The Impact of Foreign Aid on Local Development: A Grid Cell Analysis *

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Abstract

We examine the impact of geo-referenced World Bank development projects on local development using equally sized grid cells with a spatial resolution of 0.5 decimal degrees latitude $\times$ longitude as the unit of investigation. The proposed grid cell approach solves a number of endogeneity problems discussed in the aid effectiveness literature that make it difficult to identify the true effect of foreign aid on development outcomes due to the presence of unobserved heterogeneity, aggregation bias, simultaneity and/or reverse causality concerning foreign aid and economic growth, measurement errors, and endogenous sample selection bias. The estimates reveal that World Bank foreign aid projects contribute significantly to grid cell economic activity measured by night-time light growth. This finding is robust to the presence of unobserved country-year and grid-cell-specific unobserved heterogeneity, and to the inclusion of a full set of grid-cell-specific socioeconomic, demographic, conflict-related, biogeographic, and climatic controls.

Keywords: Aid Effectiveness; Geo-Referenced Aid Projects; Economic Development; Economic Growth; Grid-Cell Analysis; GIS Data; Satellite Night-Time Light Data

JEL Classification Numbers: C23, F35, O10, O20, O40, R10

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1 Introduction

In this paper, we examine the impact of geo-referenced World Bank development projects on local development using equally sized grid cells with a spatial resolution of 0.5 decimal degrees latitude × longitude (approximately 55 km × 55 km at the equator) that spans the entire globe from -180 to 180 degrees longitude and 90 to -90 degrees latitude. By narrowing down the unit of investigation to the grid cell level, we are able to control for arbitrary unobserved country-specific heterogeneity and grid-cell-specific local characteristics. This issue is crucial to identifying the true effect of foreign aid on development outcomes, since aid effectiveness might be endogenous to prevailing biogeographic, climatic, socioeconomic, and demographic conditions. Furthermore, the proposed grid cell approach is capable of solving a number of additional endogeneity problems such as aggregation bias, simultaneity and/or reverse causality in the relationship between foreign aid and economic growth, measurement errors, and endogenous sample selection bias. The estimates show that World Bank development programs contribute significantly to the economic development of the receiving and the neighboring grid cells. This observation is robust to a large battery of additional sensitivity tests.

The robustness of the main findings reflect the strength of our proposed grid-cell-level estimation approach in overcoming a series of methodological problems that severely impede proper identification of the true effect of foreign aid on development outcomes. Many of the varying results in the empirical cross-country aid effectiveness literature are closely tied to the issue of spatial resolution, as the high aggregation level impedes proper control of unobserved heterogeneity.[1]

Accounting for the plethora of confounding factors in the relationship between foreign aid and economic growth on country level is therefore a virtually impossible task.[2] Since the arbitrary small-sized grid cells are nested within countries, we are able to include a full set of country-year fixed effects (FE) in the regressions that would otherwise not be technically feasible when using cross-country data. The inclusion of a full set of country-year FE effectively accounts for arbitrary unobserved heterogeneity underlying the allocation of bilateral aid flows. More importantly, because of insufficient human capital and technical capacities across these countries, this FE specification elegantly circumvents difficulties associated with the availability and quality of key economic and institutional country-level controls (Hodler and Knight, 2011; Henderson et al., 2012; Schneider and Enste, 2000). Thus, considering these country-level controls in the grid cell empirical analysis becomes redundant since they are implicitly accounted for through the inclusion of country-year FE. Furthermore, in contrast to the proposed grid cell analysis, country-level estimates risk confounding the positive effects of aid on economic

[1] While one branch of the literature has argued that development programs designed to promote economic prosperity are unconditionally beneficial (Hansen and Tarp, 2001; Dalgaard and Hansen, 2001; Dalgaard et al., 2004), others have argued that aid is only beneficial for economic growth if allocated to countries with 'good' economic policies and institutional environments (Burnside and Dollar, 2000; Collier and Dollar, 2002; Svensson, 1999). By far the most vehement critic of development assistance is William Easterly, who argues that foreign aid, as an instrument to improve the living conditions of people, has caused more harm than good in countries with pervasive rent-seeking activities (Easterly, 2001, 2006). His criticism is founded on the observation that many empirical findings are highly sensitive to the selection of countries, the set of country-level controls, the definition of foreign aid measures, measures used for normalization of the key foreign aid variable (e.g., normalization by GDP or population), alternative economic policy measures, and the removal of potential outliers from the empirical analysis (Easterly, 2003; Easterly et al., 2004; Roodman, 2007). Even large-scale meta-analyses have produced inconclusive findings on aid effectiveness (Doucouliagos and Paldam, 2008; Mekasha and Tarp, 2013; Doucouliagos and Paldam, 2013). The interested reader is referred to Temple (2010) for a comprehensive review and discussion of the findings in the foreign aid literature.

[2] Previous studies have shown the importance of political-strategic, economic, and ideological interests of donors in the allocation of aid funds to recipient countries (Alesina and Dollar, 2000; Kuziemko and Werker, 2006; Dreher et al., 2009; Brech and Potrafke, 2014).

growth with other (perhaps unrelated) negative developments within a particular country, causing a classical aggregation bias problem. In this context, we refer to the much discussed aid fungibility problem in cross-country aid effectiveness studies (Mosley, 1986; Mosley et al., 1987; Feyzioglu et al., 1998; Pack and Pack, 1990).

Another severe problem confounding estimation results is the choice of the location where the aid projects are implemented. If aid effectiveness were endogenous to prevailing biogeographic, climatic, socioeconomic, and demographic conditions, a proper control for these local factors would be required for identification. We overcome this specific problem through the construction of local (i.e., grid cell) rather than global (i.e., country-level) measures capturing the local conditions that can be directly linked to the implementation of specific development programs across grid cells.

Furthermore, if foreign aid is allocated to countries based on their economic performance (low or high), then simultaneity and/or reverse causality become severe problems for the estimations (Mosley et al., 1987; Arndt et al., 2015; Brückner, 2013). The proposed grid cell approach mitigates this kind of endogeneity concerns, as it is fairly unlikely that donors allocate their aid funds in accordance with the spatial delineation of grid cells. However, we provide two empirical tests regarding the possibility of reverse causality and/or simultaneity in the association between foreign aid and grid cell night-time light growth. None of these tests undermine the validity of our proposed grid cell identification strategy. Thus, we have no indication that bilateral and/or multilateral aid organizations allocate aid funds based on the socioeconomic conditions of grid cells that we have constructed purely arbitrarily. Although the advantages of low aggregation level analysis are evident, to the best of the authors' knowledge, so far, only the study by Dreher and Lohmann (2015) has addressed the effects of foreign aid on a subnational level using administrative regions as the spatial unit of investigation. We prefer the use of small, equally sized grid cells over the use of administrative regions, as the latter might be endogenous to political-economic considerations of nation states. To reach the desired low aggregation level, we combine various geo-coded data sets to examine the relationship between foreign aid and economic activity at the grid cell level. The most important data source is a recently released geo-spatial database – AidData (2016) – that has started to geo-reference foreign aid projects from numerous bilateral and multilateral institutions. The current release of the AidData covers a total of 5,684 geo-referenced development programs that were qualitatively approved by the World Bank Group during the years 1995 to 2014 (AidData, 2016). We obtained basic information on the financial activity, recipient country, and sector code of each project from the World Bank's Project and Operation Website (World Bank, 2016). Based on this data, we generate various geospatial foreign aid indicators (e.g., the number of World Bank project locations and the level of project-specific annual disbursement flows) showing the extent of World Bank development projects across grid cells and years. Due to the lack of reliable income measures at grid cell level, we follow the standard approach in development economics and construct a sum of lights index based on satellite-measured night-time light data as an indicator of economic activity at the disaggregated 0.5 decimal degree grid cell level (Henderson et al., 2012). In addition, to minimize endogeneity concerns arising from omitted factors at the preferred grid cell level, we construct a full set of grid-cell-specific socioeconomic, demographic, conflict related, climatic, and biogeographic geospatial indicators. The final data set comprises 58,676 grid cells during the years 1997 to 2013, resulting in 997,492 grid-year observations. The main findings were derived from a grid cell FE regression equation with standard errors that are robust to serial autocorrelation of grid cells over time and spatial autocorrelation across grid cells within countries. The baseline grid cell FE estimates reveal that a 1% increase in the number of World Bank foreign aid projects would, ceteris paribus, increase the annual growth rate of night-time light activity by about 1.49 and 3.18 percentage points in the same year and in the second year following the implementation of specific World Bank development programs, respectively. In economic terms, this result corresponds to a $(1.49 \times 0.30) \approx 0.45$ and $(3.18 \times 0.30) \approx 0.95$ percent increase in real GDP, respectively, based on an estimated night-time light elasticity of about 0.30 with respect to real GDP, which was obtained in a large panel of 161 countries during the period 1995 to 2013. This finding is robust to the inclusion of country-year FE, grid cell FE, and to a full set of grid-cell-specific socioeconomic, demographic, biogeographic, climate, and conflict-related geospatial indicators. Moreover, the results are qualitatively robust to the definition of various geospatial World Bank foreign aid indicators (i.e., a binary variable referring to the mere presence of World Bank foreign aid projects, the log of the number of implemented World Bank aid projects, and project-specific annual disbursement flows).

We conduct a series of additional robustness tests to examine the sensitivity of the main results to various model specifications. In a first exercise, we examine the sensitivity of the baseline grid cell FE estimates to various spatial aggregation levels (i.e., country, district, 4.0, 3.5, 3.0, 2.5, 2.0, 1.5, and 1.0 decimal degree resolution level) to demonstrate the importance of spatial resolution (in particular aggregation bias) in the relationship between foreign aid and development outcomes. Next, we investigate the possibility that the main findings might be the consequence of a favorable grid by presenting coefficient estimates from the construction of 100 randomly generated grid cell images. Finally, we examine the robustness of the main findings to the issue of spatial interdependence between nearby grid cells using various spatial econometric regression models. None of the aforementioned sensitivity tests significantly affect the main conclusions regarding aid effectiveness at the disaggregated grid cell level.

The remaining parts of the paper are organized as follows. In Section 2, we discuss the merits of our proposed grid cell level identification strategy. In Section 3, we outline the econometric specification and the estimation approach. Section 4 provides a discussion of the data used at the disaggregated grid cell level. The main empirical results are presented and discussed in Section 5. Additional robustness tests are presented in Section 6. Section 7 concludes by summarizing the main results.

2 Identification Strategy on Grid Cell Level

In this section, we outline the merits of our proposed empirical grid cell approach in addressing several endogeneity problems (i.e., unobserved heterogeneity underlying the allocation of bilateral aid flows, aggregation issues, simultaneity and/or reverse causality, measurement error problems, and sample selection bias) that often impair cross-country empirical studies on the effectiveness of foreign aid on development outcomes. We point out that the identification of the true effect of foreign aid on growth is closely tied to the spatial unit of investigation. From a theoretical standpoint, empirical studies examining aid effectiveness in important areas of development such as health, education, and governance should use local performance measures, which are directly linked to the presence of specific foreign aid projects. We elaborate on these and additional technical issues to show how to resolve the identification problem in the empirical aid effectiveness literature.

Unobserved Heterogeneity Underlying Bilateral Aid Flows. Since grid cells are nested within countries, we are able to include a full set of country-year FE in the regression equation, which improve the identification of the true effect of aid projects on development outcomes. Thereby, we implicitly account for unobserved heterogeneity in the allocation of bilateral aid flows to recipient countries due to humanitarian, political-strategic, economic, cultural, and ideological determinants of donors decision (Schraeder et al., 1998; Alesina and Dollar, 2000; Kuziemko and Werker, 2006; Dreher et al., 2009; Brech and Potrafke, 2014). In addition, the inclusion of country-year fixed effects in the empirical analysis circumvents the lack of detailed and reliable data on key country-level controls regarding the institutional and economic policy environment in aid recipient countries that might affect aid effectiveness.

Aggregation Bias. The proposed grid cell approach prevents the occurrence of the well-known aggregation problems of macro-level studies by using highly disaggregated information on the aid projects and the locations where they took place: the positive effects of foreign aid on the micro level might be cancelled out by other (potential unrelated) negative effects, including aid fungibility (Mosley, 1986; Mosley et al., 1987; Feyzioglu et al., 1998; Pack and Pack, 1990), changes in prices (Rajan and Subramanian, 2011), wages (Kirwan and McMillan, 2007; Levinsohn and McMillan, 2007), and internal migration (Sanchez et al., 2007). In addition, unobserved shocks (e.g., the occurrence of famines, armed conflicts, and crop price shocks) might trigger an unexpected inflow of foreign aid funds to recipient countries during a period of severe economic deterioration (Papanek, 1972). All of these issues might worsen the humanitarian situation in the recipient country, thus counteracting the potential positive effects of the foreign aid projects on economic prosperity. We effectively account for these kinds of confounding factors through the inclusion of a full set of grid-cell-specific climatic and conflict-related controls.

Simultaneity and/or Reverse Causality. The proposed grid cell estimation approach further mitigates simultaneity and/or reverse causality concerns in the aid and growth relationship (Mosley et al., 1987; Arndt et al., 2015; Brückner, 2013).[3] Although it is conceivable that national and multinational organizations might rely on economic indicators when allocating aid funds to recipient countries or administrative regions, we have no reason to suspect that donors allocate aid funds according to the socioeconomic conditions of grid cells that we have constructed arbitrarily. To underline this point, we provide two empirical tests that confirm the validity of our grid cell identification strategy. We also do not consider emergency aid flows, thus ruling out that the foreign aid variable might be correlated with local humanitarian conditions. However, the occurrence of conflicts and severe famines due to climatic shocks in specific grid cells might cause emergency aid inflows from national and multinational aid organizations other than the World Bank that could interfere with the identification of the true effect of aid projects on development outcomes. To tackle this problem, we control for the incidence of conflicts and unexpected drought shocks in specific grid cells in all model specifications.

[3]The direction of the simultaneity bias is unclear a priori and depend on the specifications of the structural equation regarding the data generation process of the growth and foreign aid variable. As a specific example, consider a system of two simultaneous equations describing the relationship between economic growth and foreign aid. For the sake of simplicity, we dispense with the inclusion of additional exogenous variables in both equations. In the growth equation, *Aid* causes economic growth according to $Growth_t = \alpha_1 + \alpha_2 Aid_t + u_t$, where u_t is a simple error term. Similarly, the foreign aid equation is defined according to $Aid_t = \beta_1 + \beta_2 Growth_t + v_t$, where v_t is again the usual error term, which is assumed to be uncorrelated with u_t. It is a matter of simple algebra to show that the large sample property of the OLS estimator is given as $plim\ \alpha_2^{OLS} = \alpha_2 + \frac{\beta_2(1-\alpha_2\beta_2)\sigma_u^2}{\beta_2^2\sigma_u^2+\sigma_v^2}$, where σ_u^2 and σ_v^2 refers to the variance of the error terms u and v, respectively. It follows that in the presence of simultaneity (i.e., $\beta_2 \neq 0$) simple OLS estimation of α_2 becomes inconsistent and biased in the structural growth equation. Specifically, if foreign aid has a positive effect on growth (i.e., $\alpha_2 > 0$) and slow-growing countries attract more foreign aid inflows (i.e., $\beta_2 < 0$), then the direction of the simultaneity bias becomes negative.

Measurement Error Problem. Since GDP as a pecuniary measure is not available at the disaggregated grid cell level, we use satellite-measured night-time light data as a proxy for the level of economic activity in specific grid cells. It has been shown quite conclusively that the use of satellite-measured night-time light data is a more reliable measure of economic activity than officially reported GDP statistics, especially in less developed countries (Chen and Nordhaus, 2011; Henderson et al., 2012).[4] Through the use of satellite-measured night-time light data, we avoid a problem that has been discussed extensively in the literature regarding the reliability of officially reported GDP statistics in low-income countries, including the size of the shadow economy, strategic reporting, measurement error, and insufficient human and technical capacities of national statistical institutions for data collection and reporting (Schneider and Enste, 2000; Henderson et al., 2012; Galiani et al., 2017).

Endogenous Sample Selection Bias. Finally, the use of equally sized grid cells that span the entire world and the use of country-year fixed effects overcomes the missing data problems of key economic policy, governance, institutional, and socioeconomic controls prevalent in the aid effectiveness literature.[5] From a technical standpoint, standard OLS estimation becomes inconsistent if the mechanisms behind the missing country-level controls is endogenously determined (Wooldridge, 2010, Chapter 19).[6] A positive side-effect of our grid cell identification strategy is the presence of potential counterfactual observations (Bourguignon and Sundberg, 2007). Specifically, we are able to find grid cells that have similar socioeconomic, biogeographic, and climatic conditions but differ with respect to the presence of specific foreign aid projects. This allows us to identify the causal effects of foreign aid projects on grid cell development outcomes, thus mitigating biased and inconsistent estimates triggered by sample selection problems.

3 Econometric Specification and Estimation Approach

In accordance with the previous discussion on identification, we combine geocoded World Bank foreign aid projects with high-resolution geospatial indicators to estimate the following regression model in a global panel of 0.5 decimal degree grid cells. We estimate a grid cell FE regression equation with clustered standard errors that are robust to serial autocorrelation within grid cells and spatial correlation across grid cells within country-years:

$$\begin{aligned}\triangle \ln(0.01 + Light_{g,c,t}) &= \beta_0 + \beta_1 \ln(0.01 + Light_{g,c,t-1}) + \sum_{k=0}^{2} \phi_k Aid_{g,c,t-k} \\ &+ \boldsymbol{\beta}_2' \boldsymbol{X}_{g,c,t} + \boldsymbol{\beta}_3' \boldsymbol{RD}_{g,c,t} + \boldsymbol{\beta}_4' \boldsymbol{Z}_g + \lambda_{c,t} + \eta_g + \upsilon_{g,c,t}, \qquad (1)\end{aligned}$$

[4] A detailed discussion on data construction and sources as well as possible strengths and weaknesses of the satellite-measured night-time light measure is provided in the supplemental material to this paper.

[5] A non-exhaustive list of macro-level studies, each with a different set of countries and time horizon analyzed, includes Boone (1996), Burnside and Dollar (2000), Rajan and Subramanian (2008), Angeles and Neanidis (2009), and Galiani et al. (2017).

[6] Using multiple imputation techniques to overcome the endogenous sample selection bias in the aid effectiveness literature, Breitwieser and Wick (2016) found that aid effectiveness is markedly reduced in important areas such as health, education, and infrastructure after accounting for the pattern of missing data in the empirical analysis.

where $\triangle \ln(0.01 + Light_{g,c,t})$ is the annual logarithmic growth rate of light intensity in grid cell g of country c at year t.[7] The main explanatory variable, $Aid_{g,c,t}$, refers to various definitions of foreign aid assistance implemented at the grid cell level (e.g., the log of the number of active foreign aid projects and the amount of project and location-specific annual disbursement flows). We use a distributed lag specification in the variable $Aid_{g,c,t}$ to account for the possibility that the impact of foreign aid assistance on development outcomes may require some time to work (Clemens et al., 2012).

Similar to cross-country economic growth regressions, we further control for the conditional convergence effect including the first lag of the log of night-time light intensity $\ln(0.01 + Light_{g,c,t-1})$ in the grid-cell-level regression specification.

The vector $\boldsymbol{X}_{g,c,t}$ refers to a full set of geospatial demographic (e.g., log of population), climate (e.g., mean annual precipitation and temperature), conflict, and drought indicators to control for the issue that the spatial distribution of World Bank foreign aid projects may be endogenous to local grid-cell-specific conditions. The vector $\boldsymbol{RD}_{g,c,t}$ contains a full set of recodification-related binary indicators to control for erratic developments in night-time light movements and incorrect assignments of disaggregated population-level data to grid cells. We include indicator variables for grid cells with no night-time light activity, as well as population data, since we used a slight transformation of the original data (e.g., adding the small number of 0.01) to permit the inclusion of these observations in the overall analysis. Moreover, we include an indicator variable for grid cells with no satellite-measured night-time light activity but positive population size to control for potential incorrect assignment of population-level data, which may be due, for instance, to the inadequate spatial resolution of the Gridded Population of the World data set (CIESIN-FAO-CIAT, 2007).[8]

The high-resolution grid cell econometric approach thus accounts for a number of identification problems that cannot be addressed in cross-country empirical studies due to limited degrees of freedom. Specifically, we include a full set of country-year fixed effects $\lambda_{c,t}$ in the regression equation to effectively control for arbitrary unobserved heterogeneity that is both country- and time-specific and that significantly interferes with the identification of the true effect of aid on development outcomes. These country-specific factors further control for possible existing unobserved country-specific time trends in the grid cell empirical analysis.

It is conceivable that the spatial distribution of World Bank foreign aid projects across grid cells is correlated with local biogeographic conditions (e.g., land use and topographic factors), infrastructure quality (e.g., distance to the capital, next largest settlement, border, coast, and river), the occurrence of mineral deposits (e.g., diamonds and gemstones), and the distribution of ethno-linguistic groups. Since these factors vary minimally over time, they are effectively controlled for through the inclusion of the vector $\boldsymbol{Z}_g$ in the regression equation.

[7]Following Michalopoulos and Papaioannou (2013), we add to this variable a small number of 0.01 to include even those grid cells in the empirical model that show no night-time light activity. Furthermore, the variable is not in per-capita units, in contrast the usual growth regressions, which use the growth rate of per-capita income as the dependent variable.

[8]The Gridded Population of the World (GPW) dataset provides population-level data with a spatial resolution of 2.5 arc-minutes. However, population count estimates within any grid cell are derived from individual census data from relatively large subnational administrative regions. This issue introduces a considerable source of uncertainty when allocating population-level data to high-resolution grid cells (Deichmann et al., 2001). The reason is that the GPW dataset distributes population census data to 2.5 arc-minutes grid cells using an areal weighting scheme. Thus, the derived population count estimates do not necessarily correspond to the actual number of persons within a grid cell but reflect the portion of the population within 2.5 arc-minutes grid cells if the population census data were distributed across grid cells using the appropriate areal weighting scheme. The accuracy of this estimate is therefore subject to the spatial resolution of subnational administrative units that vary considerably across countries.

In the first step of the empirical analysis, we assess the model's overall predictive power and the possible endogeneity in the allocation of World Bank foreign aid projects to the inclusion of the aforementioned grid-cell-specific geospatial indicators $\boldsymbol{Z}_g$. However, there might be additional unobserved grid-cell-specific and time-constant factors not covered by these geospatial grid cell controls. Therefore, in a second step, we replace the vector $\boldsymbol{Z}_g$ with the variable η_g, which refers to grid cell fixed effects to implicitly control for all local conditions that differ across grid cells but remain constant over time. It is worth mentioning that even though the distribution of World Bank foreign aid projects might be endogenous to unobserved grid-cell-specific unobserved effects (e.g., proximity to roads and infrastructure facilities), the inclusion of η_g in the regression model further accounts for possible omitted variables that might themselves be important determinants of observed variations in satellite-measured night-time light activity across grid cells. Finally, the term υ refers to a grid-cell-specific idiosyncratic error term.

In the remaining part of this section, we discuss some econometric challenges in the estimation of Equation (1) and possible strategies to resolve these technical problems. A possible econometric challenge arises because estimating Equation (1) is equivalent to estimating a dynamic panel data model for the *level* of night-time lights. This can be seen from a simple transformation of Equation (1) by adding $\ln(0.01 + Light_{g,c,t-1})$ to both sides:

$$\begin{aligned}
\ln(0.01 + Light_{g,c,t}) &= \beta_0 + \widetilde{\beta}_1 \ln(0.01 + Light_{g,c,t-1}) + \sum_{k=0}^{2} \phi_k Aid_{g,c,t-k} \\
&+ \boldsymbol{\beta}_2' \boldsymbol{X}_{g,c,t} + \boldsymbol{\beta}_3' \boldsymbol{RD}_{g,c,t} + \boldsymbol{\beta}_4' \boldsymbol{Z}_g + \lambda_{c,t} + \eta_g + \upsilon_{g,c,t}, \qquad (2)
\end{aligned}$$

where $\widetilde{\beta}_1 = (\beta_1 + 1)$. However, the introduction of the lagged dependent variable in the regression model makes standard methods of estimation inconsistent in the presence of individual unobserved heterogeneity. It is a well-established finding that estimating Equation (2) using the FE estimator would result in dynamic panel bias in stationary observational data (i.e., $|\widetilde{\beta}_1| < 1$). Typically, night-time light intensity in the previous period is positively correlated with current night-time light levels, suggesting that $\widetilde{\beta}_1 > 0$. Given this fact, the direction of the dynamic panel bias of $\widetilde{\beta}_1$, and thus β_1 in Equation (1) would be negative (Nickell, 1981).

In contrast, pooled OLS regressions would bias the coefficient estimate of $\widetilde{\beta}_1$ upwards due to unobserved individual-level heterogeneity. The fact that the two estimators are biased in opposite directions is theoretically useful for econometric inferences. This bounding property suggests that any consistent estimator of $\widetilde{\beta}_1$, and thus β_1 in Equation (1), should provide coefficient estimates of the true causal effect somewhere between the fixed effects and pooled OLS estimates (Bond, 2002).

Difference GMM and system GMM estimation approaches have been used frequently to address the dynamic panel bias associated with the lagged dependent variable in panel data applications (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Unfortunately, the direction of bias in additional right-hand side regressors is unclear a priori. However, Hauk and Wacziarg (2009) show with Monte Carlo simulations that difference GMM and system GMM approaches lead to biased coefficient estimates in the remaining explanatory variables resulting from heterogeneity bias, measurement error, and endogeneity in the data-generating process. In addition, their Monte Carlo simulations indicate that in most cases, the system GMM estimator tends to overstate the true effects of the remaining explanatory variables, biasing the point estimators away from zero. Thus, positive point estimates become larger and negative point estimates become smaller. Given this simulation pattern, it should be clear that the use of system GMM regressions tends to provide a too optimistic picture of the effectiveness of foreign aid on night-time light growth.

Furthermore, Bazzi and Clemens (2013) and Roodman (2009) identified a number of methodological shortcomings in the usual instrumentation strategies in panel GMM estimators (e.g., instrument proliferation and weak GMM-style IVs) in the context of empirical growth regressions in general and aid effectiveness studies in particular. Their findings paint a rather bleak picture of the reliability of previous empirical studies on the relationship between foreign aid and growth relying primarily on IV estimation techniques.[9]

However, the findings of Hauk and Wacziarg (2009) show a way out of this dilemma. Although the fixed effects estimator is biased in the proposed grid cell setting, the distortion has a clear negative direction, as evidenced in the simulation study by Hauk and Wacziarg (2009). Thus, all regression coefficients derived with the fixed effects estimator are negatively biased. This observation is robust to the consideration of heterogeneity bias, measurement error, and endogeneity in the data-generating process. In contrast to the system GMM estimator, the findings in Hauk and Wacziarg (2009) suggest that if the foreign aid variable is subject to any type of endogeneity and/or measurement error, this would underestimate the true causal effect of foreign aid on satellite-measured night-time light growth.

4 Data and Variables

This section provides a detailed discussion of the construction and sources of various geospatial indicators. The global grid cell image has an arbitrary spatial resolution of 0.5 decimal degrees latitude × longitude (approximately 55 km × 55 km at the equator) that covers the entire world from -180 to 180 degrees longitude and 90 to -90 degrees latitude. This constructed grid cell image is then spatially joined to the respective country's land coverage if the grid cell centroid is within a distance of 0.05 decimal degrees of the corresponding country's border. We use the country shape files on administrative divisions from the *Seamless Digital Chart of the World*, *Base Map Version 10.0* database to identify the national boundaries of contemporary nation-states (Global Mapping International, 2010a).

Since the spatial unit of investigation is equally sized grid cells, the current analysis makes use of raster data processed using Geographic Information System (GIS) techniques. In particular, we use a recent database of geo-referenced World Bank foreign aid projects and spatially join this data to the global grid cell image to construct various geospatial foreign aid indicators. In addition to the construction of the main explanatory variable, we process geospatial data sets on satellite-measured night-time light intensity, socioeconomic, demographic and local conflict conditions, terrain characteristics, patterns of land use, climatic conditions, and the geographic distribution of ethno-linguistic groups across grid cells. The final data set covers 58,676 cross-sectional grid cells during the period 1995 to 2013 resulting in a total number of 1,114,844 grid-year observations. Given the distributed lag specification of the geospatial foreign aid indicator variable, the effective sample size employed in the empirical analysis covers the period 1997 to 2013 comprising 997,492 grid-year observations.[10]

[9]In the supplemental material to this paper, we provide coefficient estimates from difference and system GMM regressions. Even though the results based on the system GMM estimator indicate a statistically significant association between foreign aid and grid cell night-time light growth, the corresponding tests assessing the exclusion condition, relevance, and weakness of IV cast serious doubts on the reliability of the instrumentation strategy based on the use of dynamic panel data GMM estimators.

[10]Table 7 provides detailed summary statistics of the main regression variables. See also Section B in the supplemental appendix to this paper for additional information on data construction and sources of the various geospatial indicators.

4.1 Night-Time Light as a Proxy for Economic Development

The key dependent variable reflecting the level of economic activity across grid cells was derived from satellite-measured night-time light images during the period 1992 to 2013. Specifically, the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Centre (NGDC) (NOAA-NGDC, 2015) provides a digital archive of mean satellite-measured night-time light data covering the period from 1992 to 2013. These data were collected by the US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) with the primary aim of collecting moonlight cloud coverage for weather forecasts. However, an unexpected by-product is the detection of man-made night-time light at a spatial resolution level of 30 arc seconds (≈ 0.925 kilometers at the equator) with a global coverage of between -180 to 180 degrees longitude and -65 to 75 degrees latitude. Six satellites (indexed by F-series) collected 22 years of data with a total of 12 co-temporal observations. The raw data are stored as a digital number (DN) value ranging from 0 to 63, which is proportional to radiance (Elvidge et al., 1997). The use of satellite-measured night-time light as an alternative measure of economic activity has been documented in a number of empirical studies, especially in the field of remote sensing analysis.[11] Recently, Henderson et al. (2012) have shown the merits of satellite-measured night-time light data as a complement to official income measures in countries lacking high-quality national account agencies.[12] More importantly, the use of satellite-measured night-time light data is particularly relevant for research on a subnational rather than national level.[13]

Unfortunately, data from different satellite years are not radiometrically calibrated. This means that the DN values are not comparable across satellite-year observations in term of brightness. However, research undertaken by Elvidge et al. (2009, 2014) and Hsu et al. (2015) led to the development of a method for inter-annual calibration of the various satellite-year observations in order to facilitate comparisons of brightness values across different satellite F-series and years. This issue is pivotal when using this data in empirical applications with a panel data context. The reason is that DMSP-OLS satellites have no in-flight calibration, with the consequence that the optical sensors differ with respect to radiometric performance and saturation radiances.[14] In addition, the optical sensors are prone to technical degradation over time, making the comparison of DN values difficult even within the same satellite F-series. Hence, we employ the inter-annual calibration approach outlined in Elvidge et al. (2009, 2014) to convert DN data values from the various satellite-year F-series into a common range using satellite series F12 from 1999 as the reference year and Los Angeles as the reference area.[15]

After successful completion of the inter-annual calibration approach of the various satellite-year observations, we construct

[11] Croft (1978) were among the first to use this kind of data to detect major US cities. Since then, night-time light satellite images have been used to spatially disaggregate national accounts GDP values to the subnational level (Elvidge et al., 1997; Doll et al., 2000; Sutton and Costanza, 2002; Sutton et al., 2007; Ghosh et al., 2009, 2010).

[12] We refrain from using subnational income data derived from, for example, household surveys. It has been reported that individual income measures in many countries in the developing world are prone to a severe downward bias, e.g., due to subsistence strategies (Anand and Harris, 1994). Another argument against the use of household surveys is the lack of comparability of individual income levels across countries due to differences in data collection and methodology (Ebener et al., 2005). In addition, significant differences in data availability across countries and years prevent the construction of a large panel data set that can be employed in a fixed effect regression framework.

[13] See, e.g., Michalopoulos and Papaioannou (2013) for an application of satellite-measured night-time light data to ethnic groups in African countries.

[14] See Elvidge et al. (2014) for a thorough technical discussion of this issue.

[15] The interested reader is referred to Section B of the supplemental appendix to this paper for additional details on data construction and sources of inter-annual calibrated satellite night-time light DN values.

a sum of lights measure that corresponds to the sum of inter-annual calibrated DN pixel-level values within 0.5 decimal degree latitude × longitude grid cells.

Figure 10 nicely illustrates that the inter-annual calibrated sum of lights measure is positively and significantly correlated with real GDP levels in a panel of 161 countries analyzed during the period 1995 to 2013.[16] The estimated elasticity of the sum of lights measure with respect to real GDP (net of country and year fixed effects)[17] is approximately 0.30, suggesting that a 1% increase in the level of night-time light intensity corresponds approximately to a 0.30% increase in the level of real GDP, similar to the estimated elasticity reported by Henderson et al. (2012). Provided that this estimated elasticity applies equally to the subnational (i.e., grid-cell level), we are able to quantify the effectiveness of foreign aid projects across grid cells in terms of a rise in real GDP rather than in physically measured night-time light values.

4.2 Geo-Referenced World Bank Foreign Aid Project Data

In the year 2010, AidData and the World Bank started a joint collaboration of geo-referencing foreign aid assistance projects approved by the International Bank for Reconstruction and Development (IBRD) and the International Development Association (IDA) agency. The current version of the AidData database covers a total of 5,684 geocoded projects qualitatively approved for the years 1995 to 2014 (AidData, 2016). Each project usually contains information on several locations, resulting in 61,243 geocoded project-location observations. The rules of assigning latitude and longitude coordinates to project locations is detailed in the AidData geocoding methodology codebook (Strandow et al., 2011). The project locations were assigned different levels of precision codes that enable potential users to select a subset of the data based on the study design and research question (Findley et al., 2011). The geocoding system includes four precision codes that refer to different levels of spatial geocoding certainty. These codes indicate whether the specific foreign aid project corresponds to an exact location (precision code 1), or is located "near", in the "area" of, or within a 25 km radius of an exact location (precision code 2). In addition to these exact location codes, the system further includes precision codes that are analogous to a second-order administrative division (ADM2) with precision code 3 and first-order administrative division (ADM1) with precision code 4. The ADM2 regions correspond to spatial units that are analogous to districts, municipalities, or communes, whereas the ADM1 division is equivalent to geographical regions such as provinces and states. In cases where the geographic coordinates of project locations correspond to estimated latitude and longitude values or cover several administrative regions (e.g., national parks or lakes), a precision code of 5 was assigned. Nation-wide foreign aid projects are geocoded at the country level, indicating that no exact geocoding information is available (precision code 6). If geocoded information is unavailable at the project level, the methodology assumes that foreign aid flows directly to the country (precision code 7). Finally, if foreign aid financial flows go to various governmental units such as the seat of an administrative district or the country's capital, then this is geocoded with precision code 8.

[16] We use the variable *rgdpna* from the Penn World Table database, Version 9.0, indicating real GDP at constant 2005 national prices (Feenstra et al., 2015). The corresponding data are available online at http://www.rug.nl/ggdc/productivity/pwt/.

[17] The inclusion of country fixed effects accounts for cross-country cultural differences in the use of night-time lights, differences in the composition of output, public versus private lighting, national conditions of electricity generation, and geographical differences that are constant over time but differ across countries. The inclusion of year fixed effects filter out all remaining differences in lights sensitivity across satellites that have not been removed by the method of inter-annual calibration, as well as unexpected shocks in worldwide economic conditions, technological progress, and energy costs (Henderson et al., 2012).

Table 6 shows the number of geocoded foreign aid locations and the corresponding precision codes across continents during the period 1995 to 2014. Excluding project locations with unknown recipient country information, there are a total number of 59,969 project locations across all continents during the reported time span. The main beneficiary of World Bank foreign aid development assistance is Asia (27,605 project locations), followed by Africa (15,550), and Latin America and the Caribbean (11,525), Europe (4,777) and Oceania (512). As discussed above, the foreign aid project locations vary with respect to geocoded exactness, as indicated by distinct geo-referenced precision codes. Of the 59,969 geo-referenced project locations, about 43.25% (25,938) have an exact geographic assignment by latitude and longitude. About 3.89% (2,333) of the project locations are classified as being "near" some specific area or location. In addition, 25.69% (15,408) of the geocoded foreign aid projects are targeted at the ADM2 level, whereas 19.48% (11,684) of the development programs go directly to the ADM1 regional level. The remaining 7.68% of the project-location observations either go directly to the national level (1,602), are dedicated to the seat of governmental units (1,939), or have estimated geographic coordinates (1,065).

In the empirical analysis, we use project-location observations with precision codes three and smaller to investigate the impact of foreign aid assistance on grid cell satellite-measured night-time light growth. Figure 1 provides information on the geographic distribution of World Bank foreign aid project locations across continents with precision codes ≤ 3. We spatially join World Bank foreign aid project-locations to 0.5 decimal degree grid cells using GIS techniques. Figure 2 illustrates the spatial matching procedure of World Bank project-locations to grid cells for the southern part of Nigeria. Each circle corresponds to a particular World Bank project-location observation. The figure suggests that pixel-level light density values and the distribution of World Bank project locations cluster spatially. However, the causal relationship between the two outcomes may be subject to local conditions at the grid cell level (e.g., infrastructure quality, population size, and land characteristics) that we discuss in more detail in the empirical section of this paper.

We use information on the AidData project's start and end date to construct a panel data set of active project-year observations. Figure 3 shows the evolution of active project-year observations across regions during the year 1995 to 2014. The figure indicates a large increase in active project-years in Asia, which flattens out during the years 2008 to 2009. Moreover, the number of active foreign aid projects in Asia has fallen substantially since the year 2010. Africa and Latin America and the Caribbean experienced a gradual increase in active foreign aid projects up to the year 2010. However, while foreign aid assistance to Africa continued to increase after 2010, the opposite occurred in Latin America and the Caribbean. Foreign aid activities in Europe and Oceania are limited in their scope and dynamics, indicating that World Bank foreign aid activities mainly target developing countries in Asia, Africa, and Latin America and the Caribbean.

Based on the constructed panel data set of active World Bank foreign aid projects, we calculate various geospatial foreign aid indicators. First of all, we calculate the number of World Bank foreign aid project locations across grid cells and time according to the following expression:

$$NPL_{g,c,t} = \sum_{p \in M_g} WBPL_{p,g,c,t}, \tag{3}$$

where $WBPL_{p,g,c,t}$ refers to the number of World Bank project locations of project p in grid cell g of country c at time t and M_g is the set of unique World Bank projects implemented in grid cell g. As a starting point, we construct a binary variable that indicates the presence of World Bank foreign aid projects in particular grid cells:

$$\mathbf{I}(NPL_{g,c,t} > 0) = \begin{cases} 1 & \text{if} \quad NPL_{g,c,t} > 0, \\ 0 & \text{if} \quad NPL_{g,c,t} = 0. \end{cases} \tag{4}$$

This variable is designed to capture differences in development outcomes across grid cells subject to the simple presence of World Bank foreign aid projects. In addition, we further analyze the influence of foreign aid assistance on grid cell satellite-measured night-time growth using a logarithmic transformation of the number of World Bank foreign aid projects across grid cells and time:

$$\ln\left(0.01 + NPL_{g,c,t}\right). \tag{5}$$

Again, we add a small number of 0.01 to this expression to retain grid cell observations that were not supported by World Bank development programs in the empirical analysis. We use a logarithmic transformation to account for the possibility that the impact of World Bank foreign aid projects on night-time light growth might exhibit decreasing returns to scale. Beside the construction of qualitative variables indicating the presence and number of active World Bank foreign aid projects, we further focus on the amount of annual financial flows allocated to grid cells. The World Bank Project and Operations web page provides detailed information on all the World Bank's foreign aid projects since the year 1947 (World Bank, 2016). Information on the unique project ID variable from the AidData (2016) database can be used to retrieve basic information on the project such as title, recipient country, main sector code, and commitment amount. More importantly, users have access to detailed financial activity data for each project that can be downloaded in the form of Excel files. They include information on the donor, amount, and the actual date of the transaction type (e.g., commitment and disbursement flows). We downloaded the financial flow tables from the World Bank (2016) Project and Operations web page that were approved by AidData (2016) during the period 1995 to 2014. To capture the actual transfer of financial resources to projects, we focus on disbursement records instead of commitment amounts, as it may take time until financial commitments are disbursed to the recipients. For each year, we pool multiple individual funds to calculate annual foreign aid disbursement flows across aid projects. Afterwards, we transform project-specific annual disbursement flows to constant 2011 USD using exchange rates (market and estimated values) from National Accounts Statistics prepared by the Statistical Division of the United Nations (2016).

Unfortunately, information on financial activity flows is provided at the project level but *not* at the disaggregated project location level. Several methods of spatially disaggregating project-specific annual disbursement flows to locations have been discussed in the aid effectiveness literature. Usually, the disaggregation is performed based on population size or the area of the administrative unit. However, in this paper we use the number of active project locations to spatially disaggregate annual disbursement flows to grid cells. Nevertheless, we do control for area and population size across grid cells throughout the empirical analysis. We allocate annual project-specific disbursement flows to grid cells according to the following rule:

$$PWAD_{g,c,t} = \sum_{p \in M_g} \left(\frac{WBPL_{p,g,c,t}}{NPL_{p,c,t}} \right) \times PAD_{p,t}, \tag{6}$$

where $NPL_{p,c,t}$ is the total number of project locations of World Bank project p across grid cells in country c at time t and $PAD_{p,t}$ refers to the project-specific annual disbursement flow of project p at time t expressed in constant 2011 USD. Thus, the term in brackets on the right-hand side of Equation (6) is the fraction of project locations of World Bank project p that have been allocated to grid cell g in a particular country c and time t. Similar to the expression regarding the number of implemented World Bank foreign aid project locations in a specific grid cell, we employ a logarithmic transformation of project-specific annual disbursement flows:

$$\ln\left(0.01 + PWAD_{g,c,t}\right), \tag{7}$$

where we, again, add a small number to this expression to account for zero aid flows to grid cells.

4.3 Additional Geo-Spatial Indicators: Socioeconomic, Demographic, Climatic, and Biogeographic Factors

Disaggregated Population Level Data. We use the Gridded Population of the World, Version 3 (GPWv3) database from CIESIN-FAO-CIAT (2007) to construct the respective population size measures across grid cells. The raw dataset is available at a spatial resolution of 2.5 arc minutes (approximately 5 kilometers at the equator) for the years 1990, 1995, 2000, 2005, 2010, and 2015. We employ the method of linear interpolation between each five year interval to construct a yearly dataset of gridded population count data during the period 1990 to 2015. We then calculate the total number of persons by summing the population count values within 0.5 decimal degree grid cells.

Disaggregated Climate Data. Annual observations of temperature (in degrees Celsius) and precipitation (in millimeters) from monthly climate data across 0.5 decimal degree grid cells are obtained from the Climate Research Unit Time Series dataset (CRU TS Version 3.23) by Harris et al. (2014).

In addition, we use the Standardized Precipitation Evapotranspiration Index (SPEI) based on the 12-month time scale (Vicente-Serrano et al., 2010; Beguería et al., 2014). The SPEI values have a mean of 0 and a standard deviation of 1, where positive values indicate wetter weather than the local average climate trends, and vice versa. It is worth mentioning that long-term drought conditions might aggravate structural problems in less developed regions of the world, causing severe economic damage, famine, epidemics, and land degradation (Beguería et al., 2010). Thus, the inclusion of the SPEI variable effectively controls for the fact that the World Bank group might allocate foreign aid projects in response to local climatic anomalies.

Geo-Referenced Conflict Event Dataset. The UCDP Georeferenced Event Dataset (UCDP GED) presented in Sundberg and Melander (2013) is used to account for temporarily and spatially disaggregated organized violence across grid cells. The UCDP GED database provides information on three types of organized violence – state-based conflict, non-state conflict, and one-sided violence – with different georeferenced precision codes. To measure the local aspects of conflicts and their impacts on grid-cell-specific socioeconomic outcomes (e.g., economic loss, forced migration, and famines), we construct a geospatial conflict indicator that refers to the number of organized conflict events across the three different types of organized violence whose exact geographic location is known with certainty at least at the second-order administrative divisions (ADM2) level.

Remaining Geo-Spatial Indicators. We further construct a set of biogeographic variables to investigate the effectiveness of World Bank foreign aid development assistance in improving local physical, biogeographic, and resource-based conditions.

To capture the quality of infrastructure across grid cells, we first construct a full set of distance-based geospatial indicators such as the minimum distance (in kilometers) from the grid cell centroid to the country's capital city, nearest settlement (e.g., with an estimated population size of $\geq$ 100,000 in the year 2000), country border, coast, river, power transmission, road, and railroad line. In addition to these distance-based controls, we further construct the total railroad, road, and power transmission lines (in kilometers) within each 0.5 decimal degree grid cell. Moreover, we identify the urban area of each grid cell based on the Global Rural-Urban Mapping Project, Version 1 (GRUMPv1) database (CIESIN-IFPRI-CIAT, 2011).

The second set of geospatial indicators is intended to capture grid-cell-specific local topographic and land use factors such as the mean elevation value (in meters above the sea level) and land suitability for agriculture. The corresponding data are available from the Atlas of the Biosphere database from the Center of Sustainability and the Global Environment (SAGE) and Ramankutty et al. (2002). Moreover, we calculate the mean fraction of agricultural land coverage around the year 2000 within 0.5 decimal degree grid cells using the high-resolution raster dataset in Ramankutty et al. (2008). This variable provides information on the relative importance of agricultural production across grid cells. To assess the effectiveness of aid as to prevailing climate conditions, we construct the share of the grid cell area in the tropics according to the Köppen-Geiger climate classification (Peel et al., 2007).

In addition, we identify the number of diamond and other gemstone deposits within each 0.5 decimal degree grid cell (Gilmore et al., 2005; Lujala, 2009). The relevant literature on the "curse" of mineral resources would suggest that grid cells rich in diamonds and gemstones may perform differently than others in terms of night-time light growth and aid effectiveness (Sachs and Warner, 2001).

Finally, we calculate a measure of linguistic diversity based on the relative share of area inhabited by the various ethno-linguistic groups within 0.5 decimal degree grid cells. Geo-referenced data on the distribution of ethno-linguistic groups across the world are provided by the Global Mapping International (2010b) database.

5 Main Empirical Results

This section provides a detailed discussion of the main findings on aid effectiveness at the disaggregated grid cell level. We show that the relationship between the various World Bank geospatial foreign aid indicators and grid cell night-time light growth is significantly confounded by the presence of unobserved time-variant, country-specific, and grid-cell-level heterogeneity. In the remaining part of this section, we provide empirical evidence that once the regression model accounts for unobserved grid-cell-level heterogeneity, there is no reason to suspect that the main findings suffer from reverse causality in the relationship between foreign aid and grid cell night-time light growth. Additional estimates confirm the validity of our proposed grid cell approach to the issue of omitted variables bias arising from decision processes of the World Bank that have to do with expected grid cell night-time light growth.

5.1 Baseline Estimates

We start the empirical analysis with an investigation of country and grid-cell-level heterogeneity and unobserved shocks that might interfere with the identification of the true effect of World Bank foreign aid projects on night-time light growth. Table 1 presents the first results on the relationship between the growth rate of night-time light intensity and the various geospatial World Bank foreign aid indicators at the disaggregated 0.5 decimal degree grid cell level. In the empirical analysis, we use three different indicators of World Bank foreign aid projects. We first employ a simple indicator variable that takes a value of 1 if a World Bank foreign aid project took place in the particular grid cell in a given year, and zero otherwise (columns 1 to 4). Next, we use a logarithmic specification in the number of implemented World Bank foreign aid projects (column 5), and finally we use project-specific annual disbursement flows (column 6) as our preferred geospatial foreign aid indicator. For each foreign aid indicator, we provide a discussion of its short-run and corresponding long-run effects on grid-cell-level night-time light growth. The latter point is important to show whether the effects of foreign aid persist over time.

In column (1), we present coefficient estimates using a basic set of grid cell demographic, climatic, conflict, and recodification controls, temporarily leaving aside any other time-invariant and/or time-variant unobserved country and grid-cell-level heterogeneity. In this parsimonious regression model, the coefficient associated with the contemporaneous foreign aid indicator is negative and highly statistically significant at the 1% significance level. According to this result, the estimates suggest that grid cells in which World Bank foreign aid projects took place would, ceteris paribus, experience a 16.36 percentage point lower night-time light growth rate in the same year.[18] However, this model specification is heavily prone to endogeneity problems caused by unobserved country-specific and grid-cell-level heterogeneity. Therefore, in the next columns, we examine the change in the magnitude of the regression coefficients associated with the various geo-spatial foreign aid indicators to the inclusion of additional country and grid-cell-level controls to mitigate endogeneity concerns in the relationship between foreign aid and grid cell night-time light growth. Concerning the other control variables, all coefficients, with exception of the one for the SPEI Drought Index, show the expected signs and significance levels. The coefficient of the SPEI Drought Index has a positive sign, suggesting implausibly that the more droughts occur, the higher the growth of night-time light intensity is.

In column (2), we examine the sensitivity of the previous findings to the inclusion of country-year FE. In this FE specification, we are able to control for time-variant political-strategic, economic, ideological, and other factors underlying the allocation of (perhaps unobserved) bilateral aid inflows from donor to recipient countries. Furthermore, the country-year FE specification effectively accounts for the economic and institutional settings in recipient countries that might affect both the allocation and effectiveness of World Bank development programs throughout the developing world. Through the inclusion of the country-year FE, the results change substantially. The contemporaneous foreign aid indicator becomes positive and is highly significant. This suggests that the initially estimated negative coefficient associated with the contemporaneous geospatial foreign aid indicator in column (1) is heavily confounded by unobserved country and/or time-specific heterogeneity. Furthermore, the coefficient of the two years lagged foreign aid indicator increases in size and becomes highly significant. With respect to the control variables, the findings concerning the mean temperature and conflicts change. The coefficient of the mean temperature changes its sign, becoming positive, and remains highly statistically significant. Furthermore, the coefficient of conflicts becomes insignificant once country-year FE are accounted for, suggesting that the effects of civil conflicts are not limited to specific regions of a country but instead affect the country as a whole.

[18] According to the estimated light elasticity with respect to real GDP reported in section 4, this finding implies a reduction in real GDP of approximately $(16.36 \times 0.30) \approx 4.91$ percent.

To assess the sensitivity of the previous results to unobserved heterogeneity at the grid cell level, the estimates shown in column (3) include, first, a full set of grid-cell-specific geospatial indicators. These refer to a full set of topographic (e.g., the mean elevation value, standard deviation, and range of elevation), land use (e.g., a geospatial indicator of land suitability of agriculture and the fraction of the grid cell area with cropland coverage, both ranging from 0 = low to 1 = high), microgeographic (e.g., the log of the minimum distance value (in kilometers) from the grid cell centroid to the country's capital city, next-largest city, border, coast, sea-navigable river, power transmission, railroad, and road lines, and the log of the length (in kilometers) of power transmission lines, railroads, and roads within grid cells), mineral resources (e.g., the number of diamond mines and gemstone deposits), land area (e.g., the log of the grid cell land area in square kilometers), the log absolute value of the grid cell centroid latitude in decimal degrees, the share of urban area within a grid cell, the share of grid cell area in the tropics according to the Köppen-Geiger climate zone classification, and linguistic diversity factors (e.g., calculated using the relative share of land area inhabited by the various ethno-linguistic groups in a particular grid cell). After including this full set of grid cell controls, the magnitude of the coefficients associated with the contemporaneous and the two-year lagged geospatial foreign aid indicators are cut in half, but remain highly statistically significant at conventional significance levels. This finding suggests that the point estimates associated with the geospatial foreign aid indicator variables reported in column (2) are additionally confounded by the existence of grid-cell-specific factors. The results therefore confirm the arguments that the spatial allocation of World Bank foreign aid projects might be endogenous to prevailing grid-cell-specific factors (e.g., proximity to infrastructure facilities such as power transmission lines, railroads, and roads). The only significant change in the control variables is the lost significance of the coefficient of mean precipitation.

The partial R^2 in column (3) – i.e., the model's R^2 after partialling out the country-year fixed effects from the regression equation – is about 0.797, suggesting that the regression model misses other important grid-cell-specific control variables. Therefore, in column (4), we include a full set of grid cell FE in the regression equation. This FE specification implicitly controls for arbitrary time-invariant unobserved heterogeneity at the grid cell level that has not been accounted for through the inclusion of the various time-invariant grid-cell-specific geospatial controls in column (3). Consequently, the inclusion of grid-cell-specific FE in model specification (4) renders the inclusion of time-constant grid cell controls redundant in the regression equation. In this model specification, we employ the time variation within each grid cell to provide coefficient estimates of time-variant controls. The estimated coefficients associated with the contemporaneous and the two-year lagged geospatial foreign aid indicators again diminish considerably in size, but remain statistically significant.

Using the regression coefficients from this fully specified model, the estimates suggest that grid cells with World Bank foreign aid projects would have, ceteris paribus, on average a 1.49 percentage point higher growth rate in night-time light intensity in the same year. The dynamic model specification further suggests that this short-run effect persists until the second year following the implementation of the World Bank foreign aid projects. Specifically, grid cells in which foreign aid projects were implemented would, ceteris paribus, experience an approximately 3.18 percentage point increase in night-time light growth in the second year following project implementation. This finding is consistent with the notion that the implementation of foreign aid projects in particular grid cells takes time before it can be measured physically (economically) from outer space.

The remaining coefficient estimates in the fully specified model shown in column (4) are all of the expected signs. Specifically, the log of the *level* of night-time light in the previous year is negatively related to subsequent *growth* of night-time light intensity, consistent with the conditional income convergence hypothesis usually found in cross-country economic growth studies. Moreover, the baseline estimates further reveal that grid cells with a higher mean precipitation and temperature, ceteris paribus, have a lower growth rate in night-time light intensity. The coefficients of population, SPEI drought index and conflicts are insignificant. The model fit improves considerably, as indicated by the high partial R^2 of about 0.948.

The previously discussed geospatial foreign aid indicator is a very crude measure of the exposure of grid cells to World Bank development programs, as it does not distinguish between grid cells with large and small numbers of foreign aid projects. In the following, we repeat the previous regression analysis with grid cell FE, but this time using the log of the number of World Bank foreign aid projects within grid cells as the main explanatory variable. This logarithmic specification allows for the possibility that the relationship between grid cell night-time light growth and the number of World Bank foreign aid project locations may exhibit decreasing returns to scale. The corresponding results are shown in columns (5).[19] Again, the contemporaneous and the two-year lagged geospatial foreign aid indicators are positive and statistically significant. Regarding the estimated short-run magnitudes, the results suggest that a 1% increase in the number of contemporaneous World Bank foreign aid projects in a grid cell increases the growth of night-time light intensity by about 0.0032 percentage points. For the two-year lagged foreign aid variable, the corresponding increase is 0.0067 percentage points.

As the crude number of World Bank foreign aid project locations might not mirror the actual financial flows to grid cells, the last specification shown in column (6) employs the log of project-specific annual disbursements across grid cells as our preferred geospatial foreign aid indicator. Overall, the estimates once again reveal that the coefficients associated with the contemporaneous and the two-year lagged foreign aid variable are positive and statistically significant at conventional significance levels. The estimated regression coefficients suggest that a 1% increase in project-specific annual disbursement flows is, ceteris paribus, associated with a 0.0008 percentage point increase in grid cell night-time light growth in the same year following the foreign aid flow. The estimated short-run magnitude associated with the second time lag of the project-specific foreign aid financial flow variable is 0.0017 and is statistically significant at the 1% significance level. The long-run effects of foreign aid on grid-cell-level night-time light growth are considerably larger than the corresponding short-run estimates.[20] Regarding the order of economic magnitude, the estimates presented in column (6) suggest that the long-run effect of a one-year and 1% increase in project-specific annual disbursement flows would be, ceteris paribus, associated with a 0.0032 percentage point increase in overall grid cell night-time light growth. This estimate is highly statistically significant at the 1% significance level.[21]

To summarize the findings in this section, the results reveal that unobserved country-specific and grid-cell-level hetero-

[19] The results remain qualitatively unchanged when using only the number of World Bank foreign aid projects as the main explanatory variable, and are available from the authors upon request.

[20] The reason is that foreign aid has a direct (short-run) effect on grid-cell-level night-time light growth and an indirect effect that arises because of the dynamic lag specification. The latter effect occurs because foreign aid today affects the level of night-time light intensity in the next period, which in turn affects night-time light intensity two periods ahead, and so on. The direct or short-run effect of a one-time and one-unit increase of foreign aid on grid-cell-level night-time light is given by the sum of the individual coefficient estimates associated with the distributed lag specification of the various foreign aid indicator variables, i.e, $(\phi_0 + \phi_1 + \phi_2)$. Given the estimated coefficient on lagged night-time light intensity, β_1, the long-run (i.e., direct plus indirect) effect of a one-period and one-unit increase of foreign aid on grid-cell-level night-time light growth is estimated according to the formula $(\phi_0 + \phi_1 + \phi_2)/(-\beta_1)$.

[21] The standard error of the long-run effect of foreign aid is calculated according to the delta method, an approximation that is appropriate in large samples such as the one at hand.

geneity significantly interfere with the identification of the true effect of World Bank development programs on grid cell night-time light growth. This finding corroborates the well-known endogeneity concerns discussed in the empirical aid effectiveness literature. The discussion regarding the appropriateness of the various econometric approaches demonstrated that the reported grid cell FE regressions represent a rather conservative assessment of the effectiveness of World Bank development programs, as the point estimates associated with the various geospatial foreign aid indicators are likely biased toward zero.

5.2 Reverse Causality and/or Simultaneity Tests

In this section, we provide evidence confirming the validity of our proposed grid cell identification strategy from two empirical tests related to the issue of reverse causality and/or simultaneity in the relationship between foreign aid and grid cell night-time light growth. In the first empirical test, we examine the relationship between the allocation of World Bank foreign aid projects and growth of night-time light intensity. If the proposed grid-cell identification strategy is valid, then the regression coefficient associated with growth of night-time light intensity should not be significantly correlated with the various geo-spatial foreign aid indicator variables once the regression equation accounts for a full set of country and grid-cell-level controls. In the second empirical exercise, we examine the possibility of a spurious correlation between grid cell night-time light growth and the various geospatial foreign aid indicators. Specifically, the positive association between both outcomes found in the data could simply reflect the circumstance that the World Bank allocates foreign aid projects to grid cells with more favorable growth prospects. We account for this additional source of confounding factors by presenting coefficient estimates that account for the one-year forecasted value of subsequent grid cell night-time light growth.

The results of the reverse causality test regarding the various geo-spatial foreign aid indicator variables are shown in Table 2. The estimates in columns (1) to (6) show that once the regression equation accounts for unobserved grid-cell-level heterogeneity (columns 2, 4 and 6), we have no indication that the World Bank allocates foreign aid projects according to the economic status of grid cells. None of the model specifications that include grid cell FE show a statistically significant regression coefficient associated with the growth of night-time light intensity.

The second empirical test provide evidence that the main findings are not confounded by the decision process of the World Bank regarding the future growth prospects of grid cells. Table 3 reproduces the baseline estimates of the various geo-spatial foreign aid indicators with the inclusion of forecasted values for night-time light growth. We assume that for each grid cell, the World Bank incorporates all the information available in period t in order to conduct one-step forecasts based on time-series autoregressive processes. Columns (1) to (3) employs forecasted values derived from a first-order autoregressive process, whereas the calculations in columns (4) to (6) are based on a second-order autoregressive process. Reassuringly, none of these model specifications alter the main findings substantially. Overall, the empirical tests confirm the validity of our proposed grid cell identification strategy.

6 Sensitivity Analysis

This section presents a series of additional sensitivity tests in the relationship between foreign aid and grid cell night-time light growth. In a first exercise, we provide empirical evidence on the importance of spatial resolution in the aid effectiveness literature, presenting coefficient estimates at various levels of spatial aggregation (i.e., country, district, 4.0, 3.5, 3.0, 2.5, 2.0, 1.5, and 1.0 decimal degree resolution level). In addition, we rule out the possibility that the main findings might be subject to the choice of a favorable grid by presenting coefficient estimates derived from 100 randomly generated grids. Finally, we confirm the robustness of the main findings to the issue of spatial dependence through the use of various spatial panel data regression models.

6.1 Sensitivity to Spatial Grid Resolution

In this section, we examine the sensitivity of the baseline results to the issue of spatial resolution. We highlighted the merits of the proposed high spatial resolution grid-cell-level analysis through the inclusion of a large battery of grid cell and country-year fixed effects that effectively controls for arbitrary unobserved heterogeneity and possible interference due to the aggregation of positive aid effects with other (perhaps unrelated) negative effects across spatial units. We expect that decreasing the level of spatial resolution would aggravate these issues in the relationship between night-time light growth and foreign aid. To be more precise, we estimate the baseline regression model for various spatial resolution levels (i.e., country-level, district-level, 4.0, 3.5, 3.0, 2.5, 2.0, 1.5, and 1.0 decimal degree grid cells) based on the same geo-referenced data. In each of the specifications, we control for fixed effects on the corresponding level (e.g., country FE on the country level, and district FE on the district level). Except for the country-level estimates in column (1), we include a full set of country-year fixed effects throughout all grid-cell-level model specifications.[22]

Table 4 shows the baseline results for various spatial resolution levels. The estimates in columns (1) and (2) reveal that foreign aid and grid cell night-time light growth are only weakly correlated in the country- and district-level model specifications.[23] Turning to the various grid cell model specifications, the sign of the point estimates associated with the two-year lagged foreign aid variables turns from negative to positive once the level of spatial resolution increases, as shown in columns (3) to (10).[24] This is in line with the issue discussed in Section 2 that the use of relatively large spatial units can confound the positive effects of foreign aid on development outcomes with negative effects such as the occurrence of famines, conflicts, and natural disasters. Overall, the results of this sensitivity analysis strongly indicate the importance of spatial resolution to identify the true effect of foreign aid on development outcomes.

6.2 Sensitivity to Random Grid Simulation

As the previous section has shown, the size of the grid cells has an impact on the results obtained. In the following, we examine whether the main findings were the consequence of a favorably generated grid. Even though this appears unlikely, we nevertheless investigate this important issue in depth. The baseline grid cells have been constructed using

[22] It is worth mentioning that in contrast to the proposed grid cell approach, the geographic size of countries and districts might be endogenous to political-economic considerations of nation states. For example, historic differences in land endowments might have resulted in the endogenous formation of districts within countries that in turn affected the economic and demographic landscapes of these regions in ways that have persisted until today.

[23] For the country-level estimates, we find that the long-run effect of foreign aid on grid-cell-level night-time light growth is positive and statistically significant at the 5% significance level. However, these estimates are still subject to the aforementioned endogeneity concerns and aggregation issues, undermining their causal interpretation.

[24] In the literature on Geographical Information Systems, this issue is well known and discussed as the Modifiable Areal Unit Problem (MAUP), see Fotheringham and Wong (1991) and Heywood et al. (2011, p. 197) for a technical discussion of this spatial phenomenon.

-180 decimal degrees longitude and -90 decimal degrees latitude as initial grid coordinates. We use these baseline initial coordinates and simulate $r = \{1, 2, ..., 100\}$ additional random grids according to the following random initial coordinates: $(Longitude_r, Latitude_r) = (-180 - \varepsilon_r, -90 - \omega_r)$, where ε_r and ω_r both have a uniform distribution in the interval 0 and 0.5 (i.e., $\varepsilon_r, \omega_r \sim \mathcal{U}(0, 0.5)$). Figure 4 illustrates the construction of the 100 randomly simulated initial grid coordinates. As a result, we obtain 100 grids that are randomly distributed in space.

For each randomly simulated grid, we repeat the construction of the main regression variables and estimate the baseline regression model using these newly constructed grid cells. Figure 5 shows the kernel density estimates (using the Epanechnikov kernel function with a variable bandwidth) for the distribution of the main regression coefficients across the 100 simulated random grids. In each kernel density plot, a dashed vertical line is drawn to indicate the point estimates for the initial baseline grid coordinates. The corresponding summary statistics for each kernel density plot are provided in Table 8. Reassuringly, the baseline point estimates of the main regression variables are well within the expected range of magnitudes for the set of simulated random grids. This observation provides empirical evidence that the main findings are not sensitive to the chosen grid.

In Figures 6 to 8, we show the point estimates associated with the World Bank project-specific annual disbursement flow variable together with the corresponding 90% confidence interval across the 100 simulated random grids. The horizontal axis refers to the random grid identifier attached to the 100 simulated random grids, as shown in Figure 4. The estimates associated with the zero random grid identifier correspond to the baseline initial grid coordinates and are shown for comparison purposes. In each figure, a simple horizontal line is drawn to indicate zero point estimates to facilitate the assessment of statistical significance at the 10% significance level. In most cases, the point estimates of the foreign aid financial flow variable across the various simulated grids are similar in magnitude and statistical significance, indicating once again that the main findings are not the result of a chosen favorable grid.

6.3 Sensitivity to Spatial Spillovers

Another concern in the empirical analysis is that grid cells might show more night-time light growth because the government has moved factors of production to aid-targeted grid cells. If this were the case, then the presence of World Bank foreign aid projects might at least partly be picking up the redistribution of economic factors (e.g., labor and physical capital) across grid cells without increasing economic activity in the country as a whole. So if factors of production were spatially redistributed, it is conceivable that they would move mainly to nearby grid cells. To account for this possibility in the empirical analysis, we control for spatial interaction effects of World Bank foreign aid projects on nearby grid cells. If the presence of World Bank foreign aid projects is mainly due to the redistribution of production factors, then we should observe a negative and statistically significant spatial spillover effect of foreign aid on night-time light growth in nearby grid cells.

In Table 5, we examine the sensitivity of the main findings to the inclusion of various spatially lagged explanatory variables. These spatial variables were constructed based on a spatial contiguity weight matrix $\mathbf{W}$ with typical elements $w_{ij} = 1$ for neighboring grid cells that fall within a radius of approximately 0.7071 decimal degrees around the centroid of a particular grid cell and $w_{ij} = 0$ otherwise. Therefore, each grid cell has a maximum of eight neighboring grid cells – i.e., four that are directly contiguous and an additional four that are diagonally contiguous to the centroid. Figure 9 illustrates how contiguous grid cells are identified, as indicated by the direction of the eight arrows from the centroid of a particular grid cell around the settlement of Kano, a major city in northern Nigeria. The centroid of each grid cell is marked with a square.[25]

We compare the main results relative to the inclusion of several spatial explanatory variables, as reported in column (1). This specification is analogous to estimating a spatial lag model in the main explanatory variables (i.e., SLX model) to remedy potential endogeneity concerns with respect to the omission of spatially lagged independent variables in the regression model.[26]

The estimates reported in column (2) assess potential spillover effects of World Bank foreign aid projects originating from surrounding grid cells when including spatially lagged foreign aid variables in the regression equation. The positive and statistically significant coefficient associated with the second time lag of the spatially lagged foreign aid variable shows no evidence that the potential redistribution of economic factors in one grid cell triggers the economic deterioration of surrounding grid cells. In contrast, the estimates reveal that, if anything, grid cells would benefit (in terms of higher night-time light growth) from the implementation of World Bank foreign aid projects in contiguous grid cells. For completeness, the remaining columns (3) to (5) establish the robustness of the previous findings to the inclusion of additional spatially lagged independent variables.

Regarding the economic magnitudes of the spatially lagged foreign aid variable, the results indicate that a grid cell's night-time light would grow approximately 0.0064 ($= 0.0008 \times 8$) percentage points faster if each of its neighboring cells had experienced a 1% increase in project-specific annual disbursement flows two years prior to that point.

7 Conclusion

In this paper, we examined the effectiveness of geo-referenced World Bank foreign aid projects on economic activity using equally sized grid cells with a spatial resolution of 0.5 decimal degrees latitude $\times$ longitude as the unit of investigation. Our approach overcomes a number of technical problems usually discussed in the cross-country aid effectiveness literature. The high spatial resolution of our proposed grid cell identification strategy enables a detailed empirical assessment of location-specific characteristics that significantly interfere with the identification of the true effect of foreign aid on development outcomes. This novel approach deals efficiently with endogeneity problems in the relationship between foreign aid and development outcomes arising from unobserved heterogeneity, aggregation bias, simultaneity and/or reverse causality issues, measurement error problems, and endogenous sample selection bias.

The baseline estimates suggest a positive and statistically significant relationship between World Bank foreign aid projects and grid cell economic activity as measured by night-time light growth. This finding is robust to the issue of unobserved country-specific and grid-cell-level heterogeneity and to the inclusion of various grid-cell-specific geospatial controls and

[25] The resulting spatial contiguity weight matrix $\mathbf{W} = (w_{ij})_{N \times N}$, where N refers to the number of unique grid cells, has zeros on the diagonal, since by definition a grid cell is not spatially connected to itself. For ease of interpretation, we do not perform a row-standardization of the spatial contiguity weight matrix $\mathbf{W}$.

[26] Unfortunately, we are unable to estimate a fully specified fixed effects dynamic spatial panel data model along the lines described in Elhorst (2014, Chapter 4). The reason is that the large sample of 58,676 grid cells creates considerable computational burden associated with the maximum likelihood estimation of various spatial panel data models. Nevertheless, research is still ongoing to address the technical challenges in the estimation of spatial models and thus facilitate their application in Big Data analysis with large geocoded data sets (Darmofal, 2015, pp. 202–203).

model specifications.

We confirmed the main findings on aid effectiveness in a series of additional sensitivity tests. First, we examined the sensitivity of the main findings to various geographic resolution levels, providing empirical evidence that spatial aggregation significantly interferes with the identification of the true effect of foreign aid on grid cell night-time light growth. Second, we tested whether the main findings are sensitive to the specific grid selected by estimating the baseline specification using 100 simulated random grids. The results rule out the possibility that the main findings were subject to the use of a chosen favorable grid cell structure. Finally, we examined the robustness of the main results to the issue of spatial dependence across neighboring grid cells. Again, the main findings were not significantly affected by this model specification.

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A Regression Tables

Table 1: Foreign Aid and Growth of Satellite-Measured Night-Time Light Intensity Across Grid Cells (Baseline Results)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline Controls	Country-Year Fixed Effects	Grid Cell Controls	Grid Cell Fixed Effects	Grid Cell Fixed Effects	Grid Cell Fixed Effects
Geo-Spatial Foreign Aid Indicator:	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\ln(0.01 + NPL_{g,c,t})$	$\ln(0.01 + PWAD_{g,c,t})$
	Dependent Variable: Growth of Satellite-Measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$					
Panel A: *Geo-Spatial Foreign Aid Controls*						
Geo-Spatial Foreign Aid Indicator in t	-0.1636***	0.0977***	0.0439***	0.0149**	0.0032**	0.0008**
	(0.0359)	(0.0238)	(0.0161)	(0.0062)	(0.0013)	(0.0003)
Geo-Spatial Foreign Aid Indicator in $t-1$	0.0057	0.0232	0.0116	0.0029	0.0007	0.0004
	(0.0368)	(0.0261)	(0.0185)	(0.0071)	(0.0015)	(0.0004)
Geo-Spatial Foreign Aid Indicator in $t-2$	0.0281	0.1209***	0.0570***	0.0318***	0.0067***	0.0017***
	(0.0332)	(0.0228)	(0.0162)	(0.0068)	(0.0014)	(0.0004)
Panel B: *Time-Variant Grid Cell Controls*						
$\ln(0.01 + Light_{g,c,t-1})$	-0.5704***	-0.6466***	-0.6915***	-0.9126***	-0.9126***	-0.9126***
	(0.0061)	(0.0044)	(0.0041)	(0.0033)	(0.0033)	(0.0033)
$\ln(0.01 + Population_{g,c,t})$	0.1835***	0.2782***	0.1124***	-0.0132	-0.0131	-0.0132
	(0.0062)	(0.0104)	(0.0086)	(0.0082)	(0.0082)	(0.0082)
Mean Precipitation	-0.0007***	-0.0006***	-0.0001	-0.0002**	-0.0002*	-0.0002**
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Mean Temperature	-0.0142***	0.0101***	0.0106***	-0.0108*	-0.0108*	-0.0108*
	(0.0010)	(0.0019)	(0.0026)	(0.0061)	(0.0061)	(0.0061)
SPEI Drought Index	0.0356***	0.0274***	0.0222***	-0.0001	-0.0001	-0.0001
	(0.0073)	(0.0063)	(0.0051)	(0.0022)	(0.0022)	(0.0022)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0422***	0.0044	0.0040	-0.0025	-0.0025	-0.0025
	(0.0068)	(0.0061)	(0.0042)	(0.0018)	(0.0018)	(0.0018)
Panel C: *Long-Run Effect of Foreign Aid*						
Estimated Coefficient: $(\phi_0 + \phi_1 + \phi_2)/(-\beta_1)$	-0.2275***	0.3738***	0.1627***	0.0543***	0.0116***	0.0032***
Standard Error (Delta Method)	{0.0702}	{0.0367}	{0.0237}	{0.0087}	{0.0017}	{0.0005}
Number of Grid Cells	58,676	58,676	58,676	58,676	58,676	58,676
Observations	997,492	997,492	997,492	997,492	997,492	997,492
Partial R^2	0.701	0.756	0.797	0.948	0.948	0.948
Land-Use Factors	No	No	Yes	N/A	N/A	N/A
Microgeographic Factors	No	No	Yes	N/A	N/A	N/A
Share Urban Area	No	No	Yes	N/A	N/A	N/A
Linguistic Diversity	No	No	Yes	N/A	N/A	N/A
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Grid Cell Fixed Effects	No	No	No	Yes	Yes	Yes

Notes: The spatial unit of investigation refers to 0.5 decimal degrees latitude × longitude grid cells. The dependent variable is the annual growth rate in satellite-measured night-time light intensity. *ln(0.01 + Light)* is the log of the sum of digital number (DN) pixel-level values. *ln(0.01 + Population)* is the log of population, *Mean Precipitation* is the mean of total monthly precipitation (in millimeters per year), *Mean Temperature* is the mean annual temperature value (in degrees Celsius). *SPEI Drought Index* is a geospatial drought index where positive values correspond to a period of relative wetness relative to the historic (12-month) climate trend and vice versa. *ln(0.01 + Conflicts)* is the log of the number of conflict events. $\mathbf{I}(NPL_{g,c,t} > 0)$ is a geospatial foreign aid indicator that takes a value of 1 if the corresponding grid cell contains World Bank foreign aid projects and zero otherwise. $\ln(0.01 + NPL_{g,c,t})$ is the log of the number of World Bank foreign aid project locations. $\ln(0.01 + PWAD_{g,c,t})$ is the log of project-specific annual disbursement flows of World Bank foreign aid projects. *Land Use Factors* include the mean value of cropland coverage, the standard deviation of cropland, the range of cropland, and a geospatial indicator of land suitability for agriculture. *Microgeographic Factors* refers to a full set of grid cell specific *Topographic Factors* (i.e., the mean elevation value, the standard deviation of elevation, and the range of elevation), *Distance Factors* (i.e., the log of the distance from the grid cell centroid to the country's capital city, nearest settlement, coastlines, sea-navigable rivers, railroads, roads, and power transmission lines. It further includes the log of the total railroad, road, and power transmission lines), *Mineral Resources Factors* (i.e., the number of diamond mines and gemstone deposits), additional *Geospatial Factors* (i.e., the log of the grid cell area (in square km), the log absolute value of the grid cell centroid latitude in decimal degrees, and the share of the grid cell area in the tropics according to the Köppen-Geiger climate zone classification). *Share Urban Area* is the share of urban grid cell area. *Linguistic Diversity* is a measure of ethno-linguistic diversity (based on relative area coverage of the various ethno-linguistic groups). *Recodification Fixed Effects* is a full set of indicator variables that control for erratic developments in satellite-measured night-time light intensity and GIS data-related specificities (e.g., indicator variables for grid cells with zero night-time light pixel-level values and population data, and an indicator variable that identifies grid cells with zero night-time light activity but positive population-level data). *Country-Year Fixed Effects* is a full set of country-year indicator variables that account for time-variant unobserved country-level heterogeneity. *Grid Cell Fixed Effects* is a full set of indicator variables that control for arbitrary time-invariant unobserved heterogeneity within grid cells. Constant term included but not shown. See the main text for additional details on data construction and sources.

The *Partial* R^2 refers to the model's R^2 after partialling out country-year and grid cell FE from the regression model. Standard errors, robust to serial correlation within grid cells and spatial correlation across grid cells within country-years, are reported in parentheses. Standard errors for the long-run effects of foreign aid based on the delta method are reported in curly brackets.

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

Table 2: Foreign Aid and Growth of Satellite-Measured Night-Time Light Intensity: Examining the Issue of Reverse Causality

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline Controls	Grid Cell Fixed Effects	Baseline Controls	Grid Cell Fixed Effects	Baseline Controls	Grid Cell Fixed Effects
Dependent Variable:	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\ln(0.01 + NPL_{g,c,t})$	$\ln(0.01 + NPL_{g,c,t})$	$\ln(0.01 + PWAD_{g,c,t})$	$\ln(0.01 + PWAD_{g,c,t})$
$\triangle \ln(0.01 + Light_{g,c,t})$	-0.0029***	-0.0002	-0.0147***	-0.0006	-0.0437***	0.0001
	(0.0003)	(0.0002)	(0.0015)	(0.0008)	(0.0047)	(0.0027)
$\ln(0.01 + Population_{g,c,t})$	0.0269***	-0.0108***	0.1479***	-0.0603***	0.4406***	-0.1739***
	(0.0019)	(0.0031)	(0.0105)	(0.0168)	(0.0320)	(0.0512)
Mean Precipitation	-0.0001	-0.0001**	-0.0006	-0.0006*	-0.0010	-0.0025***
	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0012)	(0.0009)
Mean Temperature	-0.0016***	-0.0012*	-0.0098***	-0.0063*	-0.0238***	-0.0143
	(0.0005)	(0.0007)	(0.0027)	(0.0036)	(0.0083)	(0.0099)
SPEI Drought Index	-0.0016	-0.0005	-0.0069	-0.0021	-0.0431*	-0.0178
	(0.0014)	(0.0007)	(0.0076)	(0.0039)	(0.0234)	(0.0123)
$\ln(0.01 + Conflicts_{g,c,t})$	0.0111***	0.0012	0.0662***	0.0030	0.1894***	0.0157
	(0.0018)	(0.0011)	(0.0102)	(0.0057)	(0.0321)	(0.0194)
Number of Grid Cells	58,676	58,676	58,676	58,676	58,676	58,676
Observations	997,492	997,492	997,492	997,492	997,492	997,492
Adjusted R^2	0.332	0.682	0.366	0.716	0.325	0.659
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Cell Fixed Effects	No	Yes	No	Yes	No	Yes

Notes: The spatial unit of investigation refers to 0.5 decimal degrees latitude × longitude grid cells. The dependent variable refers to the various geo-spatial foreign aid indicator variables. $\triangle \ln(0.01 + Light_{g,c,t})$ refers to the growth of satellite-measured night-time light intensity. *ln(0.01 + Light)* refers to the log of the sum of digital number (DN) pixel-level values. *ln(0.01 + Population)* refers to the log of population, *Mean Precipitation* refers to the mean of total monthly precipitation (in millimeters per year), *Mean Temperature* refers to the mean annual temperature value (in degrees Celsius). *SPEI Drought Index* refers to a geospatial drought index where positive values correspond to a period of relative wetness relative to the historic (12-month) climate trend and vice versa. *ln(0.01 + Conflicts)* refers to the log of the number of conflict events. *Recodification Fixed Effects* refer to a full set of indicator variables that control for erratic developments in satellite-measured night-time light intensity and GIS data-related specificities (e.g., indicator variables for grid cells with zero night-time light pixel-level values and population data, and an indicator variable that identifies grid cells with zero night-time light activity but positive population-level data). *Country-Year Fixed Effects* refer to a full set of country-year indicator variables that account for time-variant unobserved country-level heterogeneity. *Grid Cell Fixed Effects* refer to a full set of indicator variables that control for arbitrary time-invariant unobserved heterogeneity within grid cells. Constant term included but not shown. See the main text for additional details on data construction and sources.

The *Partial* R^2 refers to the model's R^2 after partialling out country-year and grid cell FE from the regression model. Standard errors, robust to serial correlation within grid cells and spatial correlation across grid cells within country-years, are reported in parentheses.

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

Table 3: Foreign Aid and Growth of Satellite-Measured Night-Time Light Intensity: Controlling for Predicted Night-Time Light Growth

	(1)	(2)	(3)	(4)	(5)	(6)
	Grid Cell Fixed Effects	Grid Cell Fixed Effects	Grid Cell Fixed Effects	Grid Cell Fixed Effects	Grid Cell Fixed Effects	Grid Cell Fixed Effects
Geo-Spatial Foreign Aid Indicator:	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\ln(0.01 + NPL_{g,c,t})$	$\ln(0.01 + PWAD_{g,c,t})$	$\mathbf{I}(NPL_{g,c,t} > 0)$	$\ln(0.01 + NPL_{g,c,t})$	$\ln(0.01 + PWAD_{g,c,t})$
	Dependent Variable: Growth of Satellite-Measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$					
Panel A: *Geo-Spatial Foreign Aid Controls*						
Geo-Spatial Foreign Aid Indicator in t	0.0131**	0.0028**	0.0007**	0.0148***	0.0032***	0.0008***
	(0.0055)	(0.0011)	(0.0003)	(0.0057)	(0.0012)	(0.0003)
Geo-Spatial Foreign Aid Indicator in $t-1$	0.0032	0.0008	0.0003	0.0027	0.0006	0.0003
	(0.0057)	(0.0012)	(0.0003)	(0.0061)	(0.0013)	(0.0003)
Geo-Spatial Foreign Aid Indicator in $t-2$	0.0268***	0.0056***	0.0015***	0.0296***	0.0062***	0.0016***
	(0.0057)	(0.0012)	(0.0003)	(0.0060)	(0.0013)	(0.0004)
Panel B: *Time-Variant Grid Cell Controls*						
$\ln(0.01 + Light_{g,c,t-1})$	-0.8380***	-0.8380***	-0.8380***	-0.8644***	-0.8644***	-0.8644***
	(0.0049)	(0.0049)	(0.0049)	(0.0042)	(0.0042)	(0.0042)
$\ln(0.01 + Population_{g,c,t})$	0.0007	0.0008	0.0006	-0.0050	-0.0049	-0.0051
	(0.0073)	(0.0073)	(0.0073)	(0.0075)	(0.0075)	(0.0075)
Mean Precipitation	-0.0002*	-0.0002*	-0.0002*	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean Temperature	-0.0061	-0.0061	-0.0061	-0.0073	-0.0073	-0.0073
	(0.0052)	(0.0052)	(0.0052)	(0.0054)	(0.0054)	(0.0054)
SPEI Drought Index	-0.0004	-0.0004	-0.0004	-0.0000	-0.0000	-0.0000
	(0.0017)	(0.0017)	(0.0017)	(0.0019)	(0.0019)	(0.0019)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0022	-0.0022	-0.0022	-0.0025	-0.0025	-0.0025
	(0.0017)	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Panel C: *Forecasted Value of Night-Time Light Growth*						
Autoregressive Process	AR(1)	AR(1)	AR(1)	AR(2)	AR(2)	AR(2)
$FCV\ [\triangle \ln(0.01 + Light_{g,c,t+1})\|t]$	-0.2993***	-0.2993***	-0.2993***	-0.2230***	-0.2230***	-0.2230***
	(0.0090)	(0.0090)	(0.0090)	(0.0079)	(0.0079)	(0.0079)
Panel D: *Long-Run Effect of Foreign Aid*						
Estimated Coefficient: $(\phi_0 + \phi_1 + \phi_2)/(-\beta_1)$	0.0515***	0.0109***	0.0030***	0.0545***	0.0116***	0.0031***
Standard Error (Delta Method)	{0.0083}	{0.0017}	{0.0005}	{0.0084}	{0.0017}	{0.0005}
Number of Grid Cells	58,676	58,676	58,676	58,676	58,676	58,676
Observations	997,492	997,492	997,492	997,492	997,492	997,492
Adjusted R^2	0.957	0.957	0.957	0.954	0.954	0.954
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The spatial unit of investigation refers to 0.5 decimal degrees latitude × longitude grid cells. The dependent variable is the annual growth rate in satellite-measured night-time light intensity. $\triangle \ln(0.01+Light_{g,c,t})$ refers to the growth of satellite-measured night-time light intensity. *ln(0.01 + Light)* refers to the log of the sum of digital number (DN) pixel-level values. *ln(0.01 + Population)* refers to the log of population, *Mean Precipitation* refers to the mean of total monthly precipitation (in millimeters per year), *Mean Temperature* refers to the mean annual temperature value (in degrees Celsius). *SPEI Drought Index* refers to a geospatial drought index where positive values correspond to a period of relative wetness relative to the historic (12-month) climate trend and vice versa. *ln(0.01 + Conflicts)* refers to the log of the number of conflict events. $FCV\ [\triangle \ln(0.01 + Light_{g,c,t+1})|t]$ refers to the value of grid cell night-time light growth forecasted one period ahead given the level of information in period t. This variable is constructed based on a first-order and second-order time-series autoregressive process, respectively. *Recodification Fixed Effects* refer to a full set of indicator variables that control for erratic developments in satellite-measured night-time light intensity and GIS data-related specificities (e.g., indicator variables for grid cells with zero night-time light pixel-level values and population data, and an indicator variable that identifies grid cells with zero night-time light activity but positive population-level data). *Country-Year Fixed Effects* refer to a full set of country-year indicator variables that account for time-variant unobserved country-level heterogeneity. *Grid Cell Fixed Effects* refer to a full set of indicator variables that control for arbitrary time-invariant unobserved heterogeneity within grid cells. Constant term included but not shown. See the main text for additional details on data construction and sources. The *Partial* R^2 refers to the model's R^2 after partialling out country-year and grid cell FE from the regression model. Standard errors, robust to serial correlation within grid cells and spatial correlation across grid cells within country-years, are reported in parentheses. Standard errors for the long-run effects of foreign aid based on the delta method are reported in curly brackets.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table 4: Foreign Aid and Growth of Light Intensity (Sensitivity to Spatial Resolution Level)

Spatial Resolution (DD: Decimal Degrees):	(1) Country Estimates	(2) District Estimates	(3) Grid Cells 4.0 DD	(4) Grid Cells 3.5 DD	(5) Grid Cells 3.0 DD	(6) Grid Cells 2.5 DD	(7) Grid Cells 2.0 DD	(8) Grid Cells 1.5 DD	(9) Grid Cells 1.0 DD	(10) Grid Cells 0.5 DD
	Dependent Variable: Growth of Satellite-Measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$									
Panel A: *Geo-Spatial Foreign Aid Controls*										
$\ln(0.01 + PWAD_{g,c,t})$	0.0020*	0.0002	0.0005	0.0015*	0.0011	0.0002	0.0004	0.0009	0.0008*	0.0008**
	(0.0012)	(0.0005)	(0.0010)	(0.0009)	(0.0007)	(0.0007)	(0.0006)	(0.0005)	(0.0004)	(0.0003)
$\ln(0.01 + PWAD_{g,c,t-1})$	0.0009	0.0008*	0.0004	0.0012	0.0003	0.0006	0.0001	0.0006	0.0003	0.0004
	(0.0009)	(0.0005)	(0.0009)	(0.0008)	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
$\ln(0.01 + PWAD_{g,c,t-2})$	0.0013	0.0002	-0.0028**	-0.0018	-0.0027***	-0.0018**	-0.0016**	-0.0011**	0.0002	0.0017***
	(0.0011)	(0.0006)	(0.0011)	(0.0012)	(0.0008)	(0.0008)	(0.0007)	(0.0005)	(0.0004)	(0.0004)
Panel B: *Time-Variant Grid Cell Controls*										
$\ln(0.01 + Light_{g,c,t-1})$	-0.7287***	-0.9130***	-0.9462***	-0.9438***	-0.9421***	-0.9260***	-0.9239***	-0.9209***	-0.9154***	-0.9126***
	(0.1512)	(0.0080)	(0.0140)	(0.0121)	(0.0111)	(0.0108)	(0.0090)	(0.0069)	(0.0049)	(0.0033)
$\ln(0.01 + Population_{g,c,t})$	0.5943***	-0.0718	-0.0143	-0.1421***	-0.0662	-0.1007***	-0.0166	-0.0314*	-0.0206*	-0.0132
	(0.1812)	(0.0708)	(0.0499)	(0.0503)	(0.0416)	(0.0341)	(0.0243)	(0.0182)	(0.0113)	(0.0082)
Mean Precipitation	-0.0010***	-0.0002	-0.0005*	-0.0004	-0.0003	-0.0006***	-0.0005**	-0.0004**	-0.0001	-0.0002**
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean Temperature	-0.0335***	-0.0044	0.0008	0.0034	-0.0071	0.0020	0.0022	-0.0041	-0.0098	-0.0108*
	(0.0090)	(0.0149)	(0.0174)	(0.0178)	(0.0162)	(0.0144)	(0.0135)	(0.0110)	(0.0083)	(0.0061)
SPEI Drought Index	0.0174**	0.0032	0.0014	-0.0040	-0.0020	0.0005	-0.0022	-0.0036	-0.0036	-0.0001
	(0.0070)	(0.0049)	(0.0095)	(0.0093)	(0.0073)	(0.0066)	(0.0052)	(0.0038)	(0.0029)	(0.0022)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0040	-0.0019	0.0029	0.0003	-0.0003	0.0036	-0.0007	0.0025	-0.0029	-0.0025
	(0.0034)	(0.0024)	(0.0030)	(0.0031)	(0.0030)	(0.0027)	(0.0025)	(0.0023)	(0.0021)	(0.0018)
Panel C: *Long-Run Effect of Foreign Aid*										
Estimated Coefficient: $(\phi_0 + \phi_1 + \phi_2)/(-\beta_1)$	0.0055**	0.0013	-0.0021	0.0010	-0.0015	-0.0011	-0.0012	0.0004	0.0014**	0.0032***
Standard Error (Delta Method)	{0.0028}	{0.0009}	{0.0017}	{0.0017}	{0.0013}	{0.0011}	{0.0009}	{0.0008}	{0.0006}	{0.0005}
Number of Spatial Units	181	2,690	1,036	1,333	1,792	2,543	3,899	6,848	15,076	58,676
Observations	3,077	45,730	17,612	22,661	30,464	43,231	66,283	116,416	256,292	997,492
Partial R^2	0.815	0.923	0.936	0.941	0.941	0.941	0.943	0.947	0.949	0.948
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	No	No	No	No	No	No	No	No	No
Year Fixed Effects	Yes	No	No	No	No	No	No	No	No	No
District Fixed Effects	N/A	Yes	No	No	No	No	No	No	No	No
Country-Year Fixed Effects	N/A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid Cell Fixed Effects	N/A	N/A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The spatial unit of investigation refers to countries, districts, and various grid cell definitions as reported in the header of each column. The dependent variable refers to annual growth in satellite-measured night-time light intensity. *ln(0.01 + Light)* refers to the log of the sum of digital number (DN) pixel-level values. *ln(0.01 + Population)* refers to the log of population, *Mean Precipitation* refers to the mean of total monthly precipitation (in millimeters per year), *Mean Temperature* refers to the mean annual temperature value (in degree Celsius). *SPEI Drought Index* refers to a geospatial drought index where positive values correspond to a period of relative wetness relative to the historic (12-month) climate trend and vice versa. *ln(0.01 + Conflicts)* refers to the log of the number of conflict events. $\ln(0.01 + PWAD_{g,c,t})$ refers to the log of project-specific annual disbursement flows of World Bank foreign aid projects. *Recodification Fixed Effects* refer to a full set of indicator variables that control for erratic developments in satellite-measured night-time light intensity and GIS data-related specificities (e.g., indicator variables for grid cells with zero night-time light pixel-level values and population data, and an indicator variable that identifies grid cells with zero night-time light activity but positive population-level data). *Country Fixed Effects* refer to a full set of country ISO code indicator variables that account for unobserved country-level heterogeneity. *Year Fixed Effects* refer to a full set of time indicator variables that account for time-variant unobserved worldwide heterogeneity. *District Fixed Effects* refer to a full set of country-level ADM1 code indicator variables that account for unobserved district-level heterogeneity across countries. *Country-Year Fixed Effects* refer to a full set of country-year indicator variables that account for time-variant unobserved country-level heterogeneity. *Grid Cell Fixed Effects* refer to a full set of indicator variables that control for arbitrary time-invariant unobserved heterogeneity within grid cells. Constant term included but not shown. See the main text for additional details on data construction and sources.

The *Partial* R^2 refers to the model's R^2 after partialling out country, year, country-year, district, and grid cell FE from the regression model. Standard errors, robust to serial correlation within spatial units (i.e., countries, districts, and grid cells) and spatial correlation across spatial units (i.e., districts and grid cells) within countries, are reported in parentheses. Standard errors for the long-run effects of foreign aid based on the delta method are reported in curly brackets.

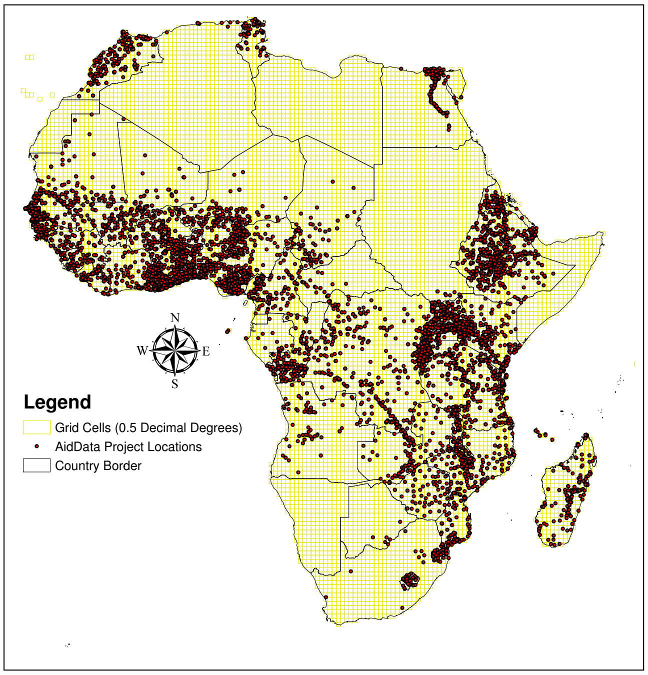
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table 5: Foreign Aid and Growth of Light Intensity (Sensitivity to Spatial Spillovers)

	(1) Baseline Estimates	(2) Spatial Model Aid Variable	(3) Spatial Model Light Variable	(4) Spatial Model Exogenous Controls	(5) Full Model Specification
	Dependent Variable: Growth of Satellite-Measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$				
Panel A: *Geo-Spatial Foreign Aid Controls*					
$\ln(0.01 + PWAD_{g,c,t})$	0.0008**	0.0006*	0.0006*	0.0006*	0.0006*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\ln(0.01 + PWAD_{g,c,t-1})$	0.0004	0.0003	0.0003	0.0003	0.0003
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\ln(0.01 + PWAD_{g,c,t-2})$	0.0017***	0.0008**	0.0008***	0.0008**	0.0008***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Panel B: *Time-Variant Grid Cell Controls*					
$\ln(0.01 + Light_{g,c,t-1})$	-0.9126***	-0.9126***	-0.9190***	-0.9126***	-0.9190***
	(0.0033)	(0.0033)	(0.0028)	(0.0033)	(0.0028)
$\ln(0.01 + Population_{g,c,t})$	-0.0132	-0.0121	-0.0144*	-0.0147	-0.0168*
	(0.0082)	(0.0081)	(0.0081)	(0.0094)	(0.0094)
Mean Precipitation	-0.0002**	-0.0002*	-0.0003**	-0.0003	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Mean Temperature	-0.0108*	-0.0107*	-0.0115*	0.0005	0.0013
	(0.0061)	(0.0061)	(0.0059)	(0.0103)	(0.0103)
SPEI Drought Index	-0.0001	-0.0001	0.0006	0.0033	0.0032
	(0.0022)	(0.0022)	(0.0021)	(0.0044)	(0.0044)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0025	-0.0024	-0.0022	-0.0024*	-0.0023*
	(0.0018)	(0.0018)	(0.0017)	(0.0014)	(0.0014)
Panel C: *Spatially Weighted Geo-Spatial Foreign Aid Controls*					
W $\ln(0.01 + PWAD_{g,c,t})$		0.0001	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
W $\ln(0.01 + PWAD_{g,c,t-1})$		0.0001	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
W $\ln(0.01 + PWAD_{g,c,t-2})$		0.0007***	0.0008***	0.0007***	0.0008***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Panel D: *Spatially Weighted Time-Variant Grid Cell Controls*					
W $\ln(0.01 + Light_{g,c,t-1})$			0.0077***		0.0077***
			(0.0007)		(0.0007)
W $\ln(0.01 + Population_{g,c,t})$				0.0003	0.0003
				(0.0005)	(0.0005)
W Mean Precipitation				0.0000	0.0000
				(0.0000)	(0.0000)
W Mean Temperature				-0.0015	-0.0017
				(0.0013)	(0.0013)
W SPEI Drought Index				-0.0005	-0.0004
				(0.0007)	(0.0007)
W $\ln(0.01 + Conflicts_{g,c,t})$				0.0000	0.0001
				(0.0006)	(0.0006)
Number of Grid Cells	58,676	58,676	58,676	58,676	58,676
Observations	997,492	997,492	997,492	997,492	997,492
Partial R^2	0.948	0.948	0.948	0.948	0.948
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Grid Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes

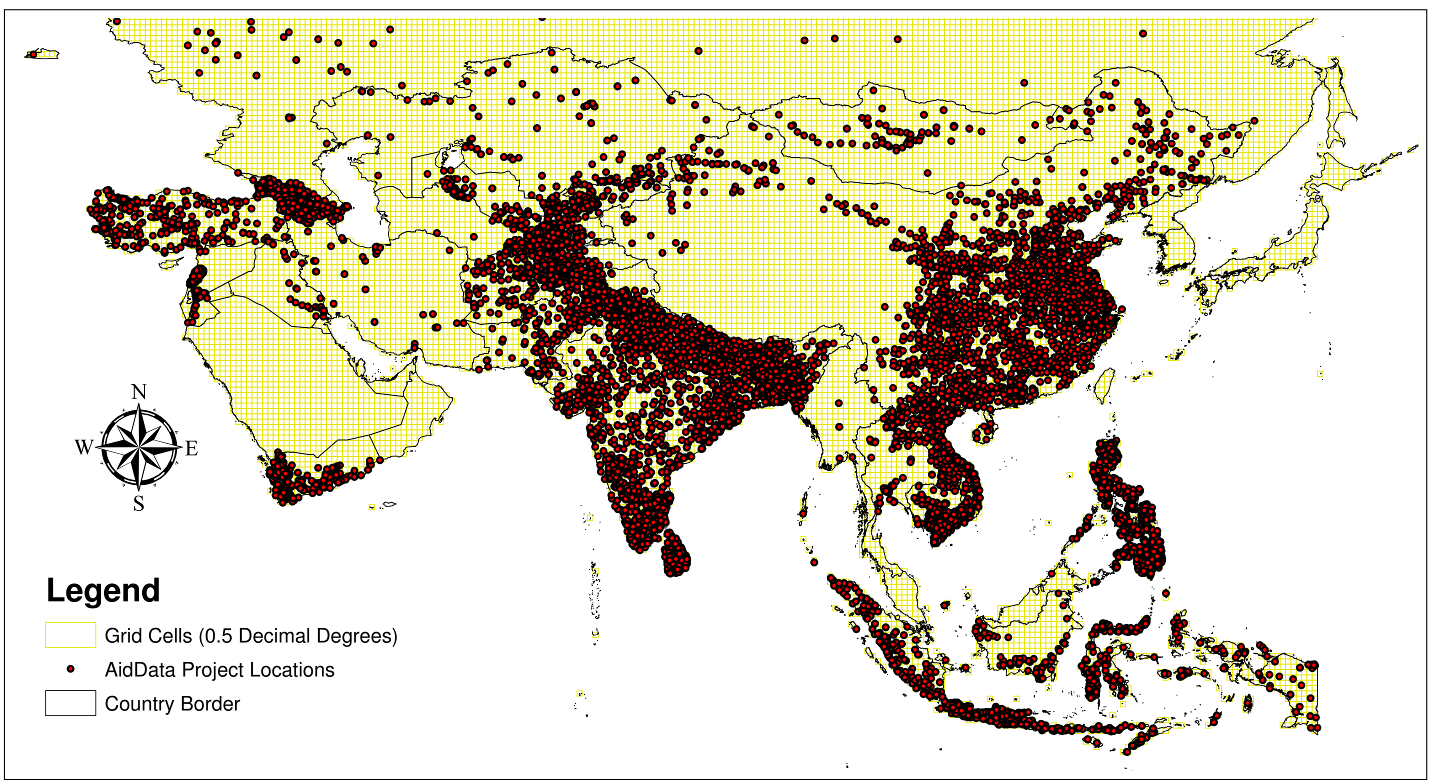
Notes: The spatial unit of investigation refers to 0.5 decimal degrees latitude × longitude grid cells. The dependent variable is the annual growth rate in satellite-measured night-time light intensity. *ln(0.01 + Light)* refers to the log of the sum of digital number (DN) pixel-level values. *ln(0.01 + Population)* refers to the log of population, *Mean Precipitation* refers to the mean of total monthly precipitation (in millimeters per year), *Mean Temperature* refers to the mean annual temperature value (in degree Celsius). *SPEI Drought Index* refers to a geospatial drought index where positive values correspond to a period of relative wetness relative to the historic (12-month) climate trend and vice versa. *ln(0.01 + Conflicts)* refers to the log of the number of conflict events. $\ln(0.01 + PWAD_{g,c,t})$ refers to the log of project-specific annual disbursement flows of World Bank foreign aid projects. The construction of the various spatially weighted explanatory variables is performed on behalf of a contiguous spatial weight matrix $\boldsymbol{W}$ with typical elements w_{ij} that takes a value of 1 for contiguous first-order neighboring grid cells and zero otherwise. *Recodification Fixed Effects* refer to a full set of indicator variables that control for erratic developments in satellite-measured night-time light intensity and GIS data-related specificities (e.g., indicator variables for grid cells with zero night-time light pixel-level values and population data, and an indicator variable that identifies grid cells with zero night-time light activity but positive population-level data). *Country-Year Fixed Effects* refer to a full set of country-year indicator variables that account for time-variant unobserved country-level heterogeneity. *Grid Cell Fixed Effects* refer to a full set of indicator variables that control for arbitrary time-invariant unobserved heterogeneity within grid cells. Constant term included but not shown. See the main text for additional details on data construction and sources.
The *Partial* R^2 refers to the model's R^2 after partialling out country-year and grid cell FE from the regression model. Standard errors, robust to serial correlation within grid cells and spatial correlation across grid cells within country-years, are reported in parentheses.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

B Figures



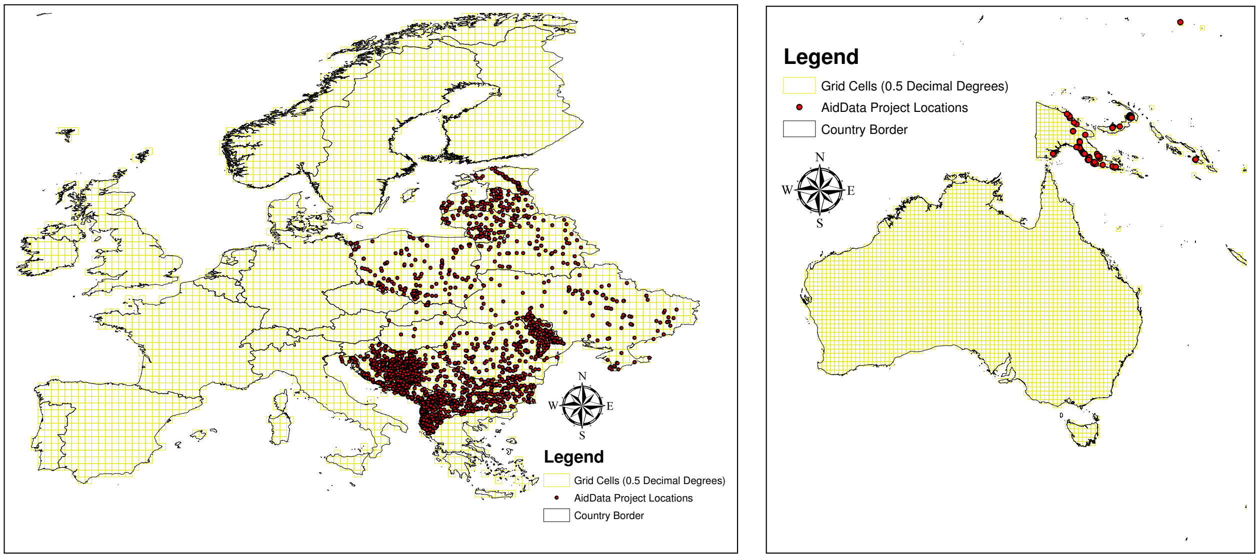
(a) Africa

(b) Americas



(c) Asia

Figure 1: Geographic Distribution of AidData Project Locations Across Continents



(d) Europe **(e)** Oceania

Figure 1: *Continued*

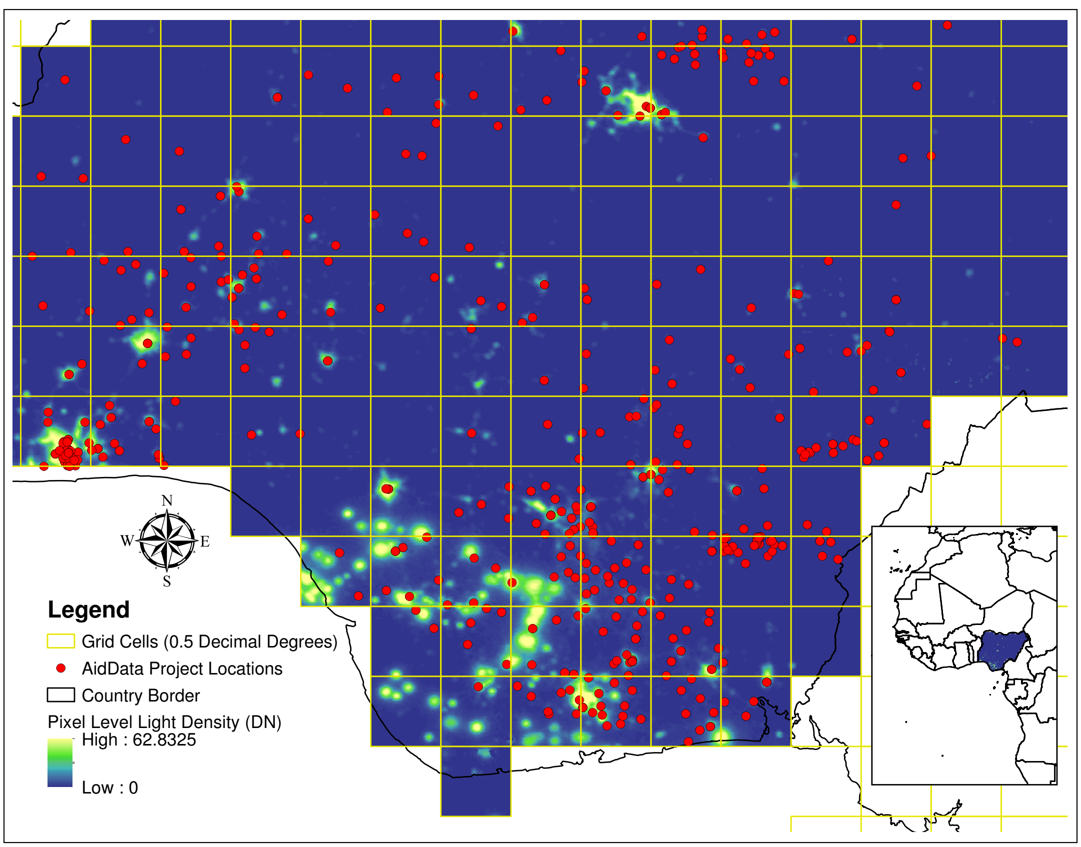


Figure 2: AidData Project Locations Across 0.5 Decimal Degree Grid Cells in Nigeria

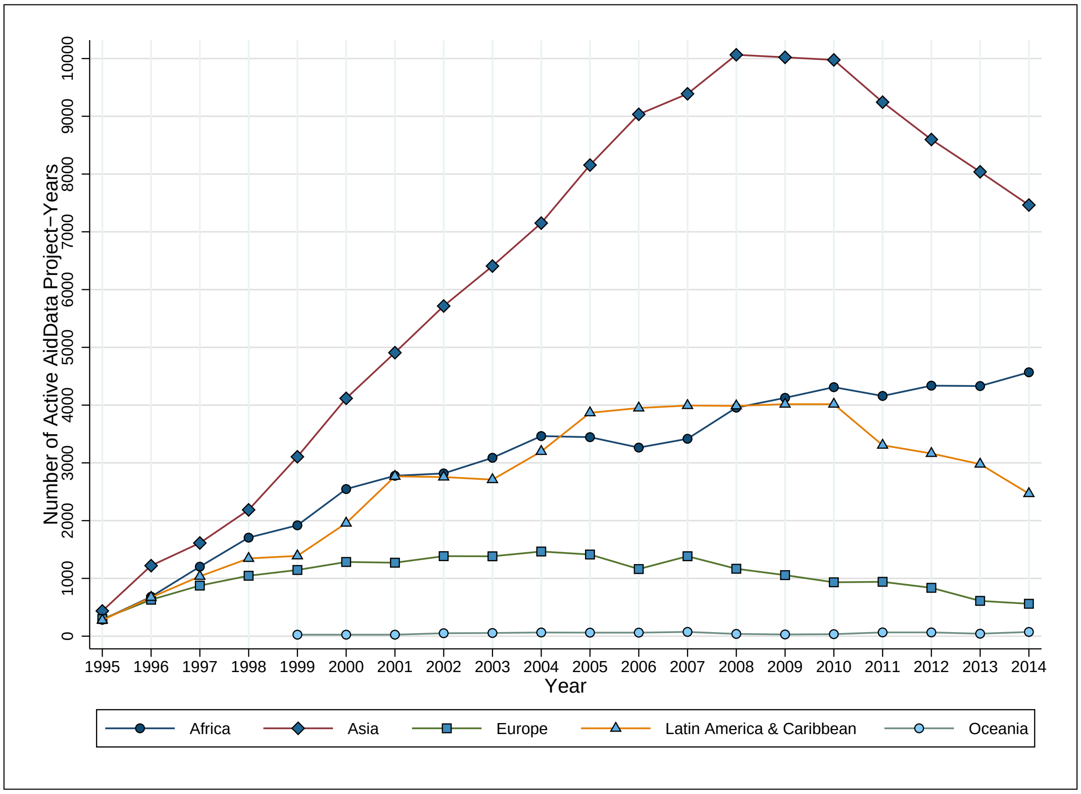


Figure 3: Number of Active AidData Project-Year Observations Across Regions

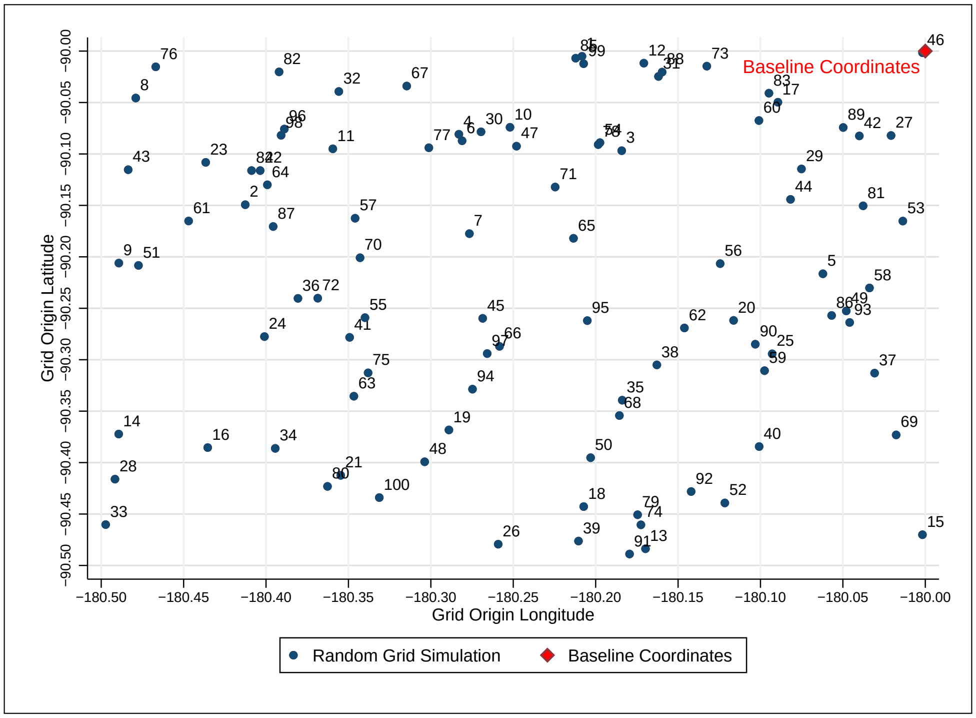


Figure 4: Simulation of 100 Initial Random Grid Coordinates

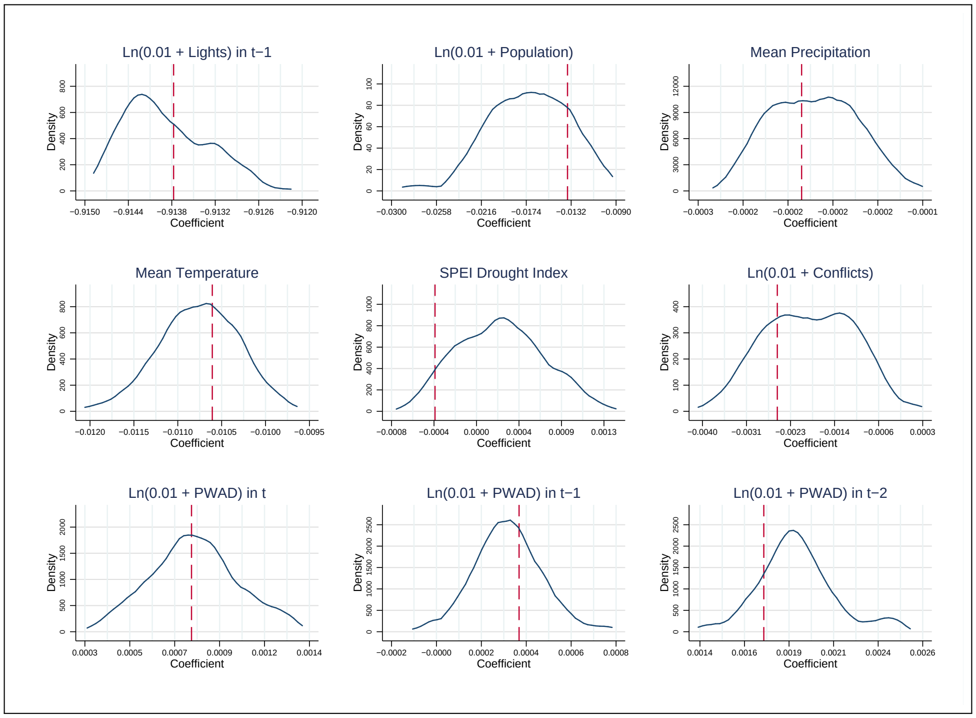


Figure 5: Distribution of Estimated Regression Coefficients Across 100 Simulated Random Grids

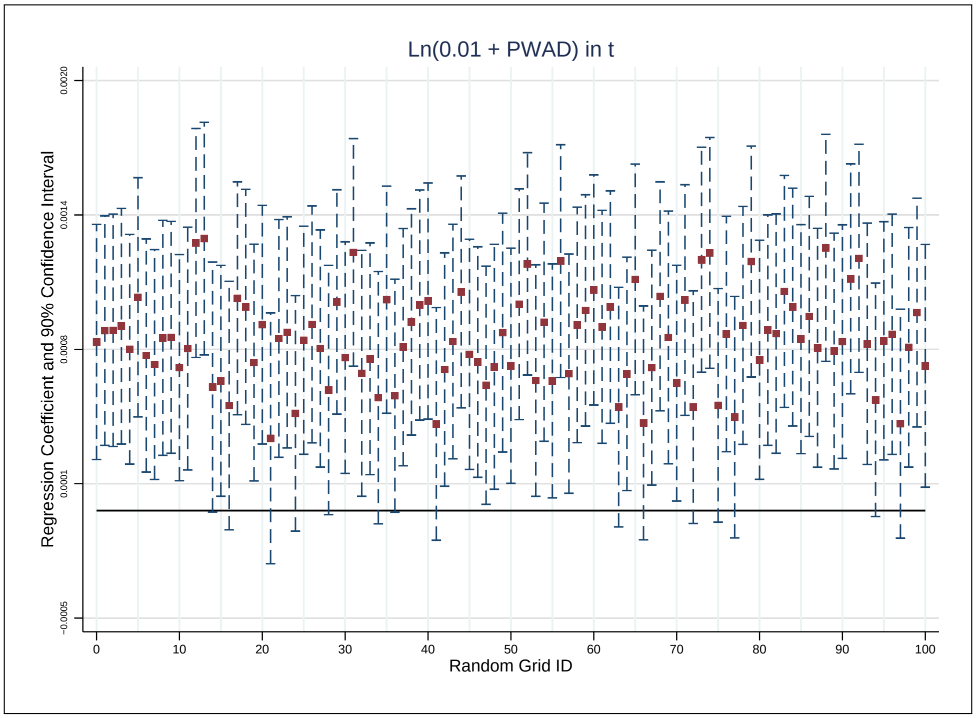


Figure 6: Range Plot of Variable $\ln(0.01 + PWAD_{g,c,t})$ Across 100 Simulated Random Grids

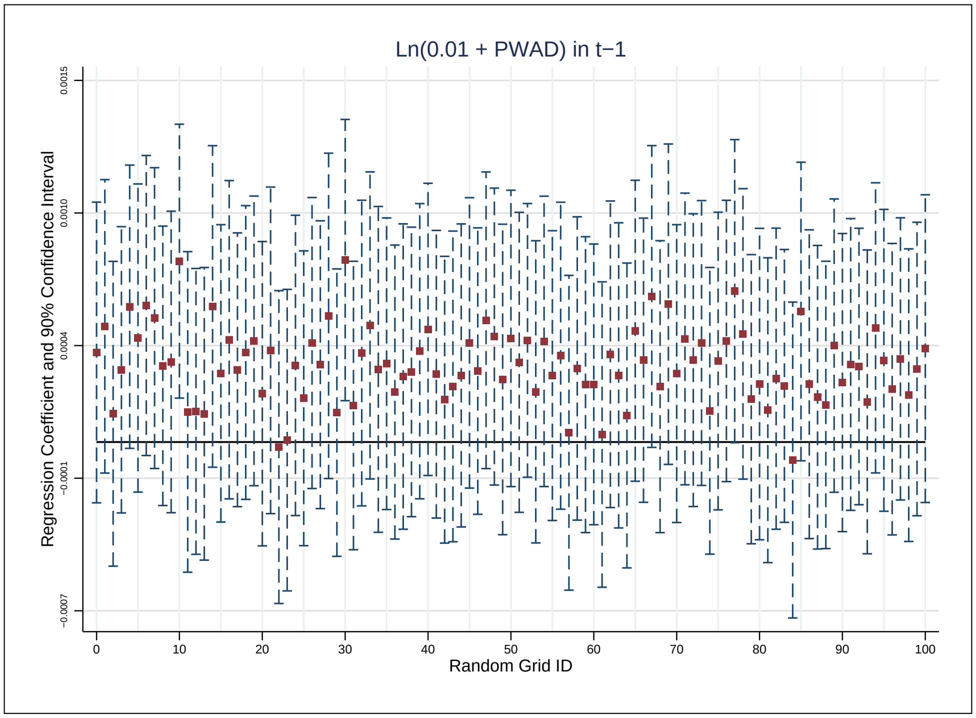


Figure 7: Range Plot of Variable $\ln(0.01 + PWAD_{g,c,t-1})$ Across 100 Simulated Random Grids

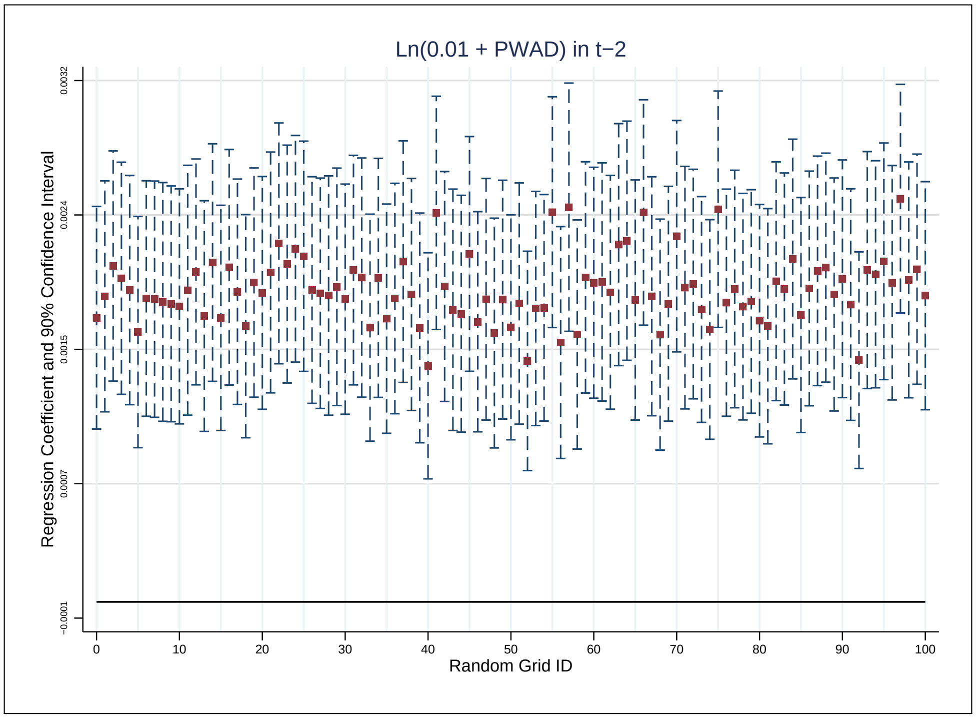


Figure 8: Range Plot of Variable $\ln(0.01 + PWAD_{g,c,t-2})$ Across 100 Simulated Random Grids

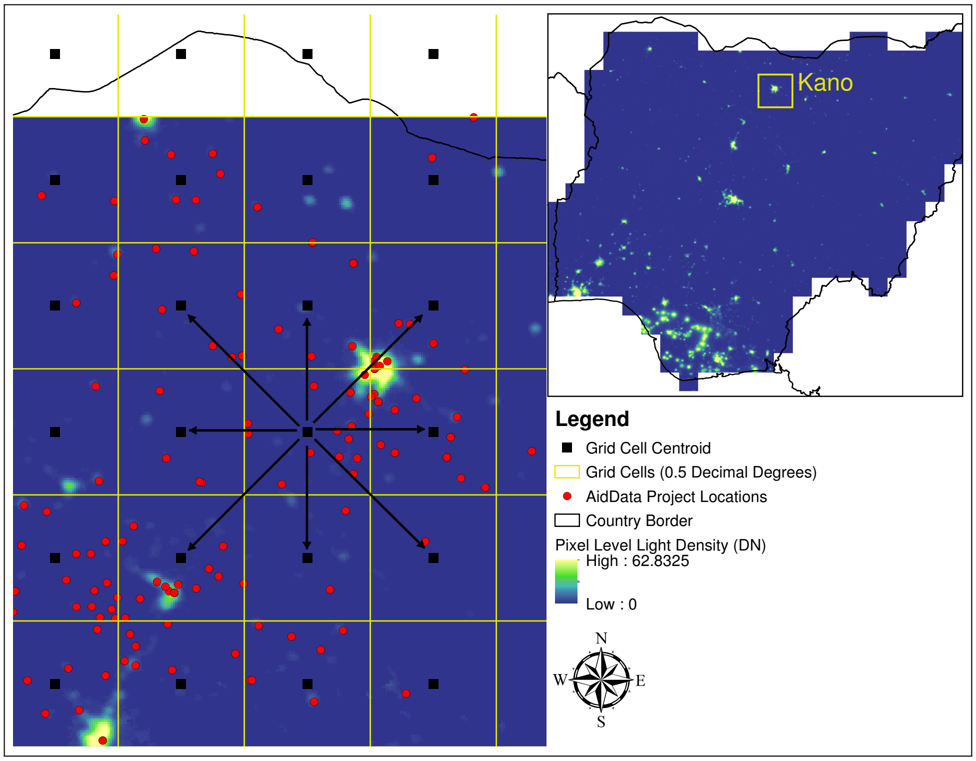


Figure 9: Illustration of Contiguous Grids From the Centroid of a Particular Grid

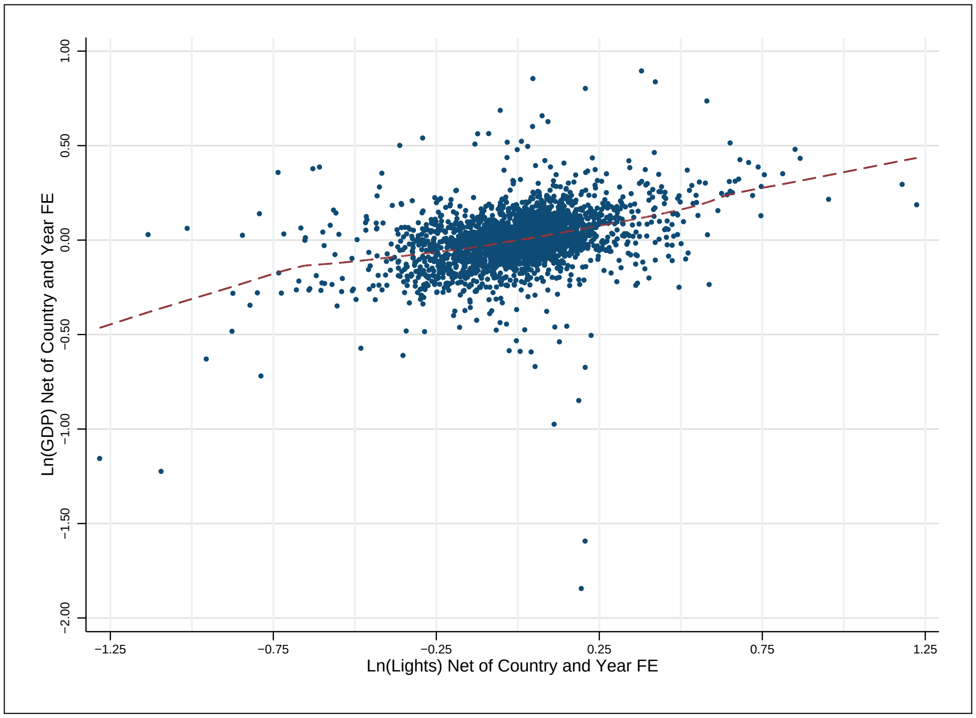


Figure 10: Relationship Between GDP and Night-Time Light Across Countries

Notes: This figure shows the empirical relationship between the logarithm of gross domestic product (GDP) and the logarithm of night-time light ($Lights$) in a panel of 161 countries during the period 1995 to 2013. The vertical axis depicts $\ln(GDP)$ net of country and year fixed effects, whereas the horizontal axis shows the corresponding $\ln(Lights)$ value net of country and year fixed effects. The dashed line corresponds to a locally weighted regression of $\ln(GDP)$ versus $\ln(Lights)$ with a bandwidth of 0.8 for calculating smoothed values. A panel fixed effects regression model with both country λ_c and year λ_t fixed effects of the form $\ln(GDP_{ct}) = \alpha + \beta \ln(Lights_{ct}) + \lambda_c + \lambda_t + e_{ct}$ yields an estimated elasticity of lights with respect to GDP of about $\beta = 0.2915$ (Robust Std. Err. $= 0.0409$) with a within-country $R^2 = 0.7624$. Number of country-year observations: 3,059.

C Descriptive Statistics

Table 6: Number of World Bank Foreign Aid Project-Locations Across Continents

	AidData Geographic Precision Codes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Exact Location	Near Location	ADM2 Level	ADM1 Level	Estimated Coordinates	Country Level	Unclear Location	Governmental Unit	Total
Project-Locations Across Continents	25,938	2,333	15,408	11,684	1,065	1,602	0	1,939	59,969
Africa	6,311	385	4,090	3,160	298	604	0	702	15,550
Asia	13,013	1,357	6,542	5,176	460	496	0	561	27,605
Europe	2,480	176	756	855	71	175	0	264	4,777
Latin America & Caribbean	3,904	398	3,961	2,366	210	305	0	381	11,525
Oceania	230	17	59	127	26	22	0	31	512

Notes: This table shows the distribution of World Bank foreign aid project-locations and the corresponding precision codes across continents during the period 1995 to 2014. See the main text for additional details regarding data construction and sources.

Table 7: Summary Statistics for the Main Regression Variables

Variable	N	Mean	SD	Minimum	Maximum	5% Percentile	25% Percentile	50% Percentile	75% Percentile	95% Percentile
Panel A: Panel Data Variables During the Period 1997 to 2013 across 58,676 Grid Cells										
Night-Time Light Growth: $\triangle \ln(0.01 + Light_{g,c,t})$	997,492	0.0428	1.7919	-15.6516	15.7924	-0.5595	0	0	0.0461	0.7045
$\ln(0.01 + Light_{g,c,t})$	997,492	1.8466	6.3605	-4.6052	12.3080	-4.6052	-4.6052	3.3776	8.1283	10.4793
$\ln(0.01 + Population_{g,c,t})$	997,492	6.7670	5.8803	-4.6052	17.1847	-4.6052	5.6630	8.5581	10.8441	13.1448
Incidence: $\mathbf{I}(Light_{g,c,t} = 0)$	997,492	0.4755	0.4994	0	1	0	0	0	1	1
Incidence: $\mathbf{I}(Population_{g,c,t} = 0)$	997,492	0.1843	0.3878	0	1	0	0	0	0	1
Incidence: $\mathbf{I}(Light_{g,c,t} = 0 \;\&\; Population_{g,c,t} > 0)$	997,492	0.3046	0.4602	0	1	0	0	0	1	1
Mean Precipitation	997,492	61.0094	59.6915	0	819.1000	4.2833	22.1333	42.1250	79.0750	184.7333
Mean Temperature	997,492	10.6794	13.5714	-23.5167	31.8083	-12.2667	-0.6500	11.4083	23.9250	27.8083
SPEI Drought Index	997,492	0.0990	0.8666	-3.6403	3.3150	-1.3615	-0.4970	0.1103	0.7111	1.5107
$\ln(0.01 + Conflicts_{g,c,t})$	997,492	-4.5329	0.6360	-4.6052	5.8944	-4.6052	-4.6052	-4.6052	-4.6052	-4.6052
Incidence: $\mathbf{I}(NPL_{g,c,t} > 0)$	997,492	0.0781	0.2684	0	1	0	0	0	0	1
Number of Project Locations: $\ln(0.01 + NPL_{g,c,t})$	997,492	-4.1929	1.4334	-4.6052	5.9027	-4.6052	-4.6052	-4.6052	-4.6052	0.0100
Annual Disbursement Flow: $\ln(0.01 + PWAD_{g,c,t})$	997,492	-3.3676	4.5279	-4.6052	20.2150	-4.6052	-4.6052	-4.6052	-4.6052	12.1329
Panel B: Cross-Sectional Variables across 58,676 Grid Cells										
Elevation	58,676	617.3876	805.2359	-1432.4720	6087.5280	30	150	355.5972	775.6250	1980.5280
Std. Dev. of Elevation	58,676	99.9327	131.0134	0	1877.981	4.0585	19.2179	50.3874	130.1112	354.5782
Range of Elevation	58,676	385.9791	494.3591	0	5263	15	73	195	510	1370
Fraction of Cropland Area	58,676	0.1070	0.1922	0	0.9999	0	0	0.0038	0.1191	0.5855
Std. Dev. of Cropland Area	58,676	0.0517	0.0782	0	0.4715	0	0	0.0068	0.0807	0.2266
Range of Cropland Area	58,676	0.1975	0.2811	0	1	0	0	0.0297	0.3275	0.8399
Land Suitability for Agriculture	58,676	0.2757	0.3196	0	1	0.0010	0.0060	0.1110	0.4920	0.9220
ln(0.01 + Distance to Capital)	58,676	6.9621	1.0998	0.5769	8.9045	5.0356	6.2175	7.0281	7.8759	8.5757
ln(0.01 + Distance to Border)	58,676	4.6086	1.5963	-4.3554	7.0934	1.4183	3.8086	4.9289	5.7761	6.5684
ln(0.01 + Distance to Coast)	58,676	5.4377	1.6800	-4.3566	7.7356	1.8690	4.7354	5.8787	6.6329	7.2678
ln(0.01 + Distance to River)	58,676	3.6312	1.5476	-4.5777	7.2044	1.0453	2.7651	3.6319	4.5159	6.3710
ln(0.01 + Distance to Nearest Settlement)	58,676	5.3193	1.1737	-4.6052	7.8769	3.3303	4.5250	5.3694	6.1842	7.1213
ln(0.01 + Distance to Power Transmission Line)	58,676	4.1913	1.9193	-4.6052	7.5572	0.7053	2.8986	4.5246	5.7283	6.7004
ln(0.01 + Distance to Railroad Line)	58,676	4.3820	1.8512	-4.5529	7.5350	1.0165	3.1459	4.6731	5.8815	6.8224
ln(0.01 + Distance to Road Line)	58,676	2.3763	1.8345	-4.5422	6.6220	-0.5385	1.1734	2.2184	3.6979	5.5032
ln(0.01 + Length of Railroad Line)	58,676	-2.1656	3.9069	-4.6052	6.4198	-4.6052	-4.6052	-4.6052	2.9109	4.7932
ln(0.01 + Length of Road Line)	58,676	1.8880	4.3763	-4.6052	7.3838	-4.6052	-4.6052	4.4353	5.2241	5.7310
ln(0.01 + Length of Power Transmission Line)	58,676	-1.8945	4.0718	-4.6052	6.3734	-4.6052	-4.6052	-4.6052	3.3444	5.1084
ln(0.01 + Grid Cell Area)	58,676	7.6790	0.3347	6.7088	8.0318	7.0286	7.4533	7.7953	7.9664	8.0291
ln(0.01 + Absolute Latitude)	58,676	3.3706	0.9263	-1.3471	4.3143	1.4493	3.0330	3.6444	4.0300	4.2306
Number of Diamond Mines	58,676	0.0222	0.3506	0	43	0	0	0	0	0
Number of Gemstone Deposits	58,676	0.0229	0.2065	0	10	0	0	0	0	0
Share of Urban Extent Area	58,676	0.0241	0.0726	0	0.9822	0	0	0	0.0025	0.1512
Share Area in the tropics	58,676	0.1539	0.3513	0	1	0	0	0	0	1
Ethno-Linguistic Diversity	58,676	0.1145	0.2068	0	0.9520	0	0	0	0.1307	0.5629

Notes: This table shows basic summary statistics for the main variables employed in the regression analysis. See the main text for additional details on data construction and sources.

Table 8: Summary Statistics of Estimated Regression Coefficients Across Simulated Random Grids

Variable	N	Mean	SD	Minimum	Maximum	5% Percentile	50% Percentile	95% Percentile
$\ln(0.01 + Light_{g,c,t-1})$	100	-0.9139	0.0006	-0.9147	-0.9124	-0.9146	-0.9140	-0.9129
$\ln(0.01 + Population_{g,c,t})$	100	-0.0171	0.0037	-0.0277	-0.0106	-0.0225	-0.0171	-0.0114
Mean Precipitation	100	-0.0002	0.0000	-0.0003	-0.0001	-0.0002	-0.0002	-0.0002
Mean Temperature	100	-0.0108	0.0004	-0.0119	-0.0098	-0.0115	-0.0108	-0.0101
SPEI Drought Index	100	0.0003	0.0004	-0.0007	0.0013	-0.0004	0.0003	0.0010
$\ln(0.01 + Conflicts_{g,c,t})$	100	-0.0019	0.0008	-0.0038	0.0000	-0.0033	-0.0019	-0.0007
$\ln(0.01 + PWAD_{g,c,t})$	100	0.0008	0.0002	0.0003	0.0013	0.0004	0.0008	0.0012
$\ln(0.01 + PWAD_{g,c,t-1})$	100	0.0003	0.0002	-0.0001	0.0008	0.0001	0.0003	0.0006
$\ln(0.01 + PWAD_{g,c,t-2})$	100	0.0019	0.0002	0.0014	0.0025	0.0016	0.0019	0.0024
Grid-Year Observations	100	1027202	2716.4620	1020034	1031560	1022448	1027727	1031042

Notes: This table shows basic summary statistics of the estimated regression coefficients across 100 simulated random grids. See the main text for additional details on data construction and estimation.