of active projects per grid cell, per year. Based on this panel, I produce four separate indicators of foreign aid.

16 First, I construct a binary variable indicating whether at least one project was located in a particular grid cell in a given year. Second, I construct a variable indicating the total number of active projects in a given grid cell and year.

17 Finally, I construct two continuous variables indicating the total annual financial flows allocated to each grid cell, one using the commitment amounts and the other using disbursements values. Both variables were constructed using information on the actual transaction dates, rather than the project duration dates, and are expressed in millions of US dollars, at constant 2011 prices. In addition, because financial information is only provided at the project level, I follow previous methodologies and assume that both commitment and disbursement amounts are distributed uniformly across project-specific locations.

18 Similarly to the outcome variable, I employ both the logarithmic and IHS transformations to account for the right-skewness in the distribution of the aid flows indicators.

## 3.3 Explanatory variables

19 **Population count.** Estimates for the total population size within grid cells (i.e. at a resolution of 30 arc-minutes) are obtained from the Gridded Population of the World Version 3 (GPWv3) database, published by CIESIN-CIAT (2005). These are available for the years 1990, 1995, 2000, 2005, 2010, and 2015. I thus employ a linear interpolation between each interval to construct an annual population count measure across grids for the whole sample period.

20 The more recent GPWv4 database (CIESIN, 2018) would serve as a more suitable population measure, as it supersedes its predecessor. Unfortunately, estimates are only available from the year 2000. To maximise sample size, I chose to use the GPWv3 indicator for the main estimations.

21 **Climate characteristics.** Yearly observations of total precipitation (in millimetres) in each grid cell are derived from the GPCP v.2.2 Combined Precipitation Data Set (Huffman et al., 2012).[7] The original data only reported daily averages for each month; as a result, this was multiplied by the number of days in each month to obtain approximate monthly totals, from which yearly totals were estimated.

22 Annual mean temperature estimates (in degrees Celsius), are obtained based on monthly meteorological statistics from GHCN/CAMS, developed at the Climate Prediction Center, NOAA/National Weather Service (Fan & van den Dool, 2008).[8]

23 The severity of drought for the entirety of a cell's rainy season (defined as the three consecutive months in which it on average rained the most during a year) is given by the Standardized Precipitation and Evapotranspiration Index (SPEI-3) value for the last month of the rainy season, from the SPEI Global Drought Monitor (Beguería *et al.*, 2014). For each month, the SPEI-3 index measures deviations from long-term normal rainfall during the three preceding months. Values are standardized with mean 0 and standard deviation 1, where negative values indicate below local average rainfall, and vice versa.

24 **Conflict.** The UCDP/PRIO Armed Conflict Dataset Version 18.1, published by Sundberg & Melander (2013), provides a comprehensive account of all individual events involving organized lethal violence, across grid cells and time. Events are categorised according to three types of conflict – state-based, non-state and one-sided violence – and each location is assigned a geo-reference precision code.

25 In line with the aid indicators, I only include those observations with an associated precision code of 1 and 2. From this sample, I construct two grid- and year-specific conflict indicators: one indicates the number of unique conflict events which took place in a given grid and year, while the other indicates the total number of deaths across conflicts.

26 **Natural resources.** I identify the presence of natural resources with a binary variable indicating whether petroleum, diamond or gem deposits where discovered within a given grid cell (Gilmore *et al.*, 2005; Lujala *et al.*, 2005; 2007; Lujala, 2009).

27 **Other indicators of poverty.** To depict the standards of health across grid cells, I use two measures indicating the rate of infant mortality and the prevalence of child malnutrition, based from raster data from the SEDAC Global Poverty Mapping project (CIESIN, 2005a; 2005b). The former gives the number of children per 10,000 live births that die before reaching their first birthday (converted to a percentage), while the latter represents the percent of children under the age of 5 that are malnourished. Both indicators are a snapshot for the year 2000 only.

28 In addition, I capture the degree of regional urbanization across grid cells using two proxies, which could be important factors in controlling for urban bias in aid allocation.

29 The first measure denotes the total travel time (in minutes) by land transportation from the grid's centroid to the nearest major city with at least 50,000 inhabitants (Uchida & Nelson, 2009). It is derived from a global high-resolution raster map of accessibility developed for the EU, using a combination of several sources collected between 1990 and 2005.

30 The second indicator measures the spherical distance in kilometres from the grid cell centroid to the national capital city in the corresponding country (Weidmann *et al.*,

2010). It is based on coordinate pairs of capital cities from the cShapes dataset v.0.4-2, and captures changes over time wherever relevant.

**Table 1:** Descriptive statistics of main variables across 10,674 grid cells (1995-2012)

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Total aid commitments (USD million) | 192,132 | 0.18 | 4.13 | 0 | 0 | 0 | 613 |
| Total aid disbursements (USD million) | 192,132 | 0.09 | 1.77 | 0 | 0 | 0 | 285 |
| Number of active aid projects | 192,132 | 0.19 | 1.03 | 0 | 0 | 0 | 42 |
| Whether a grid cell received aid | 192,132 | 0.09 | 0.27 | 0 | 0 | 0 | 1 |
| Average nighttime light emission | 192,132 | 0.04 | 0.03 | 0.01 | 0.03 | 0.05 | 0.96 |
| Drought severity | 190,585 | −0.30 | 1.01 | −6.84 | −1.02 | 0.38 | 6.11 |
| Total precipitation (mm) | 192,132 | 687 | 614 | 0.12 | 90.50 | 1,166 | 3,275 |
| Mean Temperature (°C) | 188,962 | 24.60 | 3.96 | 5.01 | 22.20 | 27.50 | 39.50 |
| Percentage of child malnutrition (below 5 years) | 187,380 | 26 | 12.90 | 1.10 | 15.20 | 35.70 | 52.50 |
| Percentage of infant mortality (before 1st birthday) | 188,280 | 9.08 | 4.37 | 1.00 | 4.95 | 12.90 | 20.30 |
| Number of conflict events | 192,132 | 0.07 | 1.40 | 0 | 0 | 0 | 244 |
| Number of conflict-related deaths | 192,132 | 1.24 | 47.10 | 0 | 0 | 0 | 15,143 |
| Total population count (thousands) | 192,132 | 81 | 257 | 0 | 2.50 | 65.60 | 12,712 |
| Population growth | 192,132 | 0.02 | 0.02 | −0.28 | 0.02 | 0.03 | 0.86 |
| Distance to capital (km) | 192,132 | 649 | 416 | 3.70 | 320 | 931 | 2,483 |
| Travel time to nearest major city (hours) | 192,006 | 11.70 | 12.10 | 0.20 | 4.52 | 14.20 | 102 |
| Presence of natural resources deposits (diamond, gem, petroleum) | 192,132 | 0.08 | 0.26 | 0 | 0 | 0 | 1 |

*Note:* Each observation is a grid/year. The travel time, child malnutrition and infant mortality variables are time-invariant.

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**1.** All variables used in the estimations were obtained from the PRIO-GRID dataset, with the exception of the aid and population data. At the request of the developers, the original source of each variable will be cited in the main text.

**2.** Due to differences in panel size between variables and the lag specification in the baseline model, the effective sample size is reduced to the period 1996-2012, equating to a total of 181,458 observations.

**3.** Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency.

**4.** The IDA offers grants and highly concessional loans (i.e. Official Development Assistance) to the poorest countries, while the IBRD offers non-concessional loans (i.e. Other Official Flows) to middle-income and creditworthy countries. Unfortunately, the dataset does not distinguish between the two arms, and other ancillary data do not have consistent information to this regard, making it impossible to study potential differences in the effects on poverty outcomes between the two types of development assistance.

**5.** One project with 194 locations in Ethiopia (Road Sector Development Program Support Project) was removed from the final sample as there were missing data on both commitments and disbursements.

**6.** The results remain fairly unchanged when these observations are instead excluded from the estimations.

**7.** The GPCP combined precipitation data were developed and computed by the NASA/Goddard Space Flight Center's Laboratory for Atmospheres as a contribution to the GEWEX Global Precipitation Climatology Project.

**8.** Both the GPCP and GHCN Gridded V2 data were provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their website at http://www.esrl.noaa.gov/psd.

# 4. Estimation Strategy

1 Following the econometric specification predominantly used in the aid effectiveness literature, the baseline reduced-form model is given by the following equation,

$$\ln\left(Light_{ic,t}\right) = \sum_{k=0}^{1} \beta_k Aid_{ic,t-k} + \beta_2' \mathbf{X}_{ic,t} + \delta_i + \lambda_t + \varepsilon_{ic,t} \qquad (4.1)$$

2 where $\ln(Light_{ic,t})$ represents the logarithm of night-time luminosity in grid cell $i = 1,\ldots,N$ of country $c = 1,\ldots,C$ in year $t = 1,\ldots,T$ (to which a constant of 0.01 was added). $Aid_{ic,t-k}$ refers to the four definitions of grid-cell-level foreign aid, as described in the previous section. The model includes a distributed lag specification to account for differences in the timing of the aid effect across projects. $\mathbf{X}_{ic,t}$ is a vector of geospatial explanatory variables to control for local conditions. $\delta_i$ and $\lambda_t$ denote grid and year fixed effects, respectively, to control for any unobserved heterogeneity. $\varepsilon_{ic,t}$ represents the grid-specific error term.

3 As noted earlier, it is possible for the above model to suffer from spatial dependence, and that a given grid cell may be susceptible to spillover effects from neighbouring grid cells. I account for this issue by estimating a spatial autoregressive model as defined by Anselin *et al.* (2008), which includes spatially lagged dependent and treatment variables. The specification can be expressed as follows,

$$\ln\left(Light_{ic,t}\right) = \rho \ln\left(\widehat{Light_{ic,t}}\right) + \textstyle\sum_{k=0}^{1} \gamma_k Aid_{ic,t-k} + \sum_{k=0}^{1} \phi_k \widehat{Aid_{ic,t-k}} + \gamma_2{}' \boldsymbol{X}_{ic,t} + \mu_i + \eta_t + \upsilon_{ic,t} \qquad (4.2)$$

4 where most variables and coefficients maintain the same interpretation as in Equation (4.1). $\ln(\widehat{Light}_{ic,t})$ and $\widehat{Aid}_{ic,t-k}$ correspond to the spatial lag operators, and $\rho$ and $\varphi_k$ denote the spatial autoregressive parameters.

5 For each grid cell *i*, the operators are defined as weighted averages of the values of the contiguous neighbouring cells, such that $\hat{z}_{ic,t} = \Sigma_j\, \hat{w}_{ij}\, z_{jc,t}$. The spatial weights $\hat{w}_{ij}$ are constructed based on a row-standardized spatial contiguity matrix **W**, an *N×N* positive matrix describing the spatial relationship between the cross-sectional grid cells. Each

element corresponds to $w_{ij}/\Sigma_j w_{ij}$, where $w_{ij} = 1$ if $i$ and $j$ are neighbours, and $w_{ij} = 0$ otherwise; diagonal elements are equal to 0 by construction.

6 One problem when using this model is that the spatial lag term is endogenous, as a result of the bidirectional nature of the spatial relation (Anselin *et al.*, 2008). This implies that the spatial distribution of $y_{ic,t}$ for each cross-section is determined by both the explanatory variables at each location $i$ and those at neighbouring locations. The simultaneity can however be accounted for through instrumentation or by fully specifying a distributional model.

## 4.1 Quantile regression with fixed effects

7 The main empirical strategy relies on a quantile regression approach suitable for panel data, developed by Koenker (2004). The benefit of this method is that it allows one to determine the effects of foreign aid at different levels of development within countries, providing a better indication of donors' performance. In addition, the fixed effects at the grid cell level, rather than the country or administrative region level, can more accurately control for any time-invariant unobserved heterogeneity.

8 To outline the mechanics behind this approach, consider the following model for the conditional quantile functions for a classical linear random effects model:

$$Q_{y_{ij}}(\tau|x_{ij}) = \alpha_i + x_{ij}^T\beta(\tau) \qquad j = 1, ..., m_i \quad i = 1, ..., n \qquad (4.3)$$

9 In this specification, the effects of $x_{ij}$ are allowed to vary dependent on the quantile $\tau$, whereas the fixed effects $\alpha_i$ are not, as they only have an $i$-specific location shift effect on the conditional quantiles.

10 Assuming that the $x_{ij}$ component contains an intercept and that $n$ is large relative to $m_i$, a penalized approach is most convenient to estimate the conditional quantiles simultaneously. The optimal FE estimator is therefore based on minimizing a weighted sum of $q$ ordinary quantile regression objective functions, such that

$$\min_{(\alpha,\beta)} \sum_{k=1}^{q}\sum_{i=1}^{n}\sum_{j=1}^{m_i} w_k \rho_{\tau_k}(y_{ij} - \alpha_i - x_{ij}^T\beta(\tau_k)) + \lambda \sum_{i=1}^{n} |\alpha_i| \qquad (4.4)$$

11 where $\rho_\tau(u) = u(\tau - \mathrm{I}(u < 0))$ denotes the piecewise linear quantile loss function. The weights $w_k$ control the relative influence of the $q$ quantiles for the estimation of the $\alpha_i$ parameters. These intercepts are shrunk toward a common value using an $l_1$ penalty term with associated penalty parameter $\lambda$, as defined by the second term in the equation. As $\lambda \to \infty$, $\to 0$ for all $i$, and the model is purged of the fixed effects. Koenker (2004) demonstrates that the penalized fixed-effect estimator is asymptotically unbiased and Gaussian.

12 For the main estimations, I analyse the effects of foreign aid on night-time luminosity at four quantiles - $25^{th}$, $50^{th}$, $75^{th}$ and $95^{th}$ - and assign equal weights $w_k$ of 0.25 to each. The penalty parameter $\lambda$ is set equal to 1, and standard errors are computed using a weighted generalised bootstrap.[1]

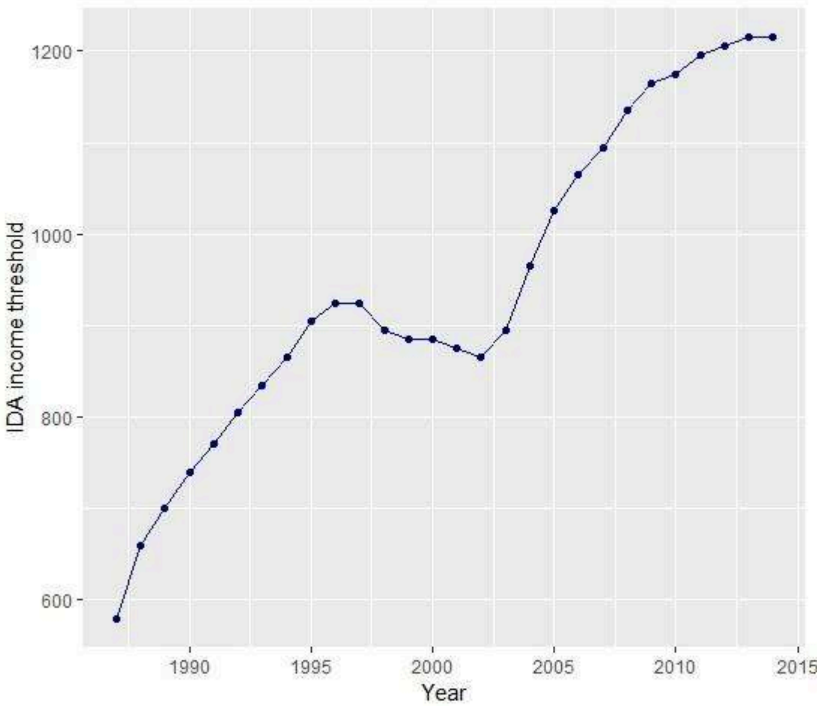
13 Unfortunately, the large cross-sectional sample of over 10,600 grid cells poses computational constraints for the estimation of a fixed effects spatial lag model in quantile regressions. To address the potential simultaneity bias, I follow the specification in Bitzer & Gören (2018) and instead include the first time lag of the spatially lagged dependent variable (i.e. $\ln(\hat{Light}_{ic,t})$).

## 4.2 Instrumental variable approach

14 Despite the use of both a highly disaggregated dataset and the quantile fixed effects approach, there may still be endogeneity in the models that remains unaccounted for. I therefore complement the above estimation strategy with one that uses an instrumental variable to identify the causal effect of foreign aid at the grid level. I adopt the methodology used in Galiani *et al.* (2017) and Dreher & Lohmann (2015), which exploits a plausible quasi-experiment created by the income threshold set by the International Development Association (IDA) for receiving concessional aid.

15 Eligibility for IDA support is contingent on two factors: lack of creditworthiness, and a country's relative poverty, which is determined by the GNI per capita being below a set "operational cut-off" measured in current US dollars. It was initially set at $580 in 1987, and has since been updated annually to account for inflation ($1,215 at the end of the sample period in 2014). Figure 1 below displays the historical evolution of the threshold.

**Figure 1:** Evolution of IDA operational cut-off in current U.S. dollars, 1987-2014




16 This arbitrary threshold – and consequently a country's position in relation to it – should therefore be exogenous to the level of economic activity within a recipient grid cell, unlike actual graduation from the IDA which is dependent on a country's economic

performance (i.e. policy, creditworthiness, vulnerability to shocks). In the case this condition does not hold, the indicator for a country being below the income threshold is interacted with a grid cell's probability of receiving aid.

17 Once the levels of the two variables are controlled for, the resulting interaction term provides a plausibly exogenous instrument. Therefore, even if the time-varying component is endogenous to the outcome variable, the exclusion restriction should only be violated if the unobserved variables driving the endogeneity were also correlated with the grid-specific component (Lang, 2016).

18 I thus estimate a two-stage least squares (2SLS) regression to identify the causal impact of foreign aid. For the sake of simplicity, I only use the first lag for each of the aid indicators as the treatment, so as to have only one endogenous variable.

19 The estimation strategy is given by the following 2 equations,

$$1^{\text{st}} \text{ stage:} \qquad Aid_{ic,t-1} = \alpha_1(IDA_{c,t-4} \times \bar{p}_i) + \alpha_2' \mathbf{X}_{ic,t} + \gamma_i + \lambda_{c,t-1} + u_{ic,t-1} \quad (4.5)$$

$$2^{\text{nd}} \text{ stage:} \qquad \ln(Light_{ic,t}) = \beta_1 Aid_{ic,t-1} + \beta_2' \mathbf{X}_{ic,t} + \delta_i + \lambda_{c,t} + e_{ic,t} \quad (4.6)$$

20 where $IDA_{c,t-4}$ is defined as a binary variable equal to 1 if the GNI per capita of country *c* is below the IDA threshold at least three periods prior to the aid disbursement, and 0 otherwise.[2] The lagged variable is based on the intuition that countries do not become ineligible for concessional aid immediately after crossing the income threshold, and should in fact remain above it for at least three consecutive years in order to begin the graduation process.

21 represents a grid cell's probability of receiving aid, defined as the number of years out of the whole sample period in which at least one project was located in a given cell. The remaining variables maintain the same interpretation as in the baseline model described in Equation (4.1). The levels of the interacted variables are accounted for through the inclusion of the grid-specific and country-year fixed effects.

22 I expect the coefficient associated with the interaction term to be positive, as countries that have crossed the operational cut-off would be on track towards graduation from the IDA, and are thus likely to see a fall in aid inflows. In addition, grid cells with a higher probability of receiving aid would be more likely to have an active project at any given time.

23 On the other hand, there is a possibility that any changes in IDA lending would be counteracted by lending from the IBRD. Results from Galiani *et al.* (2017) would suggest that this may not be an issue, and that other donors adjust their contributions in line with IDA aid.

24 A primary concern in using this methodology pertains to the strength of the instrument. In fact, in the case of this sample, only 18 countries out of the total 54 crossed the IDA threshold during the sample period. As a result, the instrument would remain constant across all years for the majority of observations, offering little variation to predict within-grid aid flows.

25 To overcome this shortcoming, I use an alternative continuous indicator for the time-varying component, which measures a country's distance from the IDA income threshold at any given point in time (i.e. $d_{ct} = GNI_{ct} - IDA_t$). In addition, I implement

both instruments only on the sub-sample of countries that have crossed the threshold at one point, corresponding to approximately 3,000 grid cells.

## NOTES DE BAS DE PAGE

**1.** Bose, A., & Chatterjee, S. (2003). Generalized Bootstrap for Estimators of Minimizers of Convex Functions. *Journal of Statistical Planning and Inference, 117(2)*, 225-239.
**2.** The annual operational cut-offs for the years 1987-2010 are obtained from the replication datasets by Galiani *et al.* (2017); the cut-offs for the remaining years between 2011 and 2014 are obtained from the World Bank's Operational Policies Manual 3.10 Annex D.

# 5. Empirical Results

1 I begin this investigation by first replicating the results obtained by Briggs (2018) and challenging the findings with additional specifications. Maintaining the same cross-sectional structure as in the original study, I estimate a model with spatial fixed effects as opposed to country fixed effects. In other words, I transform the data to deviations with respect to group means, which are composed by the neighbouring grid cells, using a spatial weight matrix similar to that described in the previous section. I then compute the estimated parameters using a standard linear model, with standard errors clustered at the country-level to allow for spatial correlation beyond the contiguous neighbours.

2 I examine both the individual and joint effects of all poverty proxies used in Briggs (2018) on the three foreign aid indicators. In all cases, the inclusion of spatial fixed effects did not significantly change the author's original results, which suggest that more prosperous grid cells are associated with higher values of aid.

3 I also carried out the above estimations using panel data, and controlling for unobserved heterogeneity at the grid cell level. For the model with the logarithm of total disbursements as a dependent variable, I find the coefficient associated with night-time luminosity to be statistically insignificant. What's more, once I include the log of total commitments as a covariate, the relationship between nightlights and disbursements becomes negative, thus suggesting a pro-poverty allocation of aid (Appendix C).

4 In the next section, I discuss the main findings on the effects of foreign aid using the two estimation strategies described in Section 4.

## 5.1 Main results

### Quantile fixed effects results

5 Table 2 below summarises the results for quantile regressions of the baseline model, using each of the four foreign aid indicators. The results suggest that, *ceteris paribus*, foreign aid generally has a positive and significant effect on night-time luminosity, although the effect is not particularly large in economic terms. The lagged terms

consistently display a greater effect, which is in line with the notion that any effect would require time to translate into an observable economic impact. For instance, looking at the median effect, an increase in the number of projects by one unit would lead to a 2.2% increase in nightlights in subsequent periods.

6 The analyses using the presence or number of active projects as indicators show a much greater impact than the two using annual financial flows. This may simply be a result of the infrequency of project-specific flows, or it may be an indication of an underlying mechanism obstructing the full impact (e.g. misuse of aid funds).

7 In addition, the results reveal the existence of heterogeneity in the effect of aid at different levels of development, confirming the merits of the chosen identification strategy.[1] The coefficients display a positive trend with respect to the quantiles, with the smallest values consistently observed at the 95$^{th}$ percentile.

8 Given the right-skewness of the night-time luminosity distribution, it is likely that the 75% percentile represents grid cells with low economic activity; therefore, the results would indicate that the marginal effect of foreign aid is greatest within a country's poorest regions.

**Table 2:** Quantile fixed effects regressions of night-time luminosity on aid indicators

| | *Dependent variable: ln(0.01 + night lights)* | | | |
|---|---|---|---|---|
| | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.95$ |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.050 | 0.060 | 0.011 | 0.019 |
| | (0.007) | (0.005) | (0.007) | (0.007) |
| Aid dummy$_{t-1}$ | 0.077 | 0.084 | 0.159 | 0.048 |
| | (0.007) | (0.006) | (0.013) | (0.007) |
| No. of projects$_t$ | 0.011 | 0.012 | 0.0002 | 0.005 |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| No. of projects$_{t-1}$ | 0.018 | 0.022 | 0.034 | 0.012 |
| | (0.002) | (0.002) | (0.003) | (0.003) |
| ln(0.01 + disbursements)$_t$ | 0.002 | 0.001 | −0.001 | 0.001 |
| | (0.0003) | (0.0002) | (0.0004) | (0.0004) |
| ln(0.01 + disbursements)$_{t-1}$ | 0.001 | 0.001 | 0.002 | −0.001 |
| | (0.0003) | (0.0003) | (0.001) | (0.0003) |
| ln(0.01 + commitments)$_t$ | 0.002 | 0.002 | 0.002 | 0.001 |
| | (0.0003) | (0.0003) | (0.001) | (0.0003) |
| ln(0.01 + commitments)$_{t-1}$ | 0.001 | 0.002 | 0.003 | -0.0001 |
| | (0.0003) | (0.0004) | (0.001) | (0.0003) |

*Note*: Each panel represents a separate quantile regression of nightlights on aid, and the coefficients indicate the treatment effect. All covariates and grid-cell fixed effects are included. Year fixed effects $\lambda_t$ are not included in the regressions, as it would otherwise result in all coefficients becoming insignificant. Bootstrapped errors based on 200 replications in parentheses.

9 For more intuitive interpretations, I also calculate the effects of aid on real GDP per capita, using estimated "exchange rates" between night-time lights and GDP by Hu & Yao (2019).[2] Unlike previous studies, they find that the elasticity varies with respect to the level of income. For instance, in the case of Equatorial Guinea - with one of the highest GDP per capita in 2017 (constant 2011 Intl$22,214) - the elasticity of GDP with respect to nightlights would equal approximately 0.96, while in the case of grid cells in Burundi (GDP per capita of Intl$668), the elasticity would be 0.36. Taking these two

cases as examples, the presence of an active project within a grid cell in Equatorial Guinea could increase real GDP per capita up to 15.3%, while for a corresponding grid cell in Burundi, the same treatment would translate into a 5.7% increase in per capita GDP.

10 It should be noted that the above results are quite sensitive to the inclusion of year or country-year fixed effects. In fact, once I include them in the analysis, all coefficients of interest become insignificant. I also carry out a standard fixed effects regression of night luminosity on the year dummy variables. Surprisingly, I find that almost all of the within-grid variation in nightlights is explained by the year fixed effects ($R^2 = 0.957$). This would explain the very small or insignificant coefficients, as there would be no room left for any of the remaining variables to have an observable impact. As such, all following regressions are estimated without the year fixed effects.

11 To further examine other forms of heterogeneous effects, I repeat each of the above regressions and include an interaction term between the respective aid indicator and the log of total population. As expected, the coefficients on the interactions are statistically significant, suggesting that the effect of aid differs depending on population density. However, the differential effect is not observed at the highest end of the distribution, particularly with regards to the contemporaneous effect.

12 Interestingly, the sign of the coefficients is not consistent across the model specifications, nor across the quantiles for some instances. For the majority of indicators, the estimates are positive, indicating that aid projects are more impactful within more densely populated grid cells, all other things being equal. However, an increase in the number of active projects would actually lead to a decrease in the effect on night luminosity with respect to the grid cell-level population.

13 Table 3 instead displays the findings from the quantile regressions of the spatial lag model. As expected, the coefficients on the aid indicators are considerably smaller compared to the baseline model, as the spatial lag of the dependent variable explains most of the variation.

14 In the case of the regressions with the binary indicator, the estimates still suggest a positive effect on night-time luminosity, though there is no longer a clear trend in the marginal returns with respect to the quantiles. One important implication from this model is that the spill-over effects appear to have a greater economic impact than the within-cell treatment. For a given grid cell, the presence of an aid project in at least one of its neighbours leads to a 7.5% increase in nightlights.

15 On the other hand, when using the log of total commitments as the aid indicator, the estimated coefficients are often statistically insignificant, especially those associated with the spatial lag operators. In addition, all the effects are arguably negligible in economic terms, where the largest observed impact to a 1% increase in total commitment flows is equal to 0.002.

**Table 3:** Quantile spatial fixed effects regression of night-time luminosity on aid indicators

| | *Dependent variable: ln(0.01 + night lights)* | | | |
|---|---|---|---|---|
| | $\tau$= 0.25 | $\tau$= 0.50 | $\tau$= 0.75 | $\tau$= 0.95 |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.006 | 0.011 | 0.008 | 0.008 |
| | (0.004) | (0.003) | (0.003) | (0.004) |
| Aid dummy$_{t-1}$ | 0.010 | 0.008 | 0.004 | −0.001 |
| | (0.004) | (0.003) | (0.003) | (0.004) |
| **W** Aid dummy$_t$ | 0.013 | 0.017 | 0.032 | 0.044 |
| | (0.014) | (0.012) | (0.011) | (0.015) |
| **W** Aid dummy$_{t-1}$ | 0.075 | 0.060 | 0.018 | 0.0003 |
| | (0.014) | (0.013) | (0.011) | (0.016) |
| **W** ln(light)$_{t-1}$ | 0.808 | 0.746 | 0.600 | 0.805 |
| | (0.006) | (0.006) | (0.003) | (0.004) |
| ln(0.01 + commitments)$_t$ | 0.0005 | 0.001 | 0.0002 | 0.0002 |
| | (0.0002) | (0.0001) | (0.0002) | (0.0001) |
| ln(0.01 + commitments)$_{t-1}$ | 0.0002 | 0.0001 | 0.00001 | −0.00003 |
| | (0.00005) | (0.00000) | (0.0001) | (0.0001) |
| **W** ln(0.01 + commitments)$_t$ | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.0002) | (0.001) | (0.001) | (0.001) |
| **W** ln(0.01 + commitments)$_{t-1}$ | −0.001 | −0.0004 | −0.0003 | −0.001 |
| | (0.0004) | (0.001) | (0.0001) | (0.001) |
| **W** ln(light)$_{t-1}$ | 0.835 | 0.752 | 0.606 | 0.810 |
| | (0.0001) | (0.001) | (0.002) | (0.004) |

*Note*: This table reports the regressions of the spatial lag models with the binary aid indicator and the log of commitments as the treatment variable, respectively. Variables pre-multiplied by **W** represent the spatial lag operators. All remaining covariates and grid fixed effects are included. Bootstrapped errors based on 200 replications in parentheses.

## Instrumental variable results

16 Table 4 reports the findings from the 2SLS estimation of the baseline model, in which the instrument is a binary variable indicating whether a country is below the IDA's income threshold, interacted with a grid cell's probability of receiving aid.

17 These results diverge substantially from the OLS estimates, showing a negative and significant effect for all four aid indicators. In addition, these effects are all much larger in economic terms. The first-stage coefficients also go against initial predictions, as they suggest that, for a given probability, a grid cell in an IDA-eligible country would receive less aid than one in a non-eligible country.

18 These unusual findings are likely driven by the weakness of the instrument, as a result of the majority of observations either having a probability of zero or having no variation in the binary indicator, leading to very low predictive power. In fact, the cluster-robust Kleibergen-Paap F-statistic is consistently below Stock & Yogo (2005)'s critical value of 16.38 across all specifications, which allows for a maximum Wald test size of 10%.

19 The results remain very similar even when using the distance from the IDA threshold as the time-varying component of the instrument. Despite providing relatively more variation in the instrument, the first-stage F-statistics also remain very low. This may again be the result of the instrument being equal to zero throughout the sample period for most observations.

**Table 4:** Panel 2SLS regressions of night-time luminosity on aid variables with grid fixed effects

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ln(distance) | −0.003 | −0.001 | −0.003 | −0.004 |
| | (0.003) | (0.002) | (0.005) | (0.006) |
| Drought index | 0.001 | 0.0004 | 0.001 | 0.001 |
| | (0.0002) | (0.0002) | (0.0005) | (0.001) |
| Precipitation | 0.00000 | 0.00000 | 0.00001 | 0.00001 |
| | (0.00000) | (0.00000) | (0.00001) | (0.00001) |
| Temperature | −0.002 | −0.002 | −0.002 | −0.003 |
| | (0.0005) | (0.0004) | (0.001) | (0.001) |
| Natural resources | 0.066 | 0.063 | 0.071 | 0.076 |
| | (0.007) | (0.007) | (0.008) | (0.009) |
| ln(conflict) | −0.001 | −0.001 | −0.002 | −0.003 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| ln(population) | −0.006 | −0.008 | −0.008 | −0.003 |
| | (0.007) | (0.006) | (0.008) | (0.008) |
| Aid dummy$_{t-1}$ | −0.261 | | | |
| | (0.038) | | | |
| No. of projects$_{t-1}$ | | −0.065 | | |
| | | (0.010) | | |
| ln(0.01 + commitments)$_{t-1}$ | | | −0.054 | |
| | | | (0.014) | |
| ln(0.01 + disbursements)$_{t-1}$ | | | | −0.079 |
| | | | | (0.025) |
| Observations | 177,913 | 177,913 | 177,913 | 177,913 |
| Adjusted $R^2$ | 0.963 | 0.969 | 0.843 | 0.712 |
| First-stage F-stat | 15.4 | 6.08 | 2.63 | 1.53 |

*Note:* The table displays the second stage regressions of the log of night-time lights on one endogenous aid indicator. The instrument used is a binary indicator for whether a country is below the IDA threshold interacted with a grid cell's probability of receiving aid. All regressions include grid and country-year fixed effects. Errors clustered at the grid-level in parentheses.

20 Table 5 below repeats the 2SLS estimations on a sub-sample of grid cells located within the countries that have crossed the IDA threshold at one point during the sample period. The results do not offer further inference compared to the estimations on the complete sample, as the coefficients are again all negative and significant, and of a similar magnitude. The results also remain unchanged when using a data sample averaged over three-year periods.

21 All the above findings would suggest that, for this particular context, the interaction is not an appropriate instrument to identify the causal impact of foreign aid at the grid cell level. Aside from the issue of low variation, the weakness of the instrument may simply be signalling that a country's position relative to the operational cut-off does not determine their aid inflows. For instance, it may be the case that most of the projects in this AidData sample are funded by the IBRD rather than the IDA, and as such, the distribution of aid projects would be less responsive to changes in IDA eligibility, contrary to the results found by Galiani *et al.* (2017).

22 Moreover, the construction of the instrument relies on values of per capita GNI expressed in current prices, which are regularly revised by the World Bank. Consequently, even a small change from historical values may result in a different implication with regards to a country's position in relation to the IDA threshold, introducing bias in the instrumental variable due to measurement error.

23 Another potential reason for the bias in the results could be that the exclusion restriction does not strictly hold. Given that the exogeneity of the instrument cannot be confirmed directly, a next step would be to relax the exclusion restriction and test for plausible exogeneity, as per the methodology by Conley *et al.* (2012).

**Table 5:** Panel 2SLS regressions of night-time luminosity on aid with grid fixed effects for sub-sample

| | *Dependent variable: ln(0.01 + night lights)* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Aid dummy$_{t-1}$ | −0.248 | | | |
| | (0.037) | | | |
| No. of projects$_{t-1}$ | | −0.061 | | |
| | | (0.009) | | |
| ln(0.01 + commitments)$_{t-1}$ | | | −0.051 | |
| | | | (0.013) | |
| ln(0.01 + disbursements)$_{t-1}$ | | | | −0.074 |
| | | | | (0.023) |
| Observations | 49,364 | 49,364 | 49,364 | 49,364 |
| Adjusted R$^2$ | 0.964 | 0.967 | 0.887 | 0.809 |
| First-stage F-stat | 15.4 | 6.04 | 2.69 | 1.61 |

*Note:* Reported estimates indicate the coefficients for the second-stage regression on the respective treatment variable given by the row heading. All covariates are included, as well as grid and country-year fixed effects. Errors clustered at the grid-level in parentheses.

## 5.2 Robustness checks

24 As a first exercise, I evaluate the robustness of the main findings to a specification in which the dependent variable is defined as the growth in night-time lights. The baseline reduced-form model would in this case be defined by the following equation,

$$\Delta \ln \left(Light_{ic,t}\right) = \alpha_1 \ln \left(Light_{ic,t-1}\right) + \sum_{k=0}^{1} \beta_k Aid_{ic,t-k} + \alpha_2' \mathbf{X}_{ic,t} + \delta_i + \lambda_t + \epsilon_{ic,t} \quad (5.1)$$

25 where $\Delta\ln(Light_{ic,t})$ represents annual logarithmic growth of night-time lights in grid cell $i$ of country $c$ in year $t$, and $\ln(Light_{ic,t-1})$ accounts for the conditional convergence effect. The remaining variables all maintain the same definitions as in the original specification.

26 Table 6 reports the results for the quantile regressions using the binary aid indicator. The direction of the coefficient associated with the term controlling for conditional convergence is as expected. For instance, looking at the lower end of the distribution, an increase in night-time lights would result in a subsequent decrease in growth of 0.19 percentage points.

27 The estimates for the effect of the presence of an aid project are robust to this specification, demonstrating a positive effect on the growth of night-time lights. In addition, the results again display a trend in the marginal return of aid across the quantiles, with the largest impact observed at the lower end of the distribution. An interesting point is that countries at lower stages of development usually display higher growth. Applying this concept, the findings would suggest that the impact of aid is strongest within “richer” grid cells. On the other hand, it is also likely that the lower end of the night-time luminosity distribution still represents poor grid cells, especially when considering that night-time lights do not change substantially from year to year.

**Table 6:** Quantile fixed effect regressions of growth of night-time luminosity on binary aid indicator

| | *Dependent variable: $\Delta ln(0.01 + night\ lights)$* | | | |
|---|---|---|---|---|
| | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.95$ |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.004 | 0.011 | 0.011 | 0.006 |
| | (0.007) | (0.003) | (0.004) | (0.007) |
| Aid dummy$_{t-1}$ | 0.026 | 0.012 | 0.003 | 0.00001 |
| | (0.003) | (0.003) | (0.001) | (0.005) |
| $\ln(0.01 + \text{lights})_{t-1}$ | −0.188 | −0.247 | −0.382 | −0.183 |
| | (0.047) | (0.064) | (0.073) | (0.038) |

*Note:* The table displays the coefficients of interest for the quantile regressions of the growth of night-time lights model. The dependent variable is defined as the first difference in the log of nightlights. All covariates and grid fixed effects are included in the regression. Bootstrapped errors based on 200 replications in parentheses.

28 I then repeat the baseline estimations on a sample which includes project locations that have been geo-referenced up to the level of second-order administrative regions (i.e. precision code 3), which corresponds to 72.5% of the full AidData sample size. The results remain consistent with those reported in Table 2 in both direction and magnitude, indicating no bias arising from the choice of the precision cut-off.

29 Following Clemens *et al.* (2012), I also estimate the baseline model on a subsample which differentiates aid projects according to the expected impact, namely “early-impact” and “late-impact”. Early-impact projects are predicted to affect development in the short-run, while late-impact projects would only produce an effect in the long-run.[3] In general, the main findings remain qualitatively unchanged by this specification. The coefficients associated with the early-impact indicator suggest a larger contemporaneous effect of aid on night-time lights, while the effect of late-impact aid is largest after a one-year lag.

30 Finally, I test the sensitivity of the results to a different variable transformation. As mentioned in Section 3.1, a small constant of 0.01 is added to the dependent and monetary aid variables when adopting the logarithmic transformation. This may create bias in the estimations, especially when considering that the night luminosity variable is standardized between 0 and 1. I therefore repeat the baseline regressions using the inverse hyperbolic sine (IHS) transformation instead, which can be expressed as follows:

$$ihs(x) = \ln\left(\sqrt{x^2 + 1} + x\right)$$

31 Compared to the natural log, the IHS transformation offers several benefits beyond adjusting for skewness. Most importantly, it retains zero and negative values, thus

mitigating potential biases arising from adding an arbitrary number to the variables of interest. In addition, it is more sensitive to changes in the underlying variable, and performs similarly to the log transformation in terms of interpretation.

32 Table 7 shows that the underlying implications are maintained, as the estimated coefficients show a positive and significant effect of aid, with a few exceptions. However, these coefficients are considerably smaller compared to those reported previously. For instance, the largest observable effect for the presence of an active project is 0.013, as opposed to 0.159 for the corresponding coefficient in Table 2.

33 This would suggest that the potential bias from the inclusion of an arbitrary constant is not negligible, and that past studies making use of the logarithmic transformation are overstating the effects of aid on development.

**Table 7:** Quantile fixed effect regressions of transformed night-time luminosity on binary aid indicator

| | *Dependent variable: ihs(night lights)* | | | |
|---|---|---|---|---|
| | $\tau = 0.25$ | $\tau = 0.50$ | $\tau = 0.75$ | $\tau = 0.95$ |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.002 | 0.003 | 0.0004 | 0.001 |
| | (0.0003) | (0.00003) | (0.0003) | (0.001) |
| Aid dummy$_{t-1}$ | 0.004 | 0.005 | 0.013 | 0.003 |
| | (0.0004) | (0.0001) | (0.0003) | (0.001) |

*Note:* The table displays the coefficients of interest for the quantile regressions of the inverse hyperbolic sine of night-time lights. All covariates and grid fixed effects are included in the regression. Bootstrapped errors shown in parentheses, based on 200 replications.

## NOTES DE BAS DE PAGE

**1.** Unfortunately, due to computational constraints, it was not possible to perform a formal test for the joint significance of the quantiles.

**2.** The authors estimate a quadratic production function for the logarithm of night lights $m(.)$ such that: $m(y) = 0.398+1.234y-0.244y^2$, where $y$ denotes the real GDP per capita in logarithm. The data was re-centred around the mean, namely 9.62.

**3.** Early-impact aid sectors include: agriculture, forestry, fishing; energy; industry; mining; trade policy; finance; transport; and communications. Late-impact sectors include: education; water and sanitation; health; social infrastructure; environmental protection; and public administration.

# 6. Conclusion

1 In this ePaper, I examine the sub-national effects of geo-referenced World Bank aid projects on economic development within African countries, measured as night-time luminosity. The unique data framework is based on a standardized grid cell structure, where the spatial unit of analysis is a single grid cell at a 0.5 x 0.5 decimal degree resolution. The advantage of this approach consists in its ability to mitigate endogeneity issues related to aggregation bias, reverse causality or sample selection.

2 Using a fixed effects quantile regression approach, I estimate the non-linear effects of foreign aid at different levels of development across approximately 10,600 grid cells over the period of 1995 to 2012. I also adopt an instrumental variable approach as a supplementary identification strategy, in case there may still remain any unaccounted-for endogeneity. I instrument the foreign aid indicators with a binary variable indicating whether a country is below the IDA's income threshold for eligibility to concessional aid, interacted with a grid cell's probability of receiving aid over the whole sample period.

3 Baseline results suggest a positive and statistically significant effect of foreign aid on night-time luminosity, albeit small in economic terms. Looking at the median effect, a one-unit increase in the number of projects would lead to a 2.2% increase in nightlights in following periods. In addition, the results imply that the marginal effect of aid is greatest within poorer regions, as the coefficients at the $95^{th}$ percentile are consistently smaller. Moreover, the estimations using a spatial lag model show clear evidence of spill-over effects of aid from neighbouring grid cells, which may even dominate the within-cell treatment. For a given grid cell, the presence of an aid project in at least one of its neighbours leads to a 7.5% increase in night-time luminosity.

4 The above findings are however fairly sensitive to different model specifications and variable transformations, namely the inclusion of year fixed effects and the use of the inverse hyperbolic sine transformation. In both cases, the coefficients are significantly smaller than those from the baseline model, which may raise concerns regarding previous studies that have overlooked these specifications.

5 Furthermore, the 2SLS results diverge substantially from the baseline estimates, showing a negative effect of foreign aid on nightlights. This is likely a result of the severe weakness of the instrument, or a potential violation in the exclusion restriction.

Hence, these findings may cast doubts on the reliability of instrumental variables to address the endogeneity of aid.

6 To conclude, the above findings suggest that foreign aid is moderately effective in fostering within-country development at the grid cell level. However, further research in this context is necessary to obtain more conclusive results. For instance, it may be more advantageous to study the impact of aid on specific development outcomes, such as health and nutrition, educational attainment or female empowerment. Nevertheless, an important next step would be to move away from reduced-form analyses, and instead develop a theoretical framework to better explain the causality chain, as well as any indirect mechanism, between aid and economic development.

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# Appendix

## A. Further summary and descriptive statistics

**Table A.1:** Summary statistics of all variables used in the estimations (1995-2012)

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| ln(0.01 + night lights) | 192,132 | −3.01 | 0.36 | −3.71 | −0.03 |
| Δ ln(0.01 + night lights) | 192,132 | 0.04 | 0.22 | −0.91 | 1.31 |
| ihs(night lights) | 192,132 | 0.04 | 0.03 | 0.01 | 0.85 |
| Binary indicator for the presence of an aid project | 192,132 | 0.09 | 0.27 | 0 | 1 |
| Number of projects | 192,132 | 0.19 | 1.03 | 0 | 42 |
| ln(0.01 + total commitments) | 192,132 | −18.00 | 2.86 | −18.40 | 6.42 |
| ihs(total commitments) | 192,132 | 0.04 | 0.33 | 0 | 7 |
| ln(0.01 + disbursements) | 192,132 | −18.00 | 2.71 | −18.40 | 5.65 |
| ihs(disbursements) | 192,132 | 0.03 | 0.26 | 0 | 6 |
| Binary indicator for being below IDA income threshold | 191,722 | 0.61 | 0.49 | 0.00 | 1.00 |
| Distance from IDA income threshold | 182,302 | 558.00 | 2,106.00 | −965.00 | 12,995.00 |
| Probability of receiving aid | 192,132 | 0.09 | 0.21 | 0 | 1 |
| Binary indicator for being below threshold * aid probability | 191,722 | 0.07 | 0.20 | 0.00 | 1.00 |
| Distance from threshold * aid probability | 182,302 | −27.80 | 193.00 | −965.00 | 7,250.00 |
| ln(0.01 + total population) | 192,132 | 9.43 | 2.37 | −4.61 | 16.40 |
| ihs(total population) | 192,132 | 10.10 | 2.28 | 0 | 17 |
| ln(distance to capital) | 192,132 | 6.22 | 0.80 | 1.31 | 7.82 |
| ihs(distance to capital) | 192,132 | 6.91 | 0.80 | 2.02 | 8.51 |
| ln(travel time to nearest city) | 192,006 | 6.19 | 0.84 | 2.48 | 8.72 |
| ihs(travel time to nearest city) | 192,006 | 6.88 | 0.84 | 3.18 | 9.41 |
| ln(0.01 + conflict events) | 192,132 | −4.49 | 0.77 | −4.61 | 5.50 |
| ihs(conflict events) | 192,132 | 0.03 | 0.24 | 0 | 6 |
| Drought severity index | 190,585 | −0.30 | 1.01 | −6.84 | 6.11 |
| Total precipitation | 192,132 | 687.00 | 614.00 | 0.12 | 3,275.00 |
| Mean Temperature | 188,962 | 24.60 | 3.96 | 5.01 | 39.50 |
| Child malnutrition rate | 187,380 | 26.00 | 12.90 | 1.10 | 52.50 |
| Infant mortality rate | 188,280 | 9.08 | 4.37 | 1.00 | 20.30 |
| Binary indicator for natural resource deposits | 192,132 | 0.08 | 0.26 | 0 | 1 |

*Note*: The unit of observation is a grid-year, across 10,674 grid cells during the period between 1995 and 2012. ihs(x) signifies the inverse hyperbolic sine function. All variables representing commitments and disbursements are expressed in millions of U.S. dollars. The distance from the IDA income threshold is measured in current U.S. dollars.

**Table A.2:** Aid projects according to status and precision code

| | AidData precision code | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Status | (1) Exact Location | (2) "Near" Location | (3) ADM2 Level | (4) ADM1 Level | (5) Estimated Coordinates | (6) Country-Wide | (7) Unclear Location | (8) Political Entity | Total |
| Completion | 16,862 | 1,178 | 10,194 | 7,280 | 680 | 1,134 | 0 | 1,547 | 38,875 |
| Dropped | 3,454 | 383 | 1,589 | 1,371 | 114 | 273 | 1 | 182 | 7367 |
| Implementation | 6,031 | 793 | 3,814 | 3,168 | 288 | 355 | 1 | 402 | 14,852 |
| All projects | 26,347 | 2,354 | 15,597 | 11,819 | 1,082 | 1,762 | 2 | 2,131 | 61,094 |

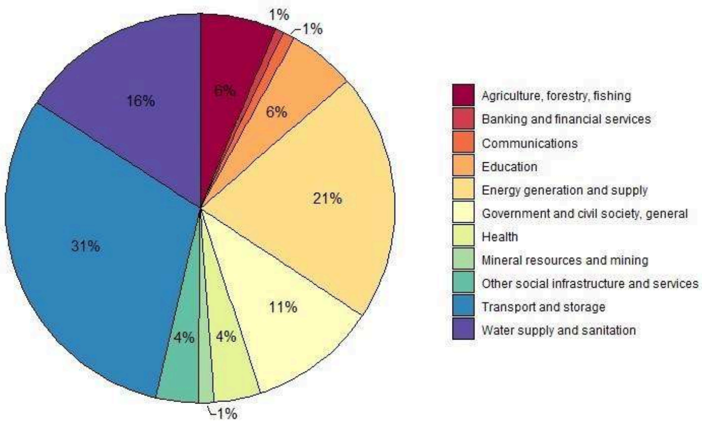
*Note*: This table shows the distribution of AidData project locations with respect to geocoding precision and status classification, during the period 1995 to 2014.

**Table A.3:** Sample of countries and years of IDA threshold crossings

| Country | Year(s) of crossing from below (from above) |
|---|---|
| Angola | 2004 |
| Cameroon | 2006 (1995) |
| Comoros | 2005 (1995) |
| Congo | 2006 (1993) |
| Cote d'Ivoire | 2009; 2012 (2011) |
| Djibouti | 2007 (1993) |
| Egypt | 1996 |
| Equatorial Guinea | 2001 |
| Ghana | 2008 |
| Lesotho | 2005 |
| Nigeria | 2005 |
| Senegal | 2007 (1994) |
| Sudan | 2009 |
| Zambia | 2008 |

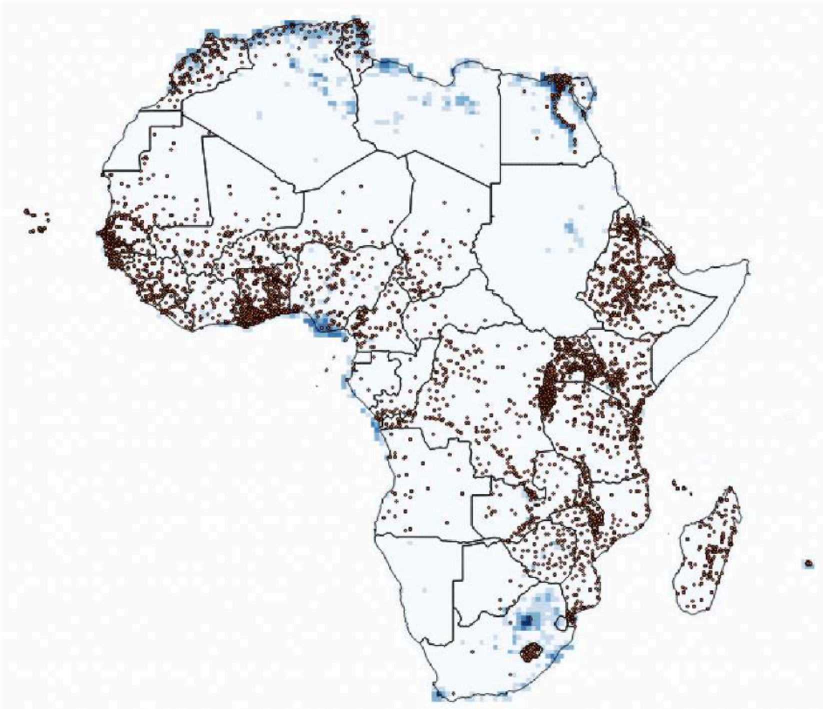
*Note:* The table illustrates the years in a country crossed the IDA income threshold between the period 1991 to 2010, either from an initial point below the cutoff or above it (latter in parenthesis).

**Figure A.1:** Distribution of aid projects according to main sector group




*Note*: This graph displays the share of total projects with an AidData precision code below 3 with respect to the sector of purpose. The chart does not include projects labelled as "Multi-sector", which amount to 74.2% of the complete sample. Projects in sectors classified as "Other" and "General environmental protection" are also excluded, as they constitute 0.03% of the total number of projects.

**Figure A.2:** Spatial relationship between completed aid projects and night-time luminosity



*Note*: Red points represent the locations of all completed World Bank projects between 1995 and 2014. Darker cells indicate grid cells with greater night-time luminosity.

## B. Complete regression tables from main estimations

**Table B.1:** Quantile fixed effect regression of night-time luminosity on binary aid indicator

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.050 | 0.060 | 0.011 | 0.019 |
| | (0.006) | (0.006) | (0.008) | (0.008) |
| Aid dummy$_{t-1}$ | 0.077 | 0.084 | 0.159 | 0.048 |
| | (0.007) | (0.006) | (0.013) | (0.008) |
| ln(distance to capital) | −0.011 | −0.012 | −0.012 | −0.010 |
| | (0.0004) | (0.0004) | (0.001) | (0.0005) |
| ln(travel time) | 0.007 | 0.009 | 0.015 | 0.004 |
| | (0.001) | (0.002) | (0.003) | (0.001) |
| CMR | −0.011 | −0.011 | −0.012 | −0.011 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| IMR | 0.003 | 0.0003 | −0.002 | −0.003 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| Drought index | 0.099 | 0.100 | 0.106 | 0.095 |
| | (0.005) | (0.005) | (0.006) | (0.005) |
| Precipitation | 0.191 | 0.194 | 0.201 | 0.181 |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Temperature | 0.194 | 0.198 | 0.216 | 0.198 |
| | (0.011) | (0.011) | (0.012) | (0.011) |
| Natural resources | −0.151 | −0.153 | −0.200 | −0.198 |
| | (0.007) | (0.005) | (0.006) | (0.007) |
| ln(0.01 + conflict) | −0.0001 | −0.0001 | −0.0002 | −0.0001 |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| ln(0.01 + population) | 0.016 | 0.016 | 0.020 | 0.016 |
| | (0.001) | (0.001) | (0.002) | (0.001) |
| Constant | −6.670 | −6.650 | −6.780 | −6.070 |
| | (0.173) | (0.173) | (0.180) | (0.166) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* Quantile regressions include fixed effects at the grid cell level. ln(travel time) indicates the log of the total travel time in minutes to the nearest city with at least 50,000 inhabitants. CMR and IMR represent child malnutrition and infant mortality rates, respectively. Bootstrapped errors based on 200 replications in parentheses.

**Table B.2:** Quantile fixed effect regression of night-time luminosity on number of aid projects

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| No. of projects$_t$ | −0.011 | −0.012 | −0.012 | −0.010 |
| | (0.0005) | (0.0005) | (0.001) | (0.001) |
| No. of projects$_{t-1}$ | 0.007 | 0.008 | 0.014 | 0.004 |
| | (0.001) | (0.002) | (0.003) | (0.002) |
| ln(distance to capital) | −0.012 | −0.012 | −0.013 | −0.011 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| ln(travel time) | 0.003 | 0.0003 | −0.002 | −0.003 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| CMR | 0.099 | 0.100 | 0.106 | 0.097 |
| | (0.006) | (0.006) | (0.007) | (0.006) |
| IMR | 0.195 | 0.198 | 0.205 | 0.184 |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Drought index | 0.195 | 0.199 | 0.216 | 0.199 |
| | (0.010) | (0.010) | (0.012) | (0.011) |
| Precipitation | −0.153 | −0.154 | −0.203 | −0.199 |
| | (0.008) | (0.006) | (0.006) | (0.007) |
| Temperature | −0.0001 | −0.0001 | −0.0002 | −0.0001 |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| Natural resources | 0.011 | 0.012 | 0.0002 | 0.005 |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| ln(0.01 + conflict) | 0.018 | 0.022 | 0.034 | 0.012 |
| | (0.002) | (0.002) | (0.003) | (0.003) |
| ln(0.01 + population) | 0.017 | 0.016 | 0.020 | 0.017 |
| | (0.002) | (0.002) | (0.002) | (0.001) |
| Constant | −6.720 | −6.700 | −6.820 | −6.120 |
| | (0.181) | (0.179) | (0.191) | (0.174) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* Quantile regressions include fixed effects at the grid cell level. ln(travel time) indicates the log of the total travel time in minutes to the nearest city with at least 50,000 inhabitants. CMR and IMR represent child malnutrition and infant mortality rates, respectively. Bootstrapped errors based on 200 replications in parentheses.

**Table B.3:** Quantile fixed effect regression of night-time luminosity on total aid disbursements

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| ln(0.01 + disbursements)$_t$ | −0.012 | −0.012 | −0.012 | −0.011 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| ln(0.01 + disbursements)$_{t-1}$ | 0.008 | 0.009 | 0.014 | 0.004 |
| | (0.002) | (0.002) | (0.003) | (0.001) |
| ln(distance to capital) | −0.013 | −0.012 | −0.013 | −0.011 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| ln(travel time) | 0.002 | 0.0001 | −0.002 | −0.003 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| CMR | 0.002 | 0.001 | −0.001 | 0.001 |
| | (0.0003) | (0.0002) | (0.0004) | (0.0004) |
| IMR | 0.001 | 0.001 | 0.002 | −0.001 |
| | (0.0003) | (0.0003) | (0.001) | (0.0003) |
| Drought index | 0.100 | 0.102 | 0.107 | 0.098 |
| | (0.006) | (0.006) | (0.006) | (0.005) |
| Precipitation | 0.205 | 0.208 | 0.216 | 0.193 |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Temperature | 0.205 | 0.209 | 0.227 | 0.209 |
| | (0.011) | (0.011) | (0.012) | (0.011) |
| Natural resources | −0.157 | −0.157 | −0.207 | −0.201 |
| | (0.008) | (0.006) | (0.007) | (0.008) |
| ln(0.01 + conflict) | −0.0002 | −0.0002 | −0.0002 | −0.0001 |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| ln(0.01 + population) | 0.018 | 0.017 | 0.020 | 0.017 |
| | (0.002) | (0.002) | (0.002) | (0.001) |
| Constant | −6.830 | −6.810 | −6.960 | −6.260 |
| | (0.192) | (0.189) | (0.194) | (0.182) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* Quantile regressions include fixed effects at the grid cell level. ln(travel time) indicates the log of the total travel time in minutes to the nearest city with at least 50,000 inhabitants. CMR and IMR represent child malnutrition and infant mortality rates, respectively. Bootstrapped errors based on 200 replications in parentheses.

**Table B.4:** Quantile fixed effect regression of night-time luminosity on total aid commitments

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| ln(0.01 + commitments)$_t$ | −0.012 | −0.012 | −0.012 | −0.011 |
| | (0.0004) | (0.0004) | (0.001) | (0.0005) |
| ln(0.01 + commitments)$_{t-1}$ | 0.008 | 0.009 | 0.014 | 0.004 |
| | (0.001) | (0.002) | (0.003) | (0.001) |
| ln(distance to capital) | −0.012 | −0.012 | −0.013 | −0.011 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| ln(travel time) | 0.002 | 0.002 | 0.002 | 0.001 |
| | (0.0003) | (0.0003) | (0.001) | (0.0003) |
| CMR | 0.001 | 0.002 | 0.003 | −0.0001 |
| | (0.0003) | (0.0003) | (0.001) | (0.0003) |
| IMR | 0.002 | 0.0001 | −0.002 | −0.003 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| Drought index | 0.100 | 0.101 | 0.107 | 0.098 |
| | (0.006) | (0.006) | (0.007) | (0.006) |
| Precipitation | 0.204 | 0.207 | 0.214 | 0.192 |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Temperature | 0.204 | 0.208 | 0.226 | 0.208 |
| | (0.011) | (0.011) | (0.012) | (0.011) |
| Natural resources | −0.157 | −0.157 | −0.207 | −0.202 |
| | (0.008) | (0.006) | (0.007) | (0.007) |
| ln(0.01 + conflict) | −0.0002 | −0.0002 | −0.0002 | −0.0001 |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| ln(0.01 + population) | 0.018 | 0.017 | 0.020 | 0.017 |
| | (0.001) | (0.001) | (0.002) | (0.001) |
| Constant | −6.800 | −6.770 | −6.880 | −6.230 |
| | (0.180) | (0.179) | (0.185) | (0.175) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* Quantile regressions include fixed effects at the grid cell level. ln(travel time) indicates the log of the total travel time in minutes to the nearest city with at least 50,000 inhabitants. CMR and IMR represent child malnutrition and infant mortality rates, respectively. Bootstrapped errors based on 200 replications in parentheses.

**Table B.5:** Quantile spatial fixed effect regression of night-time luminosity on binary aid indicator

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| **W** ln(lights)$_{t-1}$ | 0.808 | 0.746 | 0.600 | 0.805 |
| | (0.006) | (0.006) | (0.003) | (0.004) |
| Aid dummy$_t$ | 0.006 | 0.011 | 0.008 | 0.008 |
| | (0.004) | (0.003) | (0.003) | (0.004) |
| Aid dummy$_{t-1}$ | 0.010 | 0.008 | 0.004 | −0.001 |
| | (0.004) | (0.003) | (0.003) | (0.004) |
| **W** Aid dummy$_t$ | 0.013 | 0.017 | 0.032 | 0.044 |
| | (0.014) | (0.012) | (0.011) | (0.015) |
| **W** Aid dummy$_{t-1}$ | 0.075 | 0.060 | 0.018 | 0.0003 |
| | (0.014) | (0.013) | (0.011) | (0.016) |
| ln(distance to capital) | 0.015 | 0.012 | 0.008 | 0.009 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| ln(travel time) | 0.015 | 0.009 | 0.008 | 0.011 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| CMR | −0.0004 | −0.001 | −0.001 | −0.0003 |
| | (0.0002) | (0.0002) | (0.0001) | (0.0001) |
| IMR | −0.001 | −0.0003 | −0.0002 | −0.001 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) |
| Drought index | 0.004 | −0.002 | 0.0002 | −0.0001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Precipitation | −0.00000 | −0.00001 | −0.00001 | −0.00000 |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Temperature | 0.003 | 0.003 | 0.003 | 0.003 |
| | (0.0005) | (0.0005) | (0.0004) | (0.001) |
| Natural resources | −0.040 | −0.019 | −0.016 | −0.015 |
| | (0.006) | (0.004) | (0.004) | (0.004) |
| ln(0.01 + conflict) | 0.001 | 0.001 | 0.001 | 0.0004 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| ln(0.01 + population) | 0.009 | 0.010 | 0.010 | 0.006 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | −0.951 | −1.020 | −1.290 | −0.510 |
| | (0.042) | (0.038) | (0.031) | (0.041) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note*: This table reports the regressions of the spatial lag models with the binary aid indicator as the treatment variable. Variables pre-multiplied by **W** represent the spatial lag operators. ln(travel time) indicates the log of the total travel time in minutes to the nearest city. CMR and IMR represent child malnutrition and infant mortality rates, respectively. Grid cell fixed effects are included. Bootstrapped errors based on 200 replications in parentheses.

**Table B.6:** Quantile fixed effect regression of night-time luminosity growth on binary aid indicator

| | Dependent variable: $\Delta$ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| ln(0.01 + lights)$_{t-1}$ | −0.188 | −0.247 | −0.382 | −0.183 |
| | (0.006) | (0.004) | (0.004) | (0.004) |
| Aid dummy$_t$ | 0.004 | 0.011 | 0.011 | 0.006 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Aid dummy$_{t-1}$ | 0.026 | 0.012 | 0.003 | 0.00001 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| ln(distance to capital) | 0.006 | 0.002 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| ln(travel time) | 0.007 | 0.001 | −0.001 | 0.003 |
| | (0.002) | (0.001) | (0.001) | (0.002) |
| CMR | −0.0003 | −0.001 | −0.001 | −0.0002 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| IMR | −0.001 | −0.00004 | 0.0002 | −0.0002 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) |
| Drought index | 0.004 | −0.002 | −0.001 | −0.0002 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Precipitation | −0.00000 | −0.00001 | −0.00001 | −0.00000 |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Temperature | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.0004) | (0.0003) | (0.0004) | (0.0005) |
| Natural resources | −0.024 | −0.009 | −0.004 | −0.006 |
| | (0.004) | (0.003) | (0.004) | (0.003) |
| ln(0.01 + conflict) | −0.0003 | 0.001 | 0.002 | −0.0005 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| ln(0.01 + population) | 0.005 | 0.006 | 0.006 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | −0.740 | −0.794 | −1.060 | −0.278 |
| | (0.035) | (0.030) | (0.028) | (0.040) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* The table displays quantile regressions of the growth of night-time luminosity model, with the binary aid indicator as the treatment. The dependent variable is defined as the first difference in the log of nightlights. Grid fixed effects are included. Bootstrapped errors based on 200 replications in parentheses.

**Table B.7:** Quantile fixed effect regression of night-time luminosity on binary aid indicator for early-impact projects

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.059 | 0.062 | 0.002 | −0.005 |
| | (0.006) | (0.005) | (0.007) | (0.007) |
| Aid dummy$_{t-1}$ | 0.068 | 0.080 | 0.168 | 0.071 |
| | (0.004) | (0.004) | (0.010) | (0.008) |
| ln(distance to capital) | −0.011 | −0.012 | −0.012 | −0.010 |
| | (0.0003) | (0.0003) | (0.0004) | (0.0004) |
| ln(travel time) | 0.007 | 0.009 | 0.015 | 0.004 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| CMR | −0.011 | −0.011 | −0.012 | −0.011 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| IMR | 0.003 | 0.0003 | −0.002 | −0.003 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| Drought index | 0.099 | 0.100 | 0.106 | 0.096 |
| | (0.005) | (0.005) | (0.005) | (0.004) |
| Precipitation | 0.193 | 0.196 | 0.202 | 0.182 |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Temperature | 0.195 | 0.199 | 0.218 | 0.199 |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Natural resources | −0.150 | −0.152 | −0.199 | −0.198 |
| | (0.006) | (0.005) | (0.006) | (0.008) |
| ln(0.01 + conflict) | −0.0001 | −0.0001 | −0.0002 | −0.0001 |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| ln(0.01 + population) | 0.016 | 0.016 | 0.020 | 0.016 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | −6.690 | −6.670 | −6.800 | −6.100 |
| | (0.156) | (0.156) | (0.155) | (0.152) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* The table reports quantile regressions of night-time luminosity model on a binary indicator of aid, for the sub-sample of projects classified as "early-impact". Grid fixed effects are included. Bootstrapped errors based on 200 replications in parentheses.

**Table B.8:** Quantile fixed effect regression of night-time luminosity on binary aid indicator for late-impact projects

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.029 | 0.037 | −0.039 | −0.014 |
| | (0.005) | (0.005) | (0.006) | (0.008) |
| Aid dummy$_{t-1}$ | 0.082 | 0.086 | 0.161 | 0.066 |
| | (0.004) | (0.004) | (0.009) | (0.008) |
| ln(distance to capital) | −0.011 | −0.012 | −0.012 | −0.010 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| ln(travel time) | 0.007 | 0.008 | 0.015 | 0.004 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| CMR | −0.011 | −0.011 | −0.012 | −0.011 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| IMR | 0.003 | 0.0003 | −0.002 | −0.003 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| Drought index | 0.099 | 0.100 | 0.105 | 0.095 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Precipitation | 0.193 | 0.197 | 0.204 | 0.183 |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Temperature | 0.195 | 0.199 | 0.217 | 0.199 |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Natural resources | −0.153 | −0.154 | −0.202 | −0.198 |
| | (0.006) | (0.005) | (0.006) | (0.007) |
| ln(0.01 + conflict) | −0.0001 | −0.0001 | −0.0002 | −0.0001 |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| ln(0.01 + population) | 0.016 | 0.016 | 0.020 | 0.016 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | −6.700 | −6.670 | −6.800 | −6.100 |
| | (0.143) | (0.143) | (0.142) | (0.137) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* The table reports quantile regressions of night-time luminosity model on a binary indicator of aid, for the sub-sample of projects classified as "late-impact". Grid fixed effects are included. Bootstrapped errors based on 200 replications in parentheses.

**Table B.9:** Quantile fixed effect regression of night-time luminosity on binary aid indicator for late-impact projects

| | Dependent variable: ihs(night lights) | | | |
|---|---|---|---|---|
| | $\tau$=0.25 | $\tau$=0.5 | $\tau$=0.75 | $\tau$=0.95 |
| | (1) | (2) | (3) | (4) |
| Aid dummy$_t$ | 0.002 | 0.003 | 0.0004 | 0.001 |
| | (0.0003) | (0.0003) | (0.0005) | (0.0004) |
| Aid dummy$_{t-1}$ | 0.004 | 0.005 | 0.013 | 0.003 |
| | (0.0004) | (0.0003) | (0.001) | (0.0005) |
| ihs(distance to capital) | −0.001 | −0.001 | −0.001 | −0.001 |
| | (0.00002) | (0.00002) | (0.00003) | (0.00003) |
| ihs(travel time) | 0.0004 | 0.0005 | 0.001 | 0.0002 |
| | (0.0001) | (0.0001) | (0.0002) | (0.0001) |
| CMR | −0.001 | −0.001 | −0.001 | −0.001 |
| | (0.00004) | (0.00004) | (0.0001) | (0.0001) |
| IMR | −0.009 | −0.009 | −0.012 | −0.011 |
| | (0.0004) | (0.0003) | (0.0004) | (0.001) |
| Drought index | −0.00001 | −0.00001 | −0.00001 | −0.00001 |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Precipitation | 0.0002 | 0.0001 | 0.0002 | 0.001 |
| | (0.0002) | (0.0002) | (0.0004) | (0.0005) |
| Temperature | 0.005 | 0.005 | 0.005 | 0.005 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Natural resources | 0.010 | 0.010 | 0.011 | 0.010 |
| | (0.0004) | (0.0004) | (0.0005) | (0.0004) |
| ihs(conflict) | 0.010 | 0.010 | 0.011 | 0.010 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| ihs(population) | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Constant | −0.163 | −0.160 | −0.170 | −0.129 |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Observations | 173,717 | 173,717 | 173,717 | 173,717 |

*Note:* The table reports quantile regressions of night-time luminosity model on a binary indicator of aid. The dependent variable is defined as the inverse hyperbolic sine (i.e. ihs(x)) of nightlights. Regressions include grid fixed effects. Bootstrapped errors based on 200 replications in parentheses.

## C. Replication of Briggs (2018) and auxiliary regressions

**Table C.1:** OLS regressions of aid on poverty measures included sequentially

| | ln(light) | ln(time) | ln(dist) | CMR | IMR |
|---|---|---|---|---|---|
| Dependent variable: Binary variable for receiving aid | | | | | |
| | 0.217*** | −0.107*** | −0.088*** | −0.091 | 0.079 |
| | (0.036) | (0.017) | (0.024) | (0.118) | (0.303) |
| Dependent variable: Log of total value of aid commitments | | | | | |
| | 1.410*** | −0.587*** | −0.517*** | −0.809* | −0.330 |
| | (0.160) | (0.056) | (0.098) | (0.484) | (1.220) |
| Observations | 10,273 | 10,273 | 10,273 | 9,830 | 9,932 |

*Note:* Each column represents a separate regression for the two aid indicators, where the covariates include the variable referred in the column head and the log of total population. Reported estimates indicate the coefficient on the variable given by the column heading. CMR and IMR indicate the child malnutrition and infant mortality rates, respectively. All regressions include spatial fixed effects. Clustered errors are given in parenthesis. *p<0.1; **p<0.05; ***p<0.01

**Table C.2:** OLS regressions of aid on poverty measures included simultaneously

| | Dependent variable: | | |
|---|---|---|---|
| | Aid dummy | No. of projects | ln(total commitments) |
| | (1) | (2) | (3) |
| ln(light) | 0.158*** | 0.964*** | 1.210*** |
| | (0.040) | (0.243) | (0.180) |
| ln(time) | −0.087*** | −0.238*** | −0.427*** |
| | (0.021) | (0.075) | (0.078) |
| ln(dist) | −0.057* | −0.475** | −0.296** |
| | (0.031) | (0.201) | (0.123) |
| CMR | 0.034 | −0.253 | −0.012 |
| | (0.118) | (0.400) | (0.479) |
| IMR | 0.358 | 2.030 | 1.700 |
| | (0.405) | (1.400) | (1.590) |
| Observations | 9,830 | 9,830 | 9,830 |

*Note:* Regressions include spatial fixed effects and the log of population as a covariate, in addition to those given by the row headings. CMR and IMR indicate the child malnutrition and infant mortality rates, respectively. Clustered errors are given in parenthesis. *p<0.1; **p<0.05; ***p<0.01

**Table C.3:** Panel OLS regressions of aid on night-time luminosity with grid fixed effects

| | Dependent variable: | | | |
|---|---|---|---|---|
| | Aid dummy | No. projects | ln(disbursements) | ln(disbursements) |
| | (1) | (2) | (3) | (4) |
| ln(commitments) | | | | 0.745*** |
| | | | | (0.006) |
| ln(light) | 0.080*** | 0.526*** | 0.001 | −0.066*** |
| | (0.004) | (0.030) | (0.005) | (0.004) |
| ln(distance) | 0.009 | 0.011 | −0.007 | −0.012*** |
| | (0.008) | (0.096) | (0.017) | (0.004) |
| Drought index | −0.001*** | −0.018*** | −0.005*** | −0.005*** |
| | (0.0005) | (0.006) | (0.002) | (0.001) |
| Precipitation | −0.00004*** | −0.0001** | −0.00001 | 0.0001*** |
| | (0.00001) | (0.00004) | (0.00002) | (0.00001) |
| Temperature | 0.001* | 0.015** | 0.005** | 0.001 |
| | (0.001) | (0.007) | (0.002) | (0.002) |
| Natural resources | −0.030*** | −0.059* | 0.028* | 0.044*** |
| | (0.009) | (0.031) | (0.016) | (0.010) |
| ln(conflicts) | −0.002* | −0.009** | −0.004 | 0.003 |
| | (0.001) | (0.004) | (0.004) | (0.002) |
| ln(population) | 0.008*** | 1.920*** | 0.001** | −0.005*** |
| | (0.001) | (0.047) | (0.001) | (0.0004) |
| Observations | 188,021 | 188,021 | 188,021 | 188,021 |
| Adjusted $R^2$ | −0.039 | −0.039 | −0.059 | 0.726 |

*Note:* The table displays the results from panel OLS regressions for the period 1995 to 2012. all variables expressed in logarithims, with the exception of ln(distance), include a small constant of 0.01 added to the raw value. All regression include grid fixed effects. Standard errors clustered at the grid cell level are given in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

**Table C.4:** Panel OLS regressions of night-time luminosity on aid with grid fixed effects

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Aid $\text{dummy}_t$ | 0.174*** | | | |
| | (0.007) | | | |
| No. of $\text{projects}_t$ | | 0.033*** | | |
| | | (0.003) | | |
| $\ln(0.01 + \text{disbursements})_t$ | | | 0.0002 | |
| | | | (0.001) | |
| $\ln(0.01 + \text{commitments})_t$ | | | | 0.011*** |
| | | | | (0.001) |
| $\ln(\text{distance})_t$ | −0.158*** | −0.158*** | −0.159*** | −0.159*** |
| | (0.010) | (0.009) | (0.010) | (0.010) |
| Drought $\text{index}_t$ | 0.015*** | 0.015*** | 0.015*** | 0.015*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $\text{Precipitation}_t$ | −0.0001*** | −0.0001*** | −0.0001*** | −0.0001*** |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| $\text{Temperature}_t$ | 0.062*** | 0.062*** | 0.063*** | 0.063*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Natural $\text{resource}_t$ | −0.266*** | −0.266*** | −0.275*** | −0.274*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $\ln(0.01 + \text{conflicts})_t$ | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $\ln(0.01 + \text{population})_t$ | 0.023*** | 0.023*** | 0.025*** | 0.025*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Observations | 188,021 | 188,021 | 188,021 | 188,021 |
| Adjusted $R^2$ | 0.017 | 0.017 | 0.003 | 0.004 |

*Note:* The table displays the results from panel OLS regressions for the period 1995 to 2012, where the main regressor is the corresponding aid indicator at time $t$. All regression include grid fixed effects. Standard errors clustered at the grid cell level in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

**Table C.5:** Panel OLS regressions of night-time luminosity on lagged aid with grid fixed effects

| | Dependent variable: ln(0.01 + night lights) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Aid $\text{dummy}_{t-1}$ | 0.194*** | | | |
| | (0.007) | | | |
| No. of $\text{projects}_{t-1}$ | | 0.037*** | | |
| | | (0.004) | | |
| $\ln(0.01 + \text{disbursements})_{t-1}$ | | | 0.003*** | |
| | | | (0.001) | |
| $\ln(0.01 + \text{commitments})_{t-1}$ | | | | 0.009*** |
| | | | | (0.001) |
| $\ln(\text{distance})_t$ | −0.176*** | −0.175*** | −0.174*** | −0.175*** |
| | (0.012) | (0.012) | (0.012) | (0.012) |
| Drought $\text{index}_t$ | 0.017*** | 0.017*** | 0.017*** | 0.017*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $\text{Precipitation}_t$ | −0.0001*** | −0.0001*** | −0.0001*** | −0.0001*** |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| $\text{Temperature}_t$ | 0.061*** | 0.062*** | 0.062*** | 0.062*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Natural $\text{resource}_t$ | −0.272*** | −0.276*** | −0.282*** | −0.282*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $\ln(0.01 + \text{conflict})_t$ | 0.001 | 0.002 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $\ln(0.01 + \text{population})_t$ | 0.029*** | 0.030*** | 0.031*** | 0.031*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Observations | 177,573 | 177,573 | 177,573 | 177,573 |
| Adjusted $R^2$ | 0.017 | 0.008 | 0.001 | 0.002 |

*Note:* The table displays the results from panel OLS regressions where the main regressor is the corresponding aid indicator at time $t-1$. All regression include grid fixed effects. Standard errors clustered at the grid cell level are given in parenthesis.
*p<0.1; **p<0.05; ***p<0.01