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Foreign Aid and Subnational Development: A Grid Cell Analysis

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Abstract

We examine the impact of geo-referenced World Bank development programs on subnational 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, lack of key country-level controls, aggregation bias, simultaneity and/or the presence of reverse causality in the association between 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 lights 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. Additional sensitivity tests confirm the robustness of the main findings to various econometric estimators, alternative model specifications, and different spatial aggregation levels.

JEL Classifications: C23, F35, O10, O20, O40, R10

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1 Introduction

There are numerous studies in development economics debating the effectiveness of foreign aid in fostering development in areas such as education, health, governance, and economic infrastructure in low-income countries. Yet this debate is based on empirical findings that are still subject to widespread skepticism in the cross-country aid effectiveness literature.[1] The discussion in the aid effectiveness literature is centered mainly on endogeneity concerns that make it difficult to identify the causal effect of foreign aid on per capita GDP growth. Additional practical challenges include a lack of high-quality country-level controls due to the poor statistical capacities in less developed countries. Even though the aid effectiveness literature has employed a series of instrumental variables (IV) estimation techniques, none of the proposed approaches has been capable of overcoming all the endogeneity concerns typically discussed in empirical aid and growth studies.

A methodological review of the aid effectiveness literature reveals that many studies have failed to convincingly estimate the true effect of foreign aid on economic growth due to severe endogeneity problems caused by unobserved heterogeneity underlying the allocation of bilateral aid flows from donor to recipient countries, aggregation issues associated with the foreign aid measure, simultaneity issues and/or problems of reverse causality in the relationship between foreign aid and economic growth, measurement error related to both the foreign aid and the per capita GDP growth variable, and endogenous sample selection bias. Several identification strategies have been proposed to overcome some of the aforementioned technical problems in the empirical aid effectiveness literature, including the use of Two-Stage Least Squares (2SLS) estimation (Clemens et al., 2012; Galiani et al., 2017) and dynamic panel data GMM estimators (Dalgaard et al., 2004; Rajan and Subramanian, 2008). The latter have gained popularity among empirical researchers not only in the aid effectiveness literature owing to the practicability of generating internal GMM-style IVs, but in fact in almost all areas of economics. However, Bazzi and Clemens (2013) identified a number of methodological shortcomings in the usual instrumentation strategies 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.

In this paper, we argue that the ambiguous results in much of the empirical aid effectiveness literature are closely tied to the issue of spatial resolution. It seems almost impossible to account for the plethora of confounding factors in the relationship between foreign aid and economic growth if the empirical analysis

[1] While one branch of the literature has argued that development programs designed to promote economic prosperity are unconditional 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).

is based on cross-country observations. The use of a full set of country and year fixed effects (FE) has become standard in the aid effectiveness literature in panels of heterogeneous low-income countries, thus implicitly accounting for arbitrary unobserved heterogeneity across countries and time. This approach is not capable, however, of controlling for possible unobserved heterogeneity that is both country-specific and time-variant. Unfortunately, the inclusion of a full set of country-year FE to eliminate these heterogeneity problems in a typical growth regression is technically not feasible due to the restricted number of degrees of freedom in a panel of cross-country observations.

To surmount the aforementioned endogeneity concerns, we analyze the association between foreign and economic growth at the disaggregated subnational level. As the unit of investigation we use equally sized grid cells with a spatial resolution of 0.5 decimal degrees latitude $\times$ longitude (approximately 55 km $\times$ 55 km at the equator) that spans the entire globe from -180 to 180 degrees longitude and 90 to -90 degrees latitude. In contrast to cross-country analysis, the proposed grid cell approach overcomes a series of methodological problems that severely impede proper identification of the true effect of foreign aid on development outcomes. For example, since the arbitrary small-sized grid cells are typically nested within countries, we are able to include a full set of country-year FE in the regression equation 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 (e.g., political-strategic, economic, and ideological interests of donors) underlying the allocation of bilateral aid flows in less developed countries. 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. Thus, the consideration of 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.

The proposed grid cell approach proves effective in tackling the aforementioned endogeneity problems discussed in the empirical aid effectiveness literature. By narrowing down the unit of investigation to the subnational grid cell level, we are able to control for arbitrary unobserved country-specific heterogeneity and grid-cell-specific local characteristics. The latter is crucial in identifying the true effect of foreign aid on development outcomes, since aid effectiveness might be endogenous to prevailing biogeographic, climatic, socioeconomic, and demographic conditions. More importantly, empirical studies on aid effectiveness should rely on subnational rather than country-level observations, since the latter risk confounding the positive effects of aid on economic growth with other (perhaps unrelated) negative developments within a particular country. Consider the World Banks development programs to improve the economic infrastructure in low-income countries. Programs like these improve country's growth prospects, for instance, by lowering trade frictions through the provision of transport services. But if a country in which agriculture contributed significantly to overall GDP experienced a severe climatic shock that destroyed a large proportion of its arable land at the same time, then this negative event would counteract the positive effect of the specific aid project on economic growth, even though both events are completely independent of each other. Obviously, per capita GDP growth rates are influenced by many factors with partially opposing effects, thus, making them a poor indicator of foreign aid effectiveness. We overcome this specific problem through the construction of local (i.e., grid cell) rather than global (i.e., country-level) performance measures that can be directly linked to the implementation of specific development programs across grid cells. In addition, we have no reason to suspect that the proposed grid cell approach suffers from the presence of simultaneous equation bias and/or reverse causality in the relationship between foreign aid and economic growth. While this might be an issue in studies using countries or administrative districts as the unit of investigation, it appears to be of virtually no practical relevance when using small, arbitrarily sized grid cells. 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.

We combine various geo-coded data sets to examine the relationship between foreign aid and economic growth at the subnational grid cell level. The most important data source refers to a recently released geo-spatial database – namely AidData (2016) – that have started to geo-reference foreign aid projects from many 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 amount of project-specific annual disbursement flows) indicating the extent of World Bank development programs across grid cells and years. Due to the lack of reliable income measures at the subnational – in particular 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 1995 to 2013, resulting in 997,492 grid-year observations. The main findings were derived from a grid cell FE regression equation estimated using the method of Ordinary Least Squares (OLS) with standard errors that are robust to serial autocorrelation of grid cells over time and spatial autocorrelation across grid cells within countries. Nevertheless, we also report coefficient estimates using alternative estimators to cope with the methodological discussion on the appropriateness of the various econometric estimators (e.g., OLS FE versus system GMM) in the aid effectiveness literature.

The main results suggest that the implementation of World Bank development programs contribute significantly to annual growth rate in satellite-measured night-time light intensity across grid cells. 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 the estimated night-time light elasticity with respect to real GDP of about 0.30 that has been derived 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). In addition, we identify heterogeneous aid effects on grid-cell night-time light activity resulting from the project's duration and type of sectoral coding. In particular, we find that World Bank foreign aid projects in public sectors such as health services, water supply and sanitation, economic infrastructure and services, and production sectors are among the most important factors in grid cell night-time light growth.

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 report coefficient estimates derived from dynamic panel data GMM estimators (i.e., difference GMM and system GMM) to account for the endogeneity concerns frequently discussed in the cross-country aid effectiveness literature. Second, 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 grids. Finally, we examine the robustness of the main findings to the issue of spatial interdependence between nearby grid cells using various spatial econometric models. None of the aforementioned sensitivity tests significantly affect the main conclusions regarding aid effectiveness at the disaggregated grid cell level.

Despite the extensive research on empirical aid effectiveness,[2] the empirical evidence at the subnational level is rather limited. 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. As this aggregation level is still rather rough, we seek to contribute to the aid effectiveness literature in several ways. First, we propose the use of equally sized small grid cells over the use of administrative regions, as the latter might be endogenous to political-economic considerations of nation states. Second, we provide an in-depth investigation of the severity of unobserved country and grid-cell-specific heterogeneity that significantly interferes with the identification of the true effect of foreign aid on economic growth. Third, we address endogeneity issues in the existence of time-variant grid-cell-specific factors (e.g., droughts and conflict incidence) that might confound the relationship between foreign aid and development outcomes due to the omission of important local characteristics. Fourth, we report the existence of heterogeneous aid effects arising from the project's time duration and type of sectoral coding. Finally, we examine the strength of association between foreign aid and development outcomes at the subnational level to a large battery of additional sensitivity tests (e.g., use of various dynamic panel data GMM estimators, spatial aggregation levels, construction of randomly distributed grid cells, and spatial interaction between nearby grid cells) that have not been conducted in such detail in the aid effectiveness literature.

[2]The interested reader is referred to Temple (2010) for a comprehensive review and discussion of the findings in the foreign aid literature.

The remaining parts of the paper are organized as follows. In Section 2, we discuss the key challenges to identification in the empirical aid effectiveness literature and provide a discussion of possible strategies to tackle this challenge using appropriate econometric techniques. In Section 3, we outline the proposed grid cell approach to examine the relationship between World Bank foreign aid projects and night-time light growth in a worldwide panel of 0.5 decimal degrees latitude $\times$ longitude grid cells. Section 4 provides a detailed discussion on data construction and sources of various geospatial indicators 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 Key Challenges in Identifying the Effectiveness of Foreign Aid on Aggregate Growth

In this section, we review the aid effectiveness literature and provide a thorough discussion of why the bulk of cross-country empirical studies have failed to identify a causal impact of foreign aid on economic growth due to endogeneity problems including unobserved heterogeneity underlying the allocation of bilateral aid flows, aggregation issues, simultaneity and/or reverse causality in the aid and growth relationship, measurement error problems associated with the foreign aid and growth variable, and sample selection bias. We then present identification strategies that have been used in the aid effectiveness literature to overcome the aforementioned problems.

2.1 Unobserved Heterogeneity Underlying Bilateral Aid Flows

Numerous studies have sought to identify the determinants of decisions surrounding the allocation of bilateral aid flows to low-income countries. This literature appears, at least superficially, to clearly distinguish between two competing views of why and to what extent donors allocate official bilateral aid flows to developing countries worldwide. The first view is rooted in the idealistic notion that bilateral aid flows should be closely tied to a country's humanitarian needs in order to promote economic prosperity and health-related quality of life. The second view, in contrast, conceives of aid funds as a foreign policy instrument to pursue the donor's own strategic political, economic, and ideological interests in an international environment of competing nation-states. Case study and empirical results provide evidence that during the Cold War period, official bilateral aid flows were determined largely by the foreign policy considerations of donor countries.[3]

[3] For instance, McKinlay and Little (1977) found that during the period 1960 to 1970, the primary goal of the US foreign aid program was to pursue political and security interests throughout the world. In addition, McKinlay and Little (1978) determined that the decision process behind the allocation of bilateral aid in the United Kingdom between 1960 and 1970 was driven primarily by foreign policy considerations such as protecting and promoting the country's historical sphere of influence throughout the world, contrary to the official government statements about providing aid to meet humanitarian needs.

Schraeder et al. (1998) identified the key humanitarian, strategic, economic, cultural, and ideological determinants of American, Japanese, French, and Swedish bilateral aid flows to African countries in the 1980s. The authors found that the United States allocated aid to African countries predominantly for ideological reasons such as curbing communist expansion throughout Africa.[4] For Japan, the allocation of aid to African countries was motivated by a desire to establish trade relations and gain access to raw materials and mineral resources. Sweden allocated aid mainly to African countries that were not receiving aid from the United States or France, and showed eagerness to support progressive socialist regimes and countries that had replaced repressive white minority rule with constitutional systems that supported black majority rule. For France, the allocation of aid to African countries during this period was driven by a desire to expand its sphere of influence and culture (e.g., language), as manifested by a large proportion of the country's bilateral foreign aid flows going to former French colonies.

The political-strategic or foreign policy aspect of bilateral foreign aid fund allocation has been confirmed in a series of cross-country studies. For example, Alesina and Dollar (2000) showed that the pattern of bilateral aid flows in a sample of OECD donor countries is positively and significantly correlated with former colonial ties, the duration of colonization, and voting behavior by the recipient country in the United Nations General Assembly in line with the donor country's foreign policy interests. Research on the foreign policy aspect of temporary United Nations Security Council membership led to further empirical studies on the political-strategic aspects of foreign aid allocation. Kuziemko and Werker (2006) found that non-permanent Security Council membership is positively and significantly correlated with the receipt of foreign aid from the United States and the United Nations, while Dreher et al. (2009) showed that membership in the United Nations Security Council significantly predicts the amount of World Bank foreign aid funding in recipient countries. Regarding the ideological motivations for bilateral aid flows, Brech and Potrafke (2014) revealed that left-wing governments tend to give more bilateral aid to less developed countries, similar to national social welfare transfer payments designed to reduce the symptoms of individual poverty in society.

The above discussion reveals that donor countries differ substantially in the importance they attach to political-strategic, economic, and ideological interests, and that these differences significantly predict the direction and amount of aid directed to recipient countries. Obviously, the lack of detailed information on donor-specific characteristics (e.g., humanitarian, strategic, economic, cultural, and ideological aspects) significantly interfere with the econometric identification of the true effect of foreign aid on economic growth due to unobserved heterogeneity underlying the allocation of bilateral aid flows to poorer countries. For example, the United States allocated substantial amounts of foreign aid to repressive, authoritarian African countries during the 1980s (e.g., Zaire, Egypt, and Sudan) to contain communist expansion throughout Africa. For the same reason, US foreign aid to these countries did not decline even as these countries began to show clear signs of economic deterioration (Schraeder et al., 1998). Moreover, unobserved country-specific shocks (e.g., civil conflicts, negative crop price shocks, famines, and natural disasters) might trigger an unexpected inflow of foreign aid funds to recipient countries during

[4] After the end of the Cold War, the promotion of democracy and human rights protection became a key objective in the allocation of US aid (Meernik et al., 1998).

a period of severe economic deterioration (Papanek, 1972). Consequently, not controlling for humanitarian and political-strategic considerations by donor countries in the allocation of bilateral aid flows to recipient countries would result in a negative correlation between per capita GDP growth and foreign aid in cross-country analysis without any causal relationship.

Unfortunately, lack of data availability and restricted number of degrees of freedom in country-level foreign aid studies undermine the precise modeling of the aforementioned factors related to country-specific heterogeneity and unobserved shocks. Even though the inclusion of a full set of country and time fixed effects would be able to efficiently account for unobserved, time-invariant, heterogeneity across countries, and for common shocks over time, respectively, this approach cannot control for arbitrary unobserved heterogeneity that is both country-specific *and* time-variant. Furthermore, the insufficient number of degrees of freedom in country-level studies prevents a solution through inclusion of a full set of country-year fixed effects. Overall, the complexity of the decision process on the part of donor countries in allocating bilateral aid to recipient countries and the significant heterogeneity among recipients make it very unlikely to obtain a sufficient set of control variables to consistently identify the true effect of foreign aid on per capita GDP growth.

2.2 Aggregation Bias

As true with all macro-level studies, data aggregation might confound the estimated regression coefficients: the positive effects of foreign aid on the micro level might be cancelled out by other negative effects. These negative effects might be either indirect negative effects caused by the foreign aid projects themselves, or have no connection to the aid projects. Aid fungibility is one example of the possible negative indirect effects of foreign aid, and is a widely discussed issue in the literature. It generally occurs when governments put less of their own money into development efforts that are receiving aid from outside sources, in some cases diverting this money into unproductive operations such as rent-seeking and military activities (Mosley, 1986; Mosley et al., 1987; Feyzioglu et al., 1998; Pack and Pack, 1990).

Other examples include changes in prices, wages, and migration within a region. For example, large inflows of foreign aid might have the negative side effect of triggering an appreciation of the real exchange rate that undermines international competitiveness of export products in a country's manufacturing industry (Rajan and Subramanian, 2011). In addition, development assistance given in the form of food aid might harm local farmers who are net sellers of cereals (Kirwan and McMillan, 2007; Levinsohn and McMillan, 2007). Moreover, infrastructure projects might trigger regional migration flows if people lose their livelihood as a result of increased market competition (Easterly, 2003). The issue of internal migration pressure on economically prosperous regions has been discussed in the case of the Millennium Villages (Sanchez et al., 2007).

Examples of negative effects that are unrelated to foreign aid inflows include the occurrence of famines, armed conflicts, and crop price shocks in recipient countries. 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. Furthermore, the summation of various foreign aid flows into a single monetary value might cause an over-aggregation problem, as important information on the geographic and sector-specific distribution of the various foreign aid projects gets lost through aggregation. For example, negative effects of a project due to the prevailing conditions in one specific location might cancel out the positive effects of a project in another favorable location. In addition, the effectiveness of foreign aid flows in improving economic prosperity may depend on the type of foreign aid projects implemented (Asiedu and Nandwa, 2007; Rajan and Subramanian, 2008). While emergency assistance might have no effect on economic growth, investments in infrastructure projects might have a positive effect (Clemens et al., 2012). Another project characteristic that is lost in aggregation is the impact of project duration on project-level outcomes (Denizer et al., 2013; Metzger and Guenther, 2015). Arndt et al. (2015) found that foreign aid has a positive long-run impact on economic growth by stimulating a wide range of proximate factors of economic development (e.g., health conditions and human capital accumulation).

2.3 Simultaneity and/or Reverse Causality in the Aid and Growth Relationship

A further challenge for identification of the impact of foreign aid on per capita GDP growth is the possibility of simultaneity and/or reverse causality. The possibility that foreign aid inflows might be a function of per capita GDP growth (i.e., slow-growing economies might attract more foreign aid inflows than fast-growing economies due to greater humanitarian need) is a frequently discussed issue in empirical foreign aid studies, as it results in biased regression coefficients of simple OLS estimates. The argumentation is that donor countries and/or aid agencies might rely on economic, political, and humanitarian indicators when allocating aid funds to recipient countries (Feyzioglu et al., 1998).

Reviewing the relevant aid allocation literature, Doucouliagos and Paldam (2008) examine whether the regression coefficient associated with per capita GDP growth in recipient countries is significantly correlated with the amount of received aid funds. The direction of this relationship is unclear a priori. If donor countries allocate aid funds on the basis of the humanitarian needs of recipient countries, we would expect that per capita GDP growth is negatively correlated with foreign aid inflows. In contrast, the proposed association would be positive if donors provide more foreign aid to recipient countries that have been particularly successful in the implementation of foreign aid projects, as reflected in higher per capita GDP growth rates. In both cases, simple OLS estimation in which per capita GDP growth is regressed on foreign aid becomes inconsistent and biased. The direction of the simultaneity bias depends on the specification of the structural equations regarding the data generation process of the growth and foreign aid variable. However, in the simple case without additional exogenous controls, and if slow-growing recipient countries attract more foreign aid, the direction of the simultaneous equation bias of the OLS estimate associated with the foreign aid variable would be negative. More specifically, the downward bias resulting from simple OLS regressions would underestimate the effect of foreign aid on per capita GDP growth.[5]

[5] As an 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 problem of simultaneity in the aid effectiveness literature is addressed with appropriate instrumental variables (IV) estimation techniques, including 2SLS (Burnside and Dollar, 2000; Brückner, 2013; Arndt et al., 2015), and panel GMM regressions (Hansen and Tarp, 2001; Dalgaard et al., 2004; Rajan and Subramanian, 2008), although all attempts to convincingly demonstrate the existence of simultaneity bias in the aid and growth relationship have failed so far (Doucouliagos and Paldam, 2011). Other studies have used lagged values of independent and possibly endogenous right-hand-side variables as predetermined in the structural growth equation to overcome endogeneity concerns in the association between foreign aid and growth (Feyzioglu et al., 1998; Dalgaard and Hansen, 2001). The latter may look like an elegant solution to the endogeneity problem, but on closer inspection, it turns out that the positive coefficient associated with lagged aid in a regression with current per capita GDP growth as the dependent variable may be completely spurious, as it reflects the possibility of reverse causation (Roodman, 2008). The reason is that if the causality runs from growth to aid, then any positive relationship between per capita GDP growth as the dependent variable that employs *lagged* aid as an explanatory variable would simply reflect the counter-cyclical behavior of foreign aid flows with per capita GDP growth outcomes. Specifically, if better growth outcomes were followed by poor growth outcomes (by virtue of the mean reversion property of the long-run growth path) and if poor growth attracted more foreign aid, then the positive association between per capita GDP growth and lagged aid would reflect the impact of growth on foreign aid and not the other way around (Clemens et al., 2012).

2.4 Measurement Error Problem

The aid effectiveness literature is confronted with problems of data availability, as the total amount of foreign aid attributed to a country is usually incomplete due to the large number of potential donors, including multinational organizations, individual countries, and private organizations. Foreign policy considerations regarding the allocation of bilateral aid flows may, for instance, cause herding behavior among donor countries (Frot and Sant, 2011), which may not be covered by official development assistance databases. Thus, the aid effectiveness literature takes into account only a fraction of the total foreign aid flows a country receives.

In addition to the incomplete coverage of officially recorded bilateral and multilateral foreign aid flows throughout recipient countries, there also exists the well-known valuation problem of transferred aid flows from donors to recipients (Qian, 2015). For example, if a significant portion of transferred aid is spent within donor countries (e.g., due to the provision of technical assistance, administrative services, and manufacturing products), then foreign aid flows could vary across countries due to differences in labor

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.

costs, relative prices of manufacturing products, and transportation costs.

Thus, the incomplete coverage of officially recorded aid flows, the composition of aid types across recipient countries, and the way aid is valued across countries and over time lead to a serious problem of measurement error in the key foreign aid variable in the aid effectiveness literature. Even if the nature of the measurement error were purely random, this would result in a serious attenuation bias, thus biasing the regression coefficient associated with the foreign aid variable towards zero in simple OLS regressions.

Furthermore, the reliability of official statistics on GDP as an indicator of economic activity in low-income countries is a frequently discussed issue in the development economics literature. Due to insufficient statistical capacities, institutions, and law enforcement, the shadow economy often makes up a large part of the economy in developing countries (Schneider and Enste, 2000; Henderson et al., 2012). Obviously parts of the effect of transferred foreign aid will end up in the unmeasured shadow economy, leading to regressions that underestimate aid effectiveness. In addition, Galiani et al. (2017) show that recipients are only eligible for aid from the International Development Association if their per capita income is below a certain threshold. This might foster strategic reporting of GDP, which would introduce systematic measurement error in the dependent variable, leading to endogeneity of the foreign aid variable in OLS regressions. These arguments raise the fundamental question of whether GDP is a proper measure of the effects of foreign aid on development outcomes, as the use of officially reported GDP measures in low-income (aid recipient) countries as the dependent variable undermines proper identification of the causal effect of foreign aid on per capita GDP growth.

2.5 Endogenous Sample Selection Bias

Finally, the vast majority of the cross-country aid and growth studies face a serious sample selection problem in the choice of countries and the time horizon analyzed.[6] The first concern is the selection of aid-recipient countries based on recorded aid flows from official development assistance databases. The bulk of empirical studies employ data on official development assistance (ODA) from the OECD's Development Assistance Committee (DAC). This database is far from complete, as aid flows originating from non-OECD countries, the World Bank, and other multilateral organizations are not recorded. In principle, the OECD's DAC database is unsuitable for choosing aid-recipient countries for empirical analysis. Since the motives behind the allocation of aid flows to recipient countries might differ systematically among OECD, non-OECD, and other multilateral organizations, this introduces serious sample selection bias in the relationship between foreign aid and economic growth.

The second concern regarding the problem of sample selection is closely connected to the issue of omitted variables confounding the relationship between foreign aid and economic growth. The reason is that to reduce the problem of omitted variables bias in the estimation, the empirical aid effectiveness

[6] A non-exhaustive list of studies, each with different observations, includes Boone (1996), Burnside and Dollar (2000), Rajan and Subramanian (2008), Angeles and Neanidis (2009), and Galiani et al. (2017).

literature controls for a large battery of economic policy, governance, institutional, and socioeconomic controls. However, the inclusion of a large set of country-level controls creates the additional problem of sample selection bias, since the availability of data on these controls is poor in many underdeveloped countries (Hodler and Knight, 2011). The reason is that in countries in which foreign aid accounts for a large proportion of the government budget, many country-level controls are either of poor statistical quality or are simply not available because of insufficient human and technical capacities in low-income countries. This issue further aggravates the sample selection bias if the mechanisms behind the missing country-level controls are non-randomly determined.

From a technical standpoint, standard OLS estimation becomes inconsistent if the sample selection process is endogenously determined (Wooldridge, 2010, Chapter 19). This issue has been recognized in the study by Arndt et al. (2010) employing alternative estimation approaches, which explicitly accounts for the endogenous selection process in the study of aid and growth using the Heckman (1979) approach and the inverse probability weighted least squares (IPWLS) estimator. In addition, using multiple imputation techniques to overcome the endogenous sample selection problem 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.

2.6 Possible Identification Strategies to the Endogeneity Problem

The empirical aid effectiveness literature has made use of a series of possible identification strategies to overcome the aforementioned endogeneity problems. One is the use of standard IV estimation techniques if a credible time-varying instrumental variable for the potentially endogenous foreign aid variable is available that satisfies the necessary exclusion and relevance condition. However, only a few empirical studies to date have convincingly estimated the causal impact of foreign aid on per capita GDP growth (Galiani et al., 2017) due to the difficulty of identifying a credible IV in non-experimental observational data (Deaton, 2010; Temple, 2010).[7]

Difference GMM and system GMM estimation techniques (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) have enjoyed increasing popularity in the empirical aid effectiveness literature (Dalgaard et al., 2004; Rajan and Subramanian, 2008). There are two main reasons for this. First, the availability of statistical packages has made these complicated estimators available to a broader research community (Roodman, 2009a). Second, the possibility to create GMM-style IV estimates is appealing to applied economists as it circumvents the somewhat burdensome search for credible IVs for potentially endogenous variables. However, the in some cases indiscriminate use of GMM methods has raised con-

[7] The usual instrumentation strategy that employs population size as a potential IV have proven inappropriate in 2SLS applications, as it does not fulfill the necessary exclusion condition. In particular, it has been shown that population size indirectly affects economic growth through additional (potentially omitted) transmission channels in the second stage regression, thus casting serious doubts on the validity of population size as an excluded instrument in all empirical foreign aid and growth studies (Bazzi and Clemens, 2013).

cerns about the validity of the instrumentation strategies used due to instrument proliferation and weak GMM-style IVs (Roodman, 2009b; Bazzi and Clemens, 2013).

Other identification strategies used in empirical research on foreign aid include the use of natural experiments that exploit exogenous variation through quasi-randomization in combination with IV estimation techniques (Eisensee and Strömberg, 2007; Faye and Niehaus, 2012; Nunn and Qian, 2014). In addition, Randomized Controlled Trials (RCTs) have become increasingly popular in development economics to evaluate the effectiveness of specific interventions in important areas of development, such as health, education, and governance (Miguel and Kremer, 2004; Olken, 2007; Duflo et al., 2012). In contrast to the bulk of empirical aid effectiveness studies based on cross-country observations, RCTs make an important and necessary contribution to the aid effectiveness literature. This line of research provides detailed information about the effectiveness of specific intervention measures under varying experimental conditions, thus providing decision makers with guidance on the allocation of limited aid funds to a selected number of projects under certain cost and benefit considerations in order to improve the living conditions of people in less developed countries.[8] However, practical problems in the implementation of RCTs and lack of detailed understanding of the underlying mechanisms cast serious doubts about the external validity of field experiments as an efficient policy instrument to reduce poverty in the developing world (Deaton, 2010).

Overall, invalid instrumentation strategies, skepticism about the external validity of RCTs, and the inappropriateness of econometric methods to resolve all of these technical problems show why development economists have failed to convincingly identify the true effect of foreign aid on economic growth in low-income countries.

3 Grid Cell Analysis, Identification Approach, and Aid Effectiveness

In this section, we outline the proposed grid cell empirical approach to overcome the aforementioned endogeneity problems 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 rather than global performance measures that are directly linked to the presence of specific foreign aid projects. We elaborate on these and additional technical issues to resolve the identification problem in the empirical aid effectiveness literature.

[8] Duflo and Kremer (2005) provide a review of RCTs designed to increase school attendance in developing countries, suggesting that educational attainment – including school enrollment rates and test score performance – in Kenya has substantially improved through the increased availability of inexpensive health care, reduction of schooling fees, and the provision of school meals.

3.1 On the Importance of Spatial Resolution

In the foreign aid and economic growth literature, the issue of spatial resolution has not been researched adequately and is only touched on in passing in most cross-country analyses. There is striking but limited cross-country evidence that local biogeographic conditions affect aid effectiveness significantly. For example, Dalgaard et al. (2004) provide empirical evidence that the effectiveness of foreign aid flows is conditional on the share of a country's land area in the tropics. Additionally, Boone (1996) found that when the regression model includes small countries in which aid inflows account, by definition, for a much larger share of real GDP, the association between the rate of investment and the share of foreign aid to total GDP becomes highly statistically significant with the expected positive sign. It seems odd that the author excludes these observations from the overall analysis where the recipient's aid flows are larger than 15% of GDP. In contrast, small countries seem to be the most suitable unit of analysis to study the effectiveness of foreign aid when using officially reported national accounts statistics. The findings in Boone (1996) suggest that the effectiveness of foreign aid flows is closely tied to the particular location and that this issue is significantly reflected in national accounts data when using small instead of large countries.[9]

In contrast to the approaches commonly employed in the empirical aid effectiveness literature, our grid cell analysis addresses the identification problems discussed in the previous section by using equally sized grid cells with an arbitrary spatial resolution of 0.5 decimal degrees latitude $\times$ longitude (approximately 55 km $\times$ 55 km at the equator) that covers the entire world from -180 to 180 degrees longitude and 90 to -90 degrees latitude as the unit of investigation.

The proposed approach prevents the occurrence of the aforementioned aggregation problems by using highly disaggregated information on the aid projects and the locations where they took place. Because of the detailed disaggregated information, we are able to take the sector, time, and geographic distribution of the aid projects in a specific grid cell into account. In addition, the low aggregation level permits the empirical analysis to separate the effect of the implemented aid projects within a specific grid cell from (perhaps offsetting) effects of other projects and/or unrelated events taking place in more distant grid cells. The sector-specific distribution is accounted for by calculating various foreign aid variables along the main sector code. Furthermore, we examine the heterogeneity of estimated aid effects over the duration of the project. The geographic distribution of the projects within a country is accounted for by assigning the single projects to the precise location where they took place. Narrowing the analyzed area to small grid cells limits the influence of unrelated events that occurred further away. A local conflict in another part of the country is thus less likely to obscure the effect of development programs implemented in the specific grid cell under consideration. In addition, the proposed grid cell approach is suitable to control for prevailing local conditions (e.g., biogeographic, climatic, socioeconomic, and demographic factors) affecting both the allocation of development programs across grid cells and observed poverty levels.

[9] In particular, Boone (1996) argues that aid effectiveness in small countries directly reflects the impact of directed aid programs that are easier for potential donors to monitor and less fungible given the small size of the economy.

Furthermore, since grid cells are nested within countries, we are able to control for a large set of country-year fixed effects, thus implicitly accounting for unobserved heterogeneity in the allocation of bilateral aid flows to recipient countries. As outlined in the previous section, these factors are typically country-specific and time-variant and might significantly obscure the identification of the true effect of aid on development outcomes. 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.

The proposed grid cell approach further mitigates simultaneity concerns in the aid and growth relationship. Although it is conceivable that national and multinational organizations might allocate specific development programs by 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.[10] In addition, we 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 other national and multinational aid organizations 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.

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 development 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 GDP (Chen and Nordhaus, 2011; Henderson et al., 2012).[11] Through the use of satellite-measured night-time light data, we avoid a problem that has been discussed extensively in the literature of reliability of officially reported GDP statistics in recipient countries, including strategic reporting, measurement error, and insufficient human and technical capacities of national statistical institutions for data collection and reporting.

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 prevalent in the literature based on cross-country observations. A positive side-effect of this approach 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.

[10] To underline this point, we show in the sensitivity analysis that the main findings are not driven by the selection of grids.

[11] A detailed discussion on data construction and sources as well as possible strengthens and weaknesses of the satellite-measured night-time light measure is provided in the data section below.

3.2 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 degrees grid cells. The method of estimation is OLS with clustered standard errors that are robust to serial autocorrelation within grid cells and spatial correlation across grid cells within countries:

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

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.[12] The term υ refers to a grid-cell-specific idiosyncratic error term. 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 **X** 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 **RD** 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 and population data, since we used a slight transformation of the original data (e.g., adding a 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 due, for example, to the inadequate spatial resolution of the Gridded Population of the World data set (CIESIN-FAO-CIAT, 2007).[13]

[12] 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.

[13] 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.

The high-resolution grid cell econometric approach thus accounts for a number of identification problems that cannot be addressed due to limited degrees of freedom in cross-country empirical studies. 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 **Z** in the regression equation. In the first step of the empirical analysis, we therefore assess the model's overall predictive power and the possible endogeneity in the allocation of World Bank foreign aid projects to the inclusion of this set of grid-cell-specific geospatial indicators **Z**. However, there might be additional unobserved grid-cell-specific and time-constant factors not covered by these variables. Therefore, in a second step, we replace the vector **Z** 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.

In the remaining discussion, 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. As can be seen from a simple transformation of Equation (1) by adding $\ln(0.01 + Light_{g,c,t-1})$ to both sides:

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

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 OLS 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 more optimistic picture of the effectiveness of foreign aid on current night-time light growth. 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. 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. To address doubts raised in the aid effectiveness literature about the ability of econometric techniques to identify the true causal impact of foreign aid on development outcomes, we report coefficient estimates derived from pooled OLS, Fixed Effects, difference GMM, and system GMM regressions. In doing so, we confirm previous findings about the direction of bias of the various estimators (Hauk and Wacziarg, 2009) and at the same time address possible caveats to the use of dynamic panel data GMM methods in the presence of weak GMM-style IVs (Bazzi and Clemens, 2013).

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 $\times$ longitude (approximately 55 km $\times$ 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.[14]

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 ($\approx$ 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.[15] 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.[16] More importantly, the use of satellite-measured night-time light data is particularly relevant for

[14]Table 9 provides detailed summary statistics of the main regression variables. See also section D in the supplemental appendix to this paper for additional information on data construction and sources of the various geospatial indicators.

[15]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).

[16]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,

research on a subnational rather than national level.[17]

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.[18] 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.[19]

After successful completion of the inter-annual calibration approach of the various satellite-year observations, we construct a sum of lights measure that corresponds to the sum of inter-annual calibrated DN pixel-level values within 0.5 decimal degree latitude $\times$ longitude grid cells. The upper panel of Figure 1 illustrates how the sum of lights index of the inter-annual calibrated night-time light image of satellite series F18 in the year 2013 were constructed at the grid cell level. As an example, this figure shows the grid cells of Nigeria and the corresponding pixel-level DN values. Given this satellite night-time light image, the sum of lights measures were then constructed using the pixel-level DN values that fall within the corresponding boundaries of 0.5 decimal degree grid cells.

Figure 11 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.[20] The estimated elasticity of the sum of lights measure with respect to real GDP (net of country and year fixed effects)[21] 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.

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.

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

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

[19] The interested reader is referred to section D 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.

[20] 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/.

[21] 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).

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.

Table 8 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 2 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. The lower panel of Figure 1 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:

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

To assess the impact of World Bank foreign aid projects on night-time light growth across grid cells, we further differentiate Equation (7) with respect to the time duration of implemented development programs (i.e., project-specific annual disbursement flows with a minimum time duration of 3, 6, 9, 12, and 15 years).

Furthermore, the effectiveness of foreign aid flows on development outcomes may depend on the type of implemented aid projects (Rajan and Subramanian, 2008). It seems reasonable to expect that the impact of development assistance varies across the different types of aid projects categorized as social (e.g., education, health, and water supply and sanitation) and economic aid (e.g., transportation, energy supply, financial services, and agricultural and industrial assistance). Thus, we construct various financial aid flow variables according to the main sector code, as proposed by the AidData (2016) database. As argued in the economic growth and foreign aid literature, the aggregation of foreign aid flows spanning multiple sectors and purposes into one single monetary value may cause an over-aggregation problem (Tierney et al., 2011; Clemens et al., 2012). Foreign aid flows aimed at improving human health, for instance, may affect development outcomes quite differently than aid flows aimed at improving the economic infrastructure in a particular location. For this reason, we employ the main sectoral coding scheme in AidData (2016) to examine whether aid effectiveness varies by purpose. The main sector coding methodology in AidData (2016) is based on the OECD's Creditor Reporting System (CRS) database. The AidData (2016) coding scheme employs this classification to assign multi-sector coding to the available set of World Bank foreign aid projects that reflects the project's main purpose (e.g., education, health, or sanitation). It is worth mentioning that annual project-specific disbursement flows are not further stratified with respect to main sector code. Instead, we uniformly assign annual disbursement flows to multi-sector World Bank foreign aid projects.

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., 2010a; 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. In a first exercise, 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.

Thereafter, we examine the effectiveness of World Bank foreign aid projects on grid cell night-time light growth with respect to the project's duration and main sector code (e.g., education, health, and economic infrastructure).

5.1 Examining the Impact of Unobserved Country and Grid-Cell-Level Heterogeneity

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 the particular grid cell ever experienced a World Bank foreign aid project in a given year, and zero otherwise (columns 1 to 6). Next, we use a logarithmic specification in the number of implemented World Bank foreign aid projects (columns 7 and 8), and finally we use project-specific annual disbursement flows (columns 9 and 10) as our preferred geospatial foreign aid indicator.

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 points lower night-time light growth rate in the same year.[22] However, as discussed above, 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 the aforementioned endogeneity concerns in the relationship between foreign aid and grid cell night-time light growth.

The results reported in column (2) examine the change in the coefficient estimates associated with the various geospatial foreign aid indicator variables to the inclusion of country FE. Therefore, the estimated coefficients reported in this model specification utilize the within-country variation in grid cells (e.g., variation of grid cells across time and across grid cells within countries). The inclusion of country FE in the regression equation changes the empirical results substantially. Specifically, the coefficient estimates of the contemporaneous and the two-year lagged geospatial foreign aid indicator now display positive and highly statistically significant associations with grid cell night-time light growth. A grid cell in which a World Bank foreign aid project is currently taking place experiences 8.10 percentage points higher night-time light growth in the same year than grid cells without World Bank foreign aid projects. In addition, the influence of World Bank foreign aid projects that took place two years ago have an even greater effect on night-time light growth (14.60 percentage points).[23]

The estimates reported in column (3) add a full set of year FE into the regression equation to control for world-wide aggregate demand and supply shocks. The coefficients associated with the contemporaneous geospatial foreign aid indicator variable increase slightly, while the two-year lagged foreign aid variable decreases in magnitude. Nevertheless, both regression coefficients remain highly statistically significant at the 1% significance level.

In the following, 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. The corresponding estimates are shown in column (4). The main results remain qualitatively unchanged to the inclusion of country-year FE in the regression model.

Taken together, the results from model specifications (2) to (4) suggest 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, as elaborated in detail in Section 2 of this paper.

[22] According to the estimated light elasticity with respect to real GDP reported in section 4.1, this finding implies a reduction in real GDP of approximately $(16.36 \times 0.30) \approx 4.91$ percent.

[23] Similarly, this would correspond to a $(8.10 \times 0.30) \approx 2.43$ and $(14.60 \times 0.30) \approx 4.38$ percent increase in real GDP resulting from the current and two-year lagged foreign aid indicator variables, respectively.

To assess the sensitivity of the previous results to unobserved heterogeneity at the grid cell level, the estimates shown in column (5) 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 the power transmission line, railroad, and road line 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 columns (2) to (4) are additionally confounded by the existence of grid-cell-specific factors. The results therefore confirm the arguments in the discussion above, 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, railroad, and road line).

The partial R^2 in column (5) – 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 (6), 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 (5). Consequently, the inclusion of grid-cell-specific FE in model specification (6) 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. This result is expected given the efficiency loss in estimation when including grid cell FE in the regression model that removes the between-variation across grid cells within countries.

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 effect persists until the second year following the implementation of the World Bank foreign aid projects. Specifically, grid cells that were subject to foreign aid projects 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 (6) 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, ceteris paribus, have a lower growth rate in night-time light intensity. 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-specific controls and 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. Again, 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 (7) and (8).[24] The estimates with grid-cell-specific controls, shown in column (7), reveal, once again, that the contemporaneous and the two-year lagged geospatial foreign aid indicator are still positive and statistically significant at conventional significance levels. The results reported in column (8) present coefficient estimates controlling for grid cell FE. Again, the contemporaneous and the two-year lagged geospatial foreign aid indicator are positive and statistically significant. Regarding the estimated 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 remaining two model specifications employ 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. In the regressions with grid cell FE shown in column (10), 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 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.

[24] 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.

To summarize the findings in this section, the results reveal that unobserved country-specific and grid-cell-level heterogeneity 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 measured by grid cell night-time light growth, as the point estimates associated with the various geospatial foreign aid indicators are likely biased toward zero.

5.2 Foreign Aid Duration

We argued that one reason hindering the identification of the true effect of foreign aid on development outcomes might be the aggregation of short- and long-term foreign aid projects into a single monetary value. In the following analysis, we examine how the effect of aid on grid cell night-time light growth varies by the number of years since the start of World Bank foreign aid projects. We expect that foreign aid projects with a shorter duration should affect grid cell night-time light growth within a relative short period of time. The corresponding results are reported in Table 2. The estimates shown in column (1) correspond to those in Table 1, column (10) and are reproduced for comparison purposes. Summarizing the main findings from columns (2) to (6), we find that the statistical association between grid cell night-time light growth and foreign aid is the highest for World Bank development programs with durations of at least 3 and 6 years. Considering foreign aid projects with an elapsed duration of at least 9 years, the estimates reveal that only the two-year time lagged geospatial foreign aid indicator is statistically significant at the 5% significance level. Interestingly, the results shown in columns (5) and (6) suggest that World Bank foreign aid projects with an elapsed duration of at least 12 or 15 years are only weakly correlated with grid cell night-time light growth, as indicated by the regression coefficient associated with the contemporaneous and one-year lagged foreign aid variable.[25]

5.3 Different Types of Foreign Aid Projects

The AidData (2016) database provides detailed information on the main sector codes of the various World Bank foreign aid projects. This distinction makes it possible to examine in more detail the effectiveness of foreign aid flows on grid cell night-time light growth by purpose. The corresponding estimates are reported in Table 3.

In column (1), we assess the impact of World Bank foreign aid flows in the education sector on grid cell night-time light growth. It is worth mentioning that World Bank foreign aid flows in the educational sector

[25] The results were qualitatively similar when we used the log of the number of World Bank foreign aid projects rather than project-specific annual disbursement flows. The corresponding estimates are available from the authors upon request.

are not statistically correlated with grid cell night-time light growth, which is in line with previous findings in the cross-country economic growth literature (Krueger and Lindahl, 2001). The insignificant results are consistent with the idea that investments in the educational sector only have an effect on grid cell night-time light growth in the long run.

In column (2), we examine aid effectiveness in the health sector on grid cell night-time light growth. The positive and statistically significant coefficient associated with the two-year lag suggests that foreign aid flows for the provision of health services are effective in medium-term.

We further investigate aid effectiveness in the main sector water supply and sanitation, which is shown in column (3). The impact of the contemporaneous foreign aid variable is positive and statistically significant, suggesting that local improvements in this key sector are immediately reflected in higher grid cell night-time light growth. Furthermore, the aid projects in the key sector of water supply and sanitation also have a medium-term effect, as the two-year lagged variable is statistically significant as well. Together, the contemporaneous and the two-year lagged effect associated with the geospatial foreign aid indicator in the water supply and sanitation sector have the strongest impact on grid cell night-time light growth among all of the sector codes analyzed.

Institutional capacity building is an important means of improving the living conditions of people in the developing world. The estimates for this form of aid are shown in column (4). Interestingly, foreign aid projects in the key sector of government and civil society are significantly correlated with grid cell night-time light growth. The significant coefficient associated with the second time lag suggests that institutional capacity building is, once again, effective only in the medium-term.

Improvements in social welfare services (e.g., to mitigate HIV/AIDS) and economic policy are additional means by which World Bank development programs seek to improve standards of living throughout the developing world. Indeed, the results reported in column (5) reveal a strong and statistically significant effect for the second time lag associated with the geospatial foreign aid variable. This result is consistent with the idea that social education in areas such as HIV/AIDS prevention is geared toward the medium term and therefore takes some time to have a positive effect on development outcomes.

Moreover, development programs to improve economic infrastructure and services are positively related to grid cell night-time light growth, as shown in column (6). These include measures in areas such as transport, storage, communications, energy generation and supply, and banking and financial services.

Since low agricultural productivity in many parts of the developing world is a major source of widespread rural poverty, the estimates reported in column (7) examine aid effectiveness in the production sector. We found that foreign aid flows aimed, for example, at agricultural development are significantly related to grid cell night-time light growth, as indicated by the positive coefficient associated with the second time lag of the foreign aid variable.

In column (8), we report coefficient estimates that evaluate the effectiveness of World Bank foreign aid projects in the key sectors of industry, mining, and construction. These kinds of aid projects are devoted to activities such as industrial development, the extraction of mineral resources, trade, and the tourism infrastructure. We find a positive but weak statistically significant regression coefficient associated with the contemporaneous foreign aid variable.

Finally, the specification examined in column (9) investigates the effectiveness of World Bank foreign aid projects in areas such as environmental protection and integrated aid projects (e.g., urban and rural development). The relationship of such aid activities to grid cell night-time light growth is positive and highly statistically significant, as indicated by the regression coefficient of the contemporaneous foreign aid variable.

In summary, the stratified sectoral analysis reveals that World Bank foreign aid projects differ substantially in effectiveness across key sectors. This result confirms previous concerns in the aid effectiveness literature regarding a possible aggregation problem when using a single monetary foreign aid measure that incorporates a variety of aid flows into different sectors in recipient countries.

6 Robustness 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 evaluate the robustness of the main findings to various dynamic panel data GMM estimators. Next, 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 Panel GMM Estimators

As discussed in Section 3.2, the grid cell fixed effects estimator suffers from a dynamic panel bias due to the presence of the lagged dependent variable on the right-hand side of the regression equation. The Generalized Method of Moments (GMM) estimators developed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998) have become the method of choice in dynamic panel data models. Applying the estimation approach by Arellano and Bond (1991), Equation (1) is transformed into first-differences, which effectively removes the individual fixed effects from the regression model. Since $E\left[\triangle \ln(0.01 + Light_{g,c,t}) \triangle \upsilon_{g,c,t}\right] \neq 0$, standard OLS estimation of the first-difference equation is still biased. However, employing the moment conditions $E\left[\ln(0.01 + Light_{g,c,t-s}) \triangle \upsilon_{g,c,t}\right] = 0$ for $t = 3, 4, \ldots, T$ and $s = 2, 3, \ldots, (t-1)$ results in the Arellano and Bond (1991) difference GMM estimator. It is important to note that even though this estimation framework has been developed to account for dynamic panel bias, it can also deal with endogeneity problems of other right-hand side regressors. Specifically, we use additional moment conditions of the type $E\left[\ln\left(0.01 + PWAD_{g,c,t-s}\right) \triangle \upsilon_{g,c,t}\right] = 0$ to address potential endogeneity concerns in the allocation of World Bank foreign aid projects to grid cells.[26]

The difference GMM estimator suffers from a weak instruments problem in cases where β_1 approaches zero and/or if the variance of the individual fixed effect (σ_η^2) relative to the variance of the idiosyncratic error (σ_υ^2) is large.[27] The reason is that in both cases, the time series property of $\ln(0.01 + Light_{g,c,t})$ becomes highly persistent, so that lagged levels become weakly correlated for the equation in first differences (Blundell and Bond, 1998; Bond, 2002). The system GMM estimator proposed by Blundell and Bond (1998) exploits additional moment conditions for the levels equation to account for the weak instruments problem of the difference GMM estimator. Starting from the equation in levels, the authors employ lagged differences to instrument for the endogenous variables in levels.[28] Based on this approach, we define additional moment conditions $E\left[\triangle \ln(0.01 + Light_{g,c,t-1})\varepsilon_{g,c,t}\right] = 0$ and $E\left[\triangle \ln\left(0.01 + PWAD_{g,c,t-1}\right)\varepsilon_{g,c,t}\right] = 0$ for $t = 3, 4, \ldots, T$, which can be used together with the moment conditions defined for the first-difference equation, where $\varepsilon_{g,c,t} \equiv \eta_g + \upsilon_{g,c,t}$, to form a system of equations in first-differences and levels.

The fact that both GMM estimators have potential strengths and weaknesses, we present regression coefficients from both difference GMM and system GMM estimates using various assumptions about the endogeneity of the foreign aid variable. We follow the suggestion in Caselli et al. (1996) and Bond et al. (2001) by partialling out the country-year fixed effects $\lambda_{c,t}$ from the dependent variable, potential endogenous regressors, and the remaining exogenous regressors based on Equation (1). The resulting two-step GMM coefficient estimates are invariant to this data transformation, which directly follows from the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963; Baum et al., 2007).

Table 4 reports regression coefficients by applying dynamic panel data GMM estimators to the regression equation (1). The results reported in columns (1) to (4) correspond to the difference GMM estimator, whereas columns (5) to (8) show coefficient estimates using the system GMM estimator. In addition, we report coefficient estimates that instrument for the lagged dependent variable only in columns (1), (2), (5), and (6), while in columns (3), (4), (7), and (8) we instrument for the foreign aid variable as well.

We employ the two-step GMM approach with standard errors clustered with respect to country-years. This option ensures that coefficient estimates, standard errors, and test statistics are robust to arbitrary heteroscedasticity and arbitrary spatial correlation across grid cells within countries. We test the validity of both estimators by reporting the *p-value* of the Arellano-Bond test for serial autocorrelation of the

[26] Given the moment conditions set in difference GMM, values of $\ln(0.01 + Light_{g,c,t})$ and $\ln\left(0.01 + PWAD_{g,c,t}\right)$ lagged two periods and more can be used as valid GMM-style IVs for the potentially endogenous right-hand-side variables $\triangle \ln(0.01 + Light_{g,c,t-1})$, $\triangle \ln\left(0.01 + PWAD_{g,c,t}\right)$, and $\triangle \ln\left(0.01 + PWAD_{g,c,t-1}\right)$ in the first-differenced equation.

[27] Those more familiar with difference GMM applications might base the argumentation on an estimation in levels, as shown in Equation (2). In this case, the weak instruments problem occurs when $\widetilde{\beta}_1$ approaches unity.

[28] In the levels GMM equation, the endogeneity is caused by the variables $\ln(0.01 + Light_{g,c,t-1})$ and $\ln\left(0.01 + PWAD_{g,c,t}\right)$ on the right-hand side of the regression equation.

first-differenced error term and the Hansen J test of overidentifying restrictions. By construction, first-order serial correlation in the first-differenced error term is to be expected, whereas second-order serial correlation invalidates the moment conditions in the corresponding difference GMM and system GMM estimation approach (Roodman, 2009a).

Regarding the validity of GMM-style IVs, it is worth mentioning that the reported Hansen J statistic is robust to the issue of arbitrary spatial correlation of grid cells within countries. It has been shown that not controlling for the grouped data structure in the empirical analysis results in rejecting the Hansen J statistic too often (Hoxby and Paserman, 1997). In addition, Roodman (2009b), Bowsher (2002) and Andersen and Sørensen (1996) show that instrument proliferation might weaken the statistical power of the Hansen J test considerably, leading to an overly optimistic acceptance of the null of joint validity of the instruments. Thus, to limit the number of instrumental variables in difference GMM and system GMM estimation, we follow the suggestion in Roodman (2009b) and provide regression results based on a collapsed IV matrix in columns (2), (4), (6), and (8). Finally, we perform corresponding tests of under-identification and weak identification in the set of GMM-style IVs in an auxiliary 2SLS estimation approach along the lines suggested in Bazzi and Clemens (2013). The first-stage 2SLS diagnostics of testing for under-identification and weak GMM-style IVs in the first-difference and levels equations are reported in Table 5.

To summarize the main findings from the various dynamic panel data GMM regressions shown in Table 4, the results based on the difference GMM estimator indicates that neither of the regression coefficients associated with the various foreign aid variables are statistically significant at conventional significance levels throughout the model specifications (1) to (4). In contrast, the results from the system GMM regressions in columns (5) to (8) are qualitatively similar to those reported in the baseline grid cell fixed effects specifications. Specifically, the regression coefficients associated with the contemporaneous and the two-year lagged foreign aid variables are positive and statistically significant at conventional significance levels. It is worth mentioning that the estimated regression coefficients associated with the various foreign aid variables from the system GMM regressions are larger in magnitude than the corresponding grid cell fixed effects estimates, consistent with the findings reported in Hauk and Wacziarg (2009).

However, the Hansen J statistic testing for GMM-style instrument validity, the Arellano-Bond statistic testing for second order serial autocorrelation of the first-differenced error term, and the first-stage 2SLS diagnostics testing for under-identification and weak identification of GMM-style IVs along the lines suggested in Bazzi and Clemens (2013) cast serious doubts on the validity of the instrumentation strategy based on the difference GMM and system GMM estimators. First, the Hansen J test strongly rejects the null hypothesis of joint validity of the GMM-style IVs (i.e., uncorrelated with the error term $v_{g,c,t}$ in Equation (1)) across all model specifications. Second, the Arellano-Bond test rejects the null hypothesis of no second-order serial autocorrelation of the first-differenced error term in all but one model specification (i.e., column (3)), suggesting that the corresponding GMM moment conditions are violated.[29]

[29]We tried alternative minimum GMM-style IVs lag structures (i.e., from 3 to up to 10 lags) to overcome the second-order serial autocorrelation in the first-differenced error term, but none proved satisfactory. The corresponding results are available from the authors upon request.

Finally, we examine the relevance and weakness of the set of IVs in difference GMM and system GMM estimations using the methodology developed in Bazzi and Clemens (2013). Table 5 reports the first-stage 2SLS diagnostics of testing for under-identification and weak identification of GMM-style IVs across the various 2SLS auxiliary regressions. Columns (1) to (4) are based on the first-differenced equation, while columns (5) to (8) refer to the equation in levels. Even though the Kleibergen and Paap (2006) rk LM statistic suggests that the set of GMM-style IVs are relevant in all but one model specification (i.e., column (4)) at conventional significance levels, the corresponding tests assessing the weakness of GMM-style IVs are less promising. We report two tests assessing the weakness of IVs: the non-robust Cragg-Donald and heteroskedasticity-robust Kleibergen-Paap rk Wald F statistic. Focusing on the model specifications that instrument for both the lagged dependent and the possibly endogenous foreign aid variable – i.e., columns (3), (4), (7), and (8) – the Kleibergen-Paap rk Wald F statistic indicates that the set of constructed GMM-style IVs are rather weak, since the corresponding 2SLS estimates have a maximum relative OLS bias larger than 30%.[30]

In conclusion, 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 casts serious doubts on the reliability of the instrumentation strategy based on the use of dynamic panel data GMM estimators.

6.2 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 grid cell high spatial resolution 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 estimated 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 of 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 (subnational) model specifications.[31]

[30] The critical values for assessing the weakness of IVs are tabulated in Stock and Yogo (2005) for various combinations in the number of endogenous variables, instruments, and the relative size of the OLS bias. Notice that these values only apply to the non-robust Cragg-Donald Wald F statistic based on the presence of i.i.d. errors, however, we follow the suggestion in Baum et al. (2007, p. 490) and apply these critical values with caution to the Kleibergen-Paap Wald F statistic which is robust to the presence of non-i.i.d. errors. See Bazzi and Clemens (2013) on the construction of $p - values$ for both test statistics assessing the weakness of IVs.

[31] 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, differences in land endowments in former times might have resulted in the endogenous formation of districts within countries that in turn affected the economic and demographic

Table 6 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. Turning to the various grid cell model specifications, the magnitude of the point estimates associated with the various foreign aid variables tends to decrease with decreasing grid cell spatial resolution levels, as shown in columns (3) to (10).[32] This is in line with the issue discussed in Section 2.2 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. Relative to column (3), the regression coefficient associated with the contemporaneous foreign aid variable tends to decrease in magnitude and reaches the highest statistical significance in column (9), which corresponds to the model specification with the highest grid cell spatial resolution level. In a similar vein, the magnitude of the point estimate associated with the two-year lagged foreign aid variable starts rising with increasing grid cell spatial resolution, it then becomes statistically insignificant in column (9), and finally turns positive and highly statistically significant in the specification with the highest grid cell spatial resolution, as shown in column (10). Thus, the results of this sensitivity analysis strongly point to the importance of spatial resolution to identify the true effect of foreign aid on development outcomes.

6.3 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 -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 10. 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

landscape of these regions that have persisted until today.

[32] 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.

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 pattern of 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.

6.4 Sensitivity to Spatial Spillovers

The results in Section 6.2 indicate that the point estimates change if the grid cell resolution is increased, suggesting the presence of spatial interdependencies across grid cells. In addition, since the spatial unit of analysis refers to 0.5 decimal degree grid cells, it is conceivable that the spatial procedure for matching foreign aid projects does not perfectly coincide with the level of night-time light activity in the respective grid cells. Figure 9 illustrates this point based on the pixel-level DN light density values for Kano, a major city in northern Nigeria. The grid cell analysis shows that spatially connected settlements such as cities are divided across different grid cells. According to Figure 9, the distribution of World Bank foreign aid projects across urban and sub-urban areas of Kano would likely improve the living conditions of the city as a whole given its importance as a major commercial location. We control for the issue of spatial dependence through the inclusion of spatially lagged dependent and independent variables in the regression equation. The presence of spatial dependence in the data would lead to a potential omitted variable bias problem associated with the main explanatory geospatial foreign aid variable if World Bank foreign aid projects tended to cluster in space. This would result in an amplified coefficient on the foreign aid variable that to some extent captures the potential spillover effect of foreign aid projects on night-time light growth emanating from nearby grid cells.

In Table 7, 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 **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 10 illustrates how contiguous grid cells are identified, as indicated by the direction of the eight arrows from the centroid of a particular grid cell. The centroid of each grid cell is marked with a square.[33]

[33] The resulting spatial contiguity weight matrix **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

We compare the main results relative to the inclusion of several spatial explanatory variables, as reported in column (1). The estimates shown in column (2) test the robustness of the main findings to the inclusion of night-time light growth from contiguous grid cells. This specification is analogous to estimating a spatial lag model, except for the fact that we include the first time lag of the spatially lagged dependent variable in the regression model to remedy potential endogeneity concerns with respect to the inclusion of a spatially lagged dependent variable.[34] The results suggest that subsequent grid cell night-time light growth is positively associated with more prosperous neighboring grid cells. In column (3), we examine the robustness of the main results to the inclusion of spatially lagged explanatory variables. Neither of these model specifications substantially affect the main findings in this paper. The estimates reported in column (4) assess potential spillover effects of World Bank foreign aid projects originating from surrounding grid cells when including spatially lagged foreign aid variables into the regression equation. Interestingly, the estimates reveal that 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, as indicated by the positive and statistically significant coefficient associated with the second time lag of the spatially lagged foreign aid variable. This result is qualitatively robust to the inclusion of additional spatially lagged dependent and independent variables, as shown in column (5). 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.

Thus, it is important to point out that the main findings remain valid even if we control for spatial spillover effects from nearby grid cells. Furthermore, we are able to show that grid cells also benefit from the implementation of World Bank foreign aid projects in nearby grid cells, suggesting the presence of important spillover effects in the analysis of foreign aid and grid cell night-time light growth.

7 Conclusion

In this paper, we examined the effectiveness of geo-referenced World Bank foreign aid projects on development outcomes using equally sized (subnational) 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 the technical problems discussed in the cross-country aid effectiveness literature. The high spatial resolution of the proposed grid cells enables a detailed empirical analysis of location- and project-specific characteristics that significantly interfere with the identification of the true effect of foreign aid on development

row-standardization of the spatial contiguity weight matrix $\mathbf{W}$.

[34]Unfortunately, we have to admit that 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).

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, to the inclusion of various grid-cell-specific geospatial controls, various model specifications, and different estimation approaches.

We further assessed heterogeneous aid effects of World Bank foreign aid projects on grid cell night-time light growth regarding the project's time duration and main sector code. It is worth mentioning that World Bank foreign aid projects implemented in sectors such as health, water supply and sanitation, and economic infrastructure and services have strong and significant effects on grid cell night-time light growth. In addition, we find that short-term World Bank foreign aid projects (e.g., in water supply and sanitation) have a stronger effect on grid cell night-time light growth than long-term projects (e.g., in education).

We confirmed the main findings on aid effectiveness in a series of additional sensitivity tests. First, we estimated the baseline specification using dynamic panel data GMM estimators (i.e., difference GMM and system GMM). Although the regression coefficients derived from the system GMM estimator are qualitatively similar to the baseline grid cell FE specification, the corresponding diagnostic tests regarding the exclusion and relevance condition of the set of GMM-style IVs cast serious doubts on the validity of the instrumentation strategy using dynamic panel data GMM estimators. Second, 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. Third, 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 layout. 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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Appendix

A Regression Tables

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

	(1) Baseline Controls $\mathbf{I}(NPL_{g,c,t} > 0)$	(2) Country Fixed Effects $\mathbf{I}(NPL_{g,c,t} > 0)$	(3) Country and Year Fixed Effects $\mathbf{I}(NPL_{g,c,t} > 0)$	(4) Country-Year Fixed Effects $\mathbf{I}(NPL_{g,c,t} > 0)$	(5) Grid Cell Controls $\mathbf{I}(NPL_{g,c,t} > 0)$	(6) Grid Cell Fixed Effects $\mathbf{I}(NPL_{g,c,t} > 0)$	(7) Grid Cell Controls $\ln(0.01 + NPL_{g,c,t})$	(8) Grid Cell Fixed Effects $\ln(0.01 + NPL_{g,c,t})$	(9) Grid Cell Controls $\ln(0.01 + PWAD_{g,c,t})$	(10) Grid Cell Fixed Effects $\ln(0.01 + PWAD_{g,c,t})$
	Dependent Variable: Growth of Satellite-measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$									
$\ln(0.01 + Light_{g,c,t-1})$	-0.5704***	-0.6497***	-0.6488***	-0.6466***	-0.6915***	-0.9126***	-0.6916***	-0.9126***	-0.6915***	-0.9126***
	(0.0061)	(0.0046)	(0.0045)	(0.0044)	(0.0041)	(0.0033)	(0.0041)	(0.0033)	(0.0041)	(0.0033)
$\ln(0.01 + Population_{g,c,t})$	0.1835***	0.2791***	0.2790***	0.2782***	0.1124***	-0.0132	0.1123***	-0.0131	0.1126***	-0.0132
	(0.0062)	(0.0104)	(0.0104)	(0.0104)	(0.0086)	(0.0082)	(0.0086)	(0.0082)	(0.0086)	(0.0082)
Mean Precipitation	-0.0007***	-0.0005***	-0.0006***	-0.0006***	-0.0001	-0.0002**	-0.0001	-0.0002*	-0.0001	-0.0002**
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Mean Temperature	-0.0142***	0.0101***	0.0099***	0.0101***	0.0106***	-0.0108*	0.0107***	-0.0108*	0.0106***	-0.0108*
	(0.0010)	(0.0019)	(0.0019)	(0.0019)	(0.0026)	(0.0061)	(0.0026)	(0.0061)	(0.0026)	(0.0061)
SPEI Drought Index	0.0356***	0.0255***	0.0235***	0.0274***	0.0222***	-0.0001	0.0222***	-0.0001	0.0223***	-0.0001
	(0.0073)	(0.0056)	(0.0053)	(0.0063)	(0.0051)	(0.0022)	(0.0051)	(0.0022)	(0.0051)	(0.0022)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0422***	0.0019	0.0013	0.0044	0.0040	-0.0025	0.0037	-0.0025	0.0039	-0.0025
	(0.0068)	(0.0057)	(0.0057)	(0.0061)	(0.0042)	(0.0018)	(0.0042)	(0.0018)	(0.0042)	(0.0018)
Geo-Spatial Foreign Aid Indicator in t	-0.1636***	0.0810***	0.0912***	0.0977***	0.0439***	0.0149**	0.0099***	0.0032**	0.0030***	0.0008**
	(0.0359)	(0.0235)	(0.0227)	(0.0238)	(0.0161)	(0.0062)	(0.0034)	(0.0013)	(0.0009)	(0.0003)
Geo-Spatial Foreign Aid Indicator in $t-1$	0.0057	0.0212	0.0249	0.0232	0.0116	0.0029	0.0026	0.0007	0.0010	0.0004
	(0.0368)	(0.0265)	(0.0257)	(0.0261)	(0.0185)	(0.0071)	(0.0040)	(0.0015)	(0.0010)	(0.0004)
Geo-Spatial Foreign Aid Indicator in $t-2$	0.0281	0.1460***	0.1184***	0.1209***	0.0570***	0.0318***	0.0119***	0.0067***	0.0031***	0.0017***
	(0.0332)	(0.0227)	(0.0227)	(0.0228)	(0.0162)	(0.0068)	(0.0034)	(0.0014)	(0.0009)	(0.0004)
Number of Grid Cells	58,676	58,676	58,676	58,676	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	997,492	997,492	997,492	997,492
Partial R^2	0.701	0.756	0.757	0.756	0.797	0.948	0.797	0.948	0.797	0.948
Topographic Factors	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Land-Use Factors	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Microgeographic Factors	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Mineral Resources	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Land Area	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Absolute Latitude	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Share Urban Area	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Share Area Tropics	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Linguistic Diversity	No	No	No	No	Yes	N/A	Yes	N/A	Yes	N/A
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	No	Yes	Yes	No	No	No	No	No	No	No
Year Fixed Effects	No	No	Yes	No	No	No	No	No	No	No
Country-Year Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid Cell Fixed Effects	No	No	No	No	No	Yes	No	Yes	No	Yes

Notes: If not otherwise stated, the spatial unit of investigation refers to 0.5 decimal degrees latitude $\times$ longitude grid cells. The dependent variable refers to annual growth in satellite-measured night-time light intensity.

Independent variables: *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 indicate wetter weather than the historic (12-month) climate trend and vice versa. *ln(0.01 + Conflicts)* refers to the log of the number of conflict events. $\mathbf{I}(NPL_{g,c,t} > 0)$ refers to 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. $\ln(0.01 + NPL_{g,c,t})$ refers to the log of the number of World Bank foreign aid project locations. $\ln(0.01 + PWAD_{g,c,t})$ refers to the log of project-specific annual disbursement flows of World Bank foreign aid projects. *Topographic Factors* include the mean elevation value (in meters above sea level), the standard deviation of elevation, and the range of elevation, *Land Use Factors* include the mean value of cropland coverage (fraction ranging from 0 = low to 1 = high), the standard deviation of cropland, the range of cropland, and a geospatial indicator of land suitability for agriculture (ranging from 0 = low to 1 = high). *Microgeographic Factors* include the log of the distance from the grid cell centroid to the country's capital city, nearest settlement (e.g., with an estimated population $\geq$ 100,000 in the year 2000) border, coast, sea-navigable river, power transmission, railroad, and road lines. It further includes the log of the total railroad, road, and power transmission lines (in kilometers). *Mineral Resources* include the number of diamond mines and gemstone deposits. *Land Area* includes the log of the grid cell area (in square km). *Absolute Latitude* is the log absolute value of the grid cell centroid latitude in decimal degrees. *Share Urban Area* is the share of urban grid cell area. *Share Area Tropics* is the share of grid cell area in the tropics according to the Köppen-Geiger climate zone classification. *Linguistic Diversity* refers to a measure of ethno-linguistic diversity (based on relative area coverage of the various ethno-linguistic groups). *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 world-wide heterogeneity. *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.

The *Partial* R^2 refers to the model's R^2 after partialling out country, year, 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 countries, are reported in parentheses.

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

Table 2: Foreign Aid and Growth of Light Intensity (Foreign Aid Time Duration Analysis)

	(1) Baseline Estimates	(2) Foreign Aid Projects Duration ≥ 3 Years	(3) Foreign Aid Projects Duration ≥ 6 Years	(4) Foreign Aid Projects Duration ≥ 9 Years	(5) Foreign Aid Projects Duration ≥ 12 Years	(6) Foreign Aid Projects Duration ≥ 15 Years
	Dependent Variable: Growth of Satellite-measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$					
$\ln(0.01 + Light_{g,c,t-1})$	-0.9126***	-0.9126***	-0.9126***	-0.9126***	-0.9126***	-0.9126***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
$\ln(0.01 + Population_{g,c,t})$	-0.0132	-0.0132	-0.0133	-0.0136*	-0.0138*	-0.0138*
	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0083)	(0.0083)
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	-0.0108*	-0.0108*	-0.0108*	-0.0109*	-0.0109*	-0.0109*
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)
SPEI Drought Index	-0.0001	-0.0001	-0.0001	-0.0002	-0.0002	-0.0002
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0025	-0.0025	-0.0025	-0.0024	-0.0024	-0.0025
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
$\ln(0.01 + PWAD_{g,c,t})$	0.0008**	0.0008**	0.0008**	0.0002	0.0018*	-0.0029
	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0010)	(0.0027)
$\ln(0.01 + PWAD_{g,c,t-1})$	0.0004	0.0003	0.0005	0.0007	0.0015	0.0032*
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0010)	(0.0017)
$\ln(0.01 + PWAD_{g,c,t-2})$	0.0017***	0.0017***	0.0015***	0.0012**	0.0009	-0.0011
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0009)	(0.0011)
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	0.948	0.948	0.948	0.948	0.948	0.948
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: If not otherwise stated, the spatial unit of investigation refers to 0.5 decimal degrees latitude $\times$ longitude grid cells. The dependent variable refers to annual growth in satellite-measured night-time light intensity.

Independent variables: *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 indicate wetter weather 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-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.

The *Partial* R^2 refers to the model's R^2 after partialling out country, year, 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 countries, 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 Light Intensity (Main Sector Code Analysis)

	(1) Education	(2) Health	(3) Water Supply and Sanitation	(4) Government and Civil Society	(5) Other Social Infrastructure and Services	(6) Economic Infrastructure and Services	(7) Production Sectors	(8) Industry, Mining, and Construction	(9) Multi-Sector/ Cross-Cutting
	Dependent Variable: Growth of Satellite-measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$								
$\ln(0.01 + Light_{g,c,t-1})$	-0.9126***	-0.9126***	-0.9126***	-0.9126***	-0.9126***	-0.9126***	-0.9126***	-0.9126***	-0.9126***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
$\ln(0.01 + Population_{g,c,t})$	-0.0138*	-0.0138*	-0.0134	-0.0134	-0.0136*	-0.0132	-0.0133	-0.0136*	-0.0138*
	(0.0083)	(0.0083)	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)
Mean Precipitation	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0002*	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean Temperature	-0.0109*	-0.0109*	-0.0108*	-0.0109*	-0.0109*	-0.0108*	-0.0109*	-0.0109*	-0.0109*
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)
SPEI Drought Index	-0.0002	-0.0002	-0.0001	-0.0002	-0.0002	-0.0001	-0.0002	-0.0001	-0.0002
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0024	-0.0024	-0.0024	-0.0024	-0.0025	-0.0025	-0.0025	-0.0024	-0.0025
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
$\ln(0.01 + PWAD_{g,c,t})$	-0.0002	0.0015	0.0046**	0.0003	-0.0015	0.0020	0.0024	0.0053*	0.0099***
	(0.0022)	(0.0023)	(0.0019)	(0.0014)	(0.0021)	(0.0015)	(0.0019)	(0.0031)	(0.0032)
$\ln(0.01 + PWAD_{g,c,t-1})$	0.0005	0.0000	0.0014	0.0005	-0.0011	0.0006	0.0011	0.0047	-0.0001
	(0.0027)	(0.0029)	(0.0023)	(0.0015)	(0.0023)	(0.0016)	(0.0022)	(0.0037)	(0.0033)
$\ln(0.01 + PWAD_{g,c,t-2})$	0.0033	0.0066**	0.0050**	0.0067***	0.0074***	0.0083***	0.0049***	0.0039	0.0037
	(0.0026)	(0.0026)	(0.0022)	(0.0015)	(0.0022)	(0.0015)	(0.0018)	(0.0031)	(0.0031)
Number of Grid Cells	58,676	58,676	58,676	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	997,492	997,492	997,492
Partial R^2	0.948	0.948	0.948	0.948	0.948	0.948	0.948	0.948	0.948
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: If not otherwise stated, the spatial unit of investigation refers to 0.5 decimal degrees latitude $\times$ longitude grid cells. The dependent variable refers to annual growth in satellite-measured night-time light intensity.

Independent variables: *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 indicate wetter weather 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-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.

The *Partial* R^2 refers to the model's R^2 after partialling out country, year, 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 countries, are reported in parentheses.

*: 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 Dynamic Panel Data GMM Estimators)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator	Difference-GMM	Difference-GMM	Difference-GMM	Difference-GMM	System-GMM	System-GMM	System-GMM	System-GMM
Endogenous Variables	Light	Light	Light, Aid	Light, Aid	Light	Light	Light, Aid	Light, Aid
Collapsed IV Matrix	No	Yes	No	Yes	No	Yes	No	Yes
	Dependent Variable: Growth of Satellite-measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$							
$\ln(0.01 + Light_{g,c,t-1})$	-0.9979***	-1.0009***	-0.9973***	-1.0018***	-0.8379***	-0.8430***	-0.8385***	-0.8411***
	(0.0060)	(0.0050)	(0.0060)	(0.0048)	(0.0041)	(0.0042)	(0.0041)	(0.0042)
$\ln(0.01 + Population_{g,c,t})$	0.0027	0.0076	0.0045	0.0067	0.4423***	0.4811***	0.4417***	0.4740***
	(0.0320)	(0.0208)	(0.0315)	(0.0203)	(0.0159)	(0.0189)	(0.0153)	(0.0188)
Mean Precipitation	-0.0002**	-0.0003***	-0.0002**	-0.0003***	-0.0010***	-0.0008***	-0.0010***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Mean Temperature	-0.0125*	-0.0135**	-0.0111*	-0.0131**	0.0190***	0.0232***	0.0183***	0.0231***
	(0.0067)	(0.0060)	(0.0064)	(0.0061)	(0.0029)	(0.0032)	(0.0027)	(0.0032)
SPEI Drought Index	0.0009	0.0011	0.0012	0.0014	0.0371***	0.0343***	0.0364***	0.0340***
	(0.0026)	(0.0023)	(0.0029)	(0.0024)	(0.0080)	(0.0083)	(0.0078)	(0.0082)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0012	-0.0009	-0.0013	-0.0010	0.0045	0.0021	0.0049	0.0019
	(0.0010)	(0.0009)	(0.0011)	(0.0010)	(0.0032)	(0.0022)	(0.0038)	(0.0022)
$\ln(0.01 + PWAD_{g,c,t})$	0.0004	0.0000	-0.0086	-0.0032	0.0087***	0.0072***	0.0307**	0.0148
	(0.0006)	(0.0003)	(0.0086)	(0.0057)	(0.0014)	(0.0013)	(0.0141)	(0.0228)
$\ln(0.01 + PWAD_{g,c,t-1})$	0.0003	0.0003	0.0058	-0.0009	0.0022	0.0019	-0.0177	-0.0054
	(0.0004)	(0.0003)	(0.0109)	(0.0065)	(0.0014)	(0.0012)	(0.0131)	(0.0192)
$\ln(0.01 + PWAD_{g,c,t-2})$	0.0004	0.0000	0.0001	-0.0002	0.0077***	0.0061***	0.0061***	0.0033**
	(0.0011)	(0.0003)	(0.0012)	(0.0006)	(0.0014)	(0.0012)	(0.0018)	(0.0015)
Number of Grid Cells	58,676	58,676	58,676	58,676	58,676	58,676	58,676	58,676
Observations	938,816	938,816	938,816	938,816	997,492	997,492	997,492	997,492
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out
Number of Endogenous Variables	1	1	3	3	1	1	3	3
Number of IVs	163	28	312	42	191	40	354	52
GMM-Style IVs: Lagged Levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GMM-Style IVs: Lagged Differences	No	No	No	No	Yes	Yes	Yes	Yes
Minimum IVs Lag Structure	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2
Arellano-Bond Test for AR(1) $(p-value)$	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Arellano-Bond Test for AR(2) $(p-value)$	0.0850	0.0513	0.1022	0.0433	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Hansen J Test of IVs $(p-value)$	< 0.0001	< 0.0001	< 0.0001	0.0005	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Notes: If not otherwise stated, the spatial unit of investigation refers to 0.5 decimal degrees latitude $\times$ longitude grid cells. The dependent variable refers to annual growth in satellite-measured night-time light intensity.

Independent variables: *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 indicate wetter weather 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* refers 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. Constant term included but not shown.

Standard errors, robust to serial correlation within grid cells and spatial correlation across grid cells within countries, are reported in parentheses.

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

Table 5: Foreign Aid and Growth of Light Intensity (Instrumentation Strength of GMM-Style IVs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model Specification	Difference	Difference	Difference	Difference	Level	Level	Level	Level
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Endogenous Variables	Light	Light	Light, Aid	Light, Aid	Light	Light	Light, Aid	Light, Aid
Collapsed IV Matrix	No	Yes	No	Yes	No	Yes	No	Yes
	First Stage 2SLS Diagnostics: Testing for Underidentification and Weak GMM-Style IVs							
Kleibergen-Paap rk LM Statistic ($p - value$)	< 0.0001	< 0.0001	0.0166	0.1073	< 0.0001	< 0.0001	0.0830	0.0003
Cragg-Donald Wald F Statistic	2835.1619	20314.6492	51.8422	59.0918	1421.5022	11760.9085	85.3549	220.4363
H_0: Maximum relative OLS bias $> 10\%$ ($p - value$)	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
H_0: Maximum relative OLS bias $> 30\%$ ($p - value$)	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Kleibergen-Paap rk Wald F Statistic	269.4599	261.8229	3.3027	1.5536	198.9278	340.4973	3.3421	2.9243
H_0: Maximum relative OLS bias $> 10\%$ ($p - value$)	< 0.0001	< 0.0001	1.0000	1.0000	< 0.0001	< 0.0001	1.0000	1.0000
H_0: Maximum relative OLS bias $> 30\%$ ($p - value$)	< 0.0001	< 0.0001	0.4619	0.9996	< 0.0001	< 0.0001	0.4162	0.6520
Number of Grid Cells	58,676	58,676	58,676	58,676	58,676	58,676	58,676	58,676
Observations	938,816	938,816	938,816	938,816	997,492	997,492	997,492	997,492
Recodification Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out	Partialled Out
Number of Endogenous Variables	1	1	3	3	1	1	2	2
Number of IVs	163	28	312	42	164	28	315	43
GMM-Style IVs: Lagged Levels	Yes	Yes	Yes	Yes	No	No	No	No
GMM-Style IVs: Lagged Differences	No	No	No	No	Yes	Yes	Yes	Yes
Minimum IVs Lag Structure	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2	≥ 2

Notes: This table reports first-stage 2SLS diagnostics, testing for under-identification and weak identification of the set of GMM-style IVs. The estimates reported in columns (1) to (4) and (5) to (8) refer to the first-differenced and level equation of the baseline specification reported in Equation 1. The critical values for assessing the weakness of IVs are tabulated in Stock and Yogo (2005) for various combinations in the number of endogenous variables, instruments, and the relative size of the OLS bias. It is important to note that these critical values are only valid for the non-robust Cragg-Donald Wald F statistic based on the presence of i.i.d. errors. However, following the suggestion in Baum et al. (2007, p. 490), we apply these critical values with caution to the Kleibergen-Paap Wald F statistic, which is robust to the presence of non-i.i.d. errors. See the main text for additional details.

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. Constant term included but not shown.

Standard errors, robust to serial correlation within grid cells and spatial correlation across grid cells within countries, are reported in parentheses.

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

Table 6: Foreign Aid and Growth of Light Intensity (Sensitivity to Spatial Resolution Level)

	(1) Country Estimates	(2) District Estimates	(3) Grid Cell Size 4.0 Decimal Degrees	(4) Grid Cell Size 3.5 Decimal Degrees	(5) Grid Cell Size 3.0 Decimal Degrees	(6) Grid Cell Size 2.5 Decimal Degrees	(7) Grid Cell Size 2.0 Decimal Degrees	(8) Grid Cell Size 1.5 Decimal Degrees	(9) Grid Cell Size 1.0 Decimal Degrees	(10) Grid Cell Size 0.5 Decimal Degrees
	Dependent Variable: Growth of Satellite-measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$									
$\ln(0.01 + Light_{g,c,t-1})$	-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)
$\ln(0.01 + PWAD_{g,c,t})$	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)
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.

Independent variables: *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 indicate wetter weather 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 world-wide 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.

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.

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

Table 7: Foreign Aid and Growth of Light Intensity (Sensitivity to Spatial Spillovers)

	(1) Baseline Estimates	(2) Spatial Lag Light Variable	(3) Spatial Lag Control Variables	(4) Spatial Lag Foreign Aid Variable	(5) Full Model Specification
	Dependent Variable: Growth of Satellite-measured Night-Time Light Intensity: $\triangle \ln(0.01 + Light_{g,c,t})$				
Panel A: *Grid Cell Controls*					
$\ln(0.01 + Light_{g,c,t-1})$	-0.9126***	-0.9190***	-0.9126***	-0.9126***	-0.9190***
	(0.0033)	(0.0028)	(0.0033)	(0.0033)	(0.0028)
$\ln(0.01 + Population_{g,c,t})$	-0.0132	-0.0155*	-0.0159*	-0.0121	-0.0168*
	(0.0082)	(0.0082)	(0.0095)	(0.0081)	(0.0094)
Mean Precipitation	-0.0002**	-0.0003**	-0.0003	-0.0002*	-0.0003
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Mean Temperature	-0.0108*	-0.0116**	0.0005	-0.0107*	0.0013
	(0.0061)	(0.0059)	(0.0103)	(0.0061)	(0.0103)
SPEI Drought Index	-0.0001	0.0006	0.0035	-0.0001	0.0032
	(0.0022)	(0.0021)	(0.0044)	(0.0022)	(0.0044)
$\ln(0.01 + Conflicts_{g,c,t})$	-0.0025	-0.0023	-0.0025*	-0.0024	-0.0023*
	(0.0018)	(0.0017)	(0.0014)	(0.0018)	(0.0014)
$\ln(0.01 + PWAD_{g,c,t})$	0.0008**	0.0007**	0.0008**	0.0006*	0.0006*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\ln(0.01 + PWAD_{g,c,t-1})$	0.0004	0.0004	0.0004	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
$\ln(0.01 + PWAD_{g,c,t-2})$	0.0017***	0.0018***	0.0017***	0.0008**	0.0008***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Panel B: *Spatially Weighted 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)
W $\ln(0.01 + PWAD_{g,c,t})$				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)
W $\ln(0.01 + PWAD_{g,c,t-2})$				0.0007***	0.0008***
				(0.0002)	(0.0002)
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: If not otherwise stated, the spatial unit of investigation refers to 0.5 decimal degrees latitude $\times$ longitude grid cells. The dependent variable refers to annual growth in satellite-measured night-time light intensity.

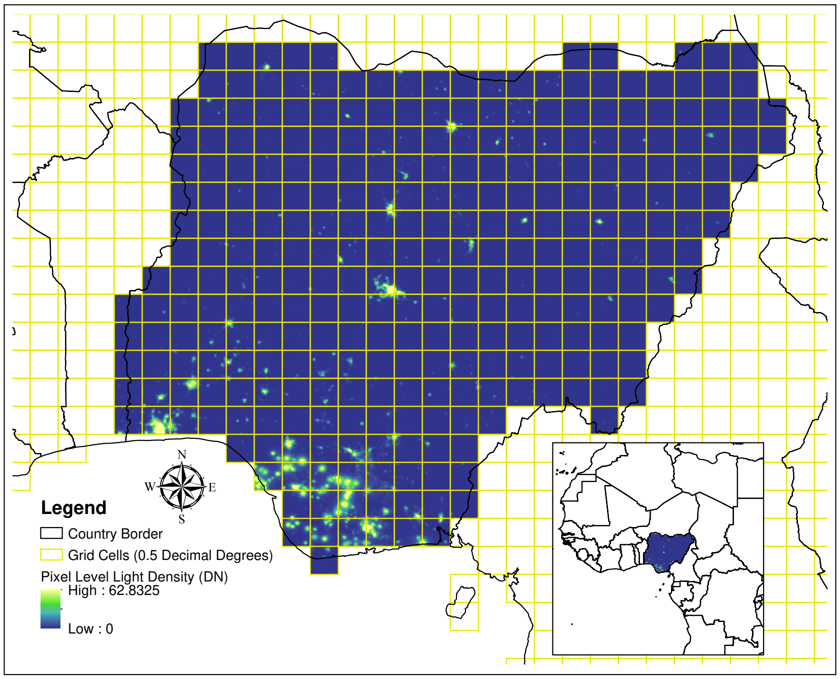
Independent variables: *ln(0.01 + Light)* refers to the log of the sum of digital number (DN) pixel-level values. *ln(0.01 + Population)* refers to the log of population, *Mean Precipitation* refers to the mean of total monthly precipitation (in millimeters per year), *Mean Temperature* refers to the mean annual temperature value (in Degree Celsius). *SPEI Drought Index* refers to a geospatial drought index where positive values indicate wetter weather 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.

The *Partial* R^2 refers to the model's R^2 after partialling out country, year, country-year, and grid cell FE from the regression model.

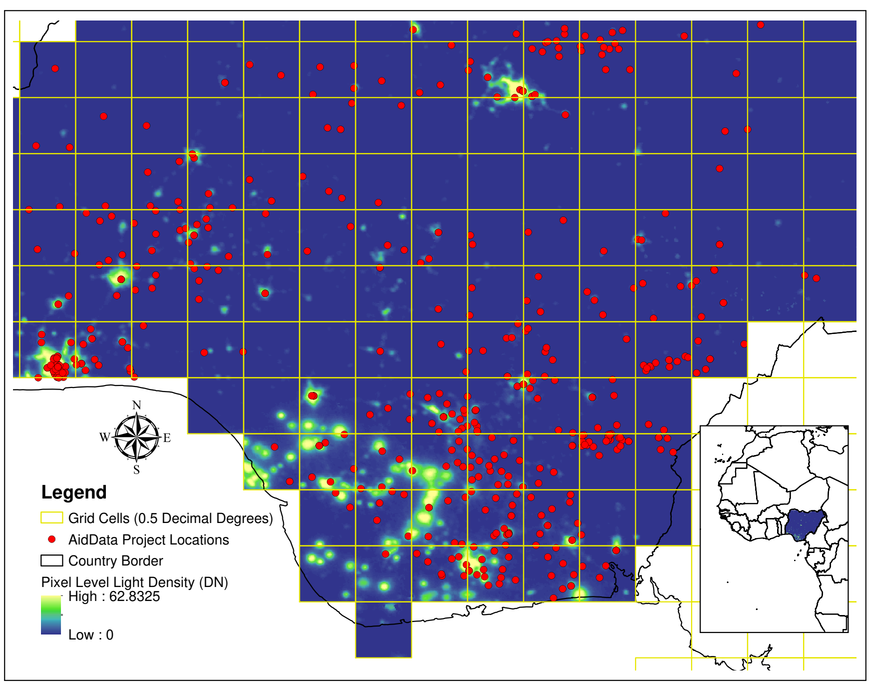
Standard errors, robust to serial correlation within grid cells and spatial correlation across grid cells within countries, are reported in parentheses.

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

B Figures

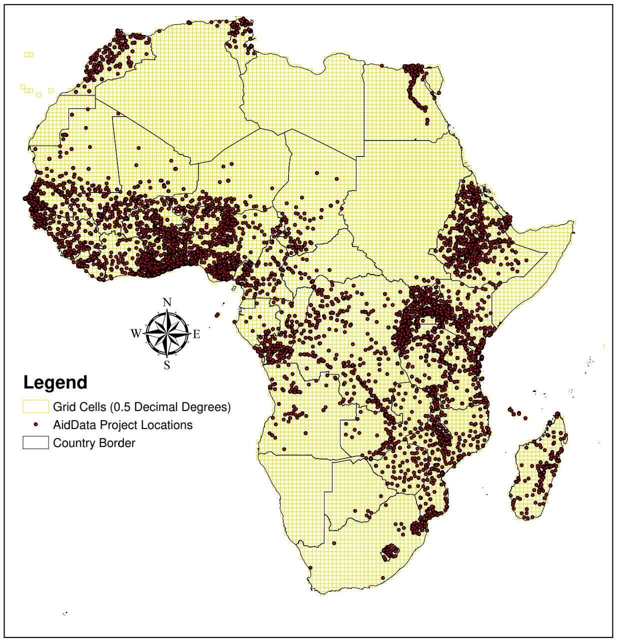


(a) Pixel-level Light Density across 0.5 Decimal Degree Grid Cells

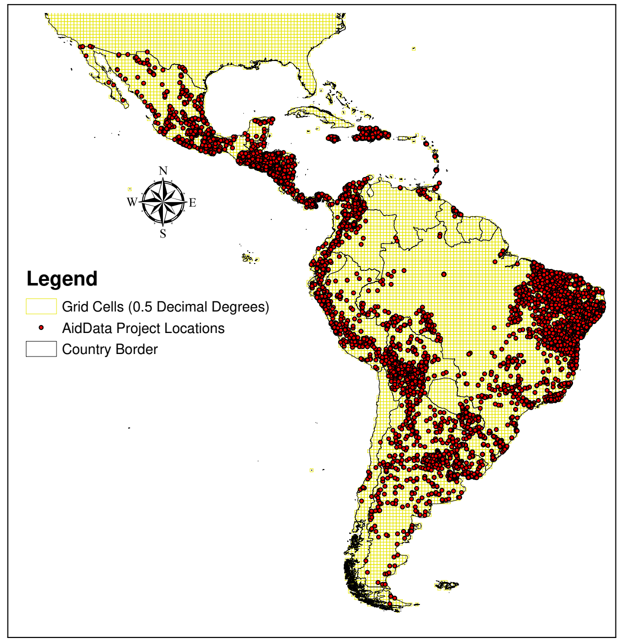


(b) AidData Project Locations Across 0.5 Decimal Degree Grid Cells

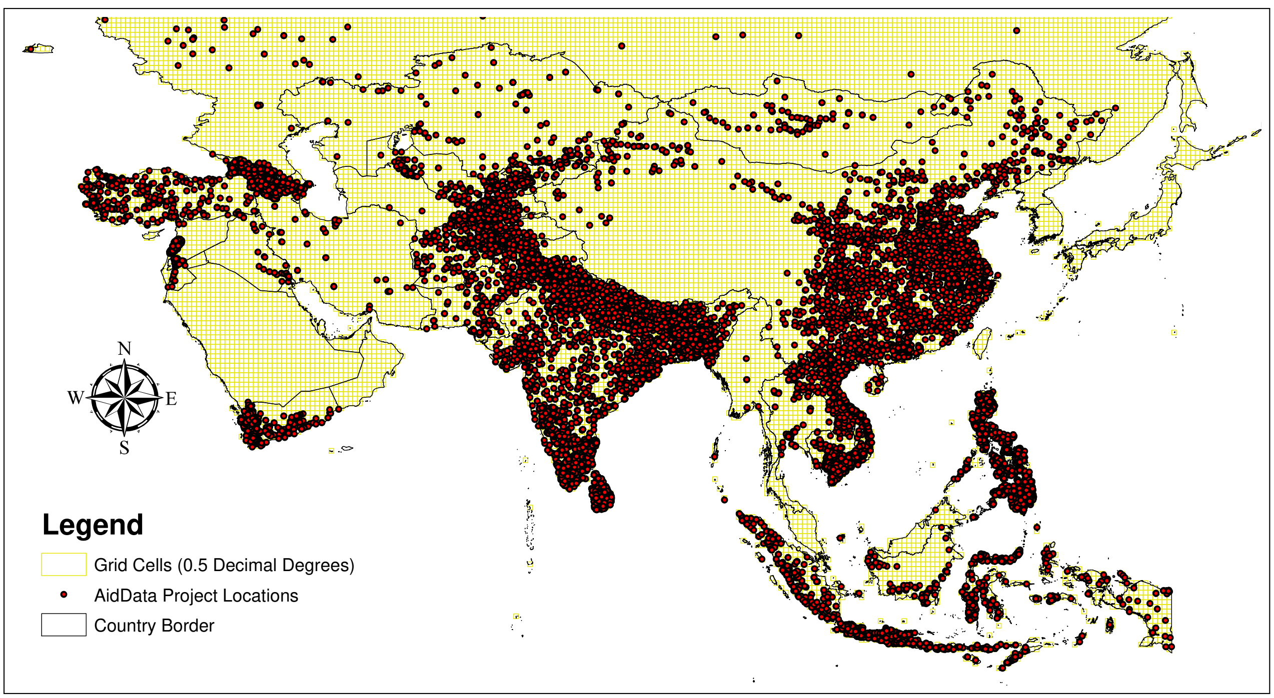
Figure 1: Pixel-level Light Density and AidData Project Locations across Grid Cells in Nigeria



(a) Africa

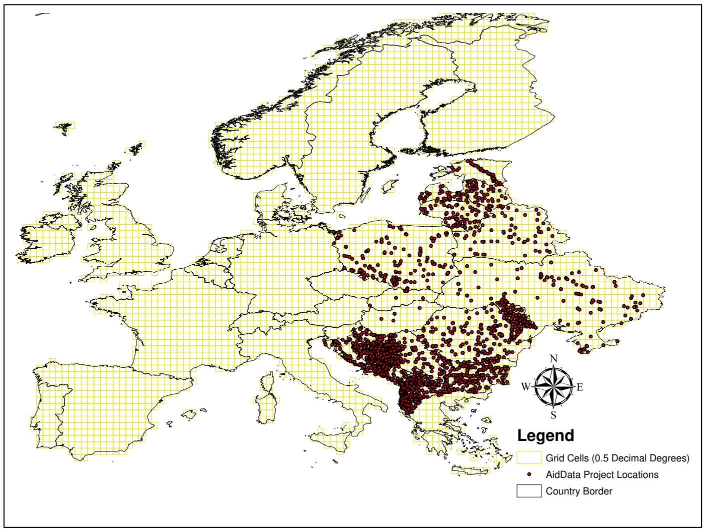


(b) Americas

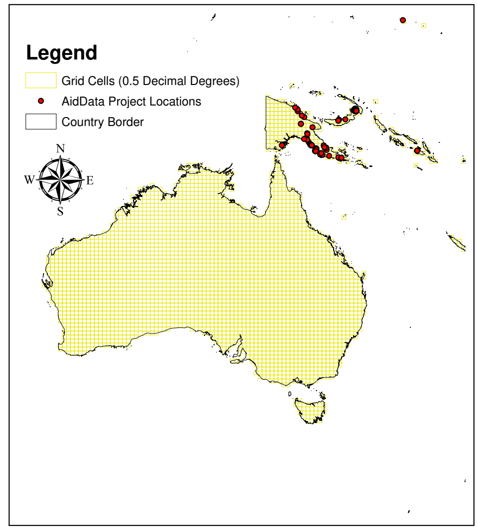


(c) Asia

Figure 2: Geographic Distribution of AidData Project Locations Across Continents



(d) Europe



(e) Oceania

Figure 2: *Continued*

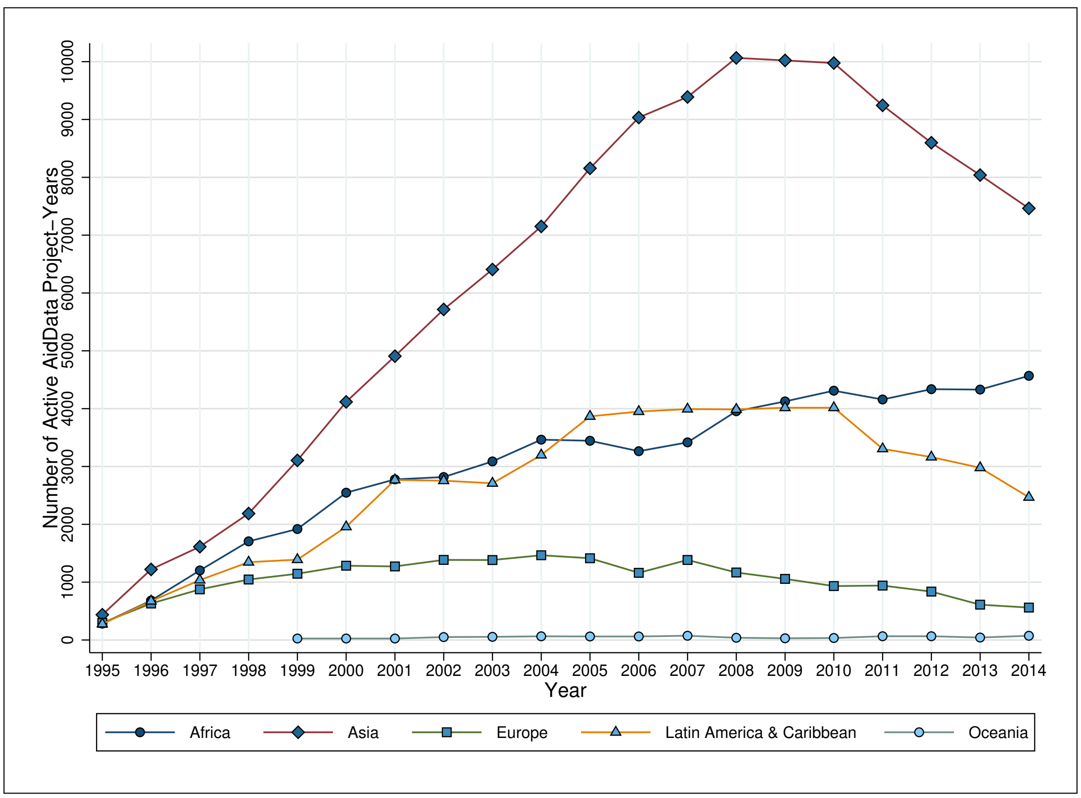


Figure 3: Number of Active AidData Project-Year Observations Across Regions

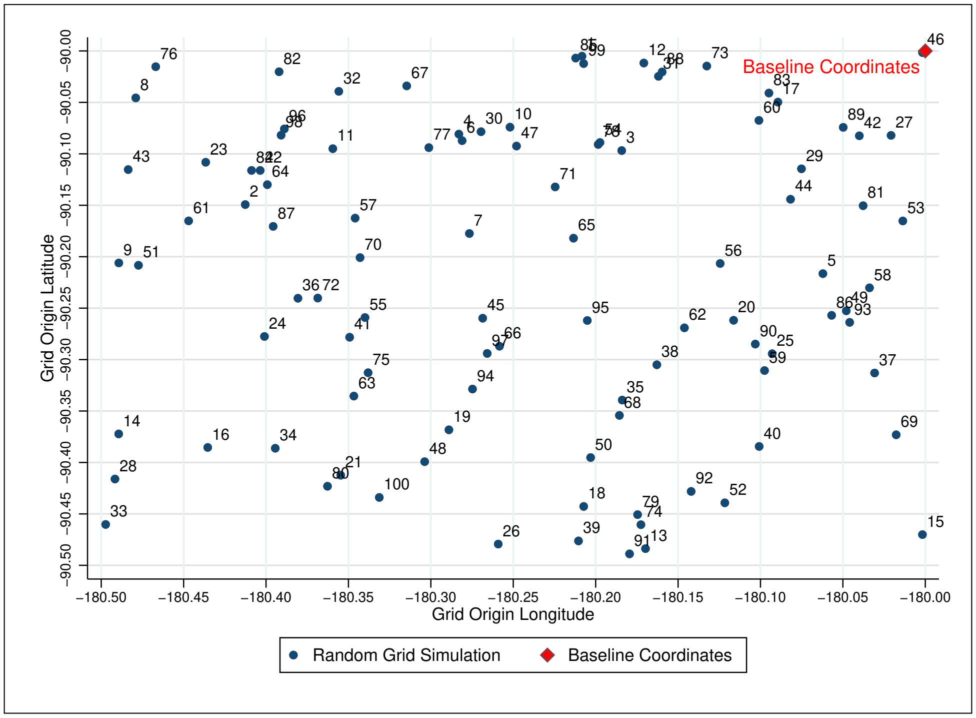


Figure 4: Simulation of 100 Initial Random Grid Coordinates

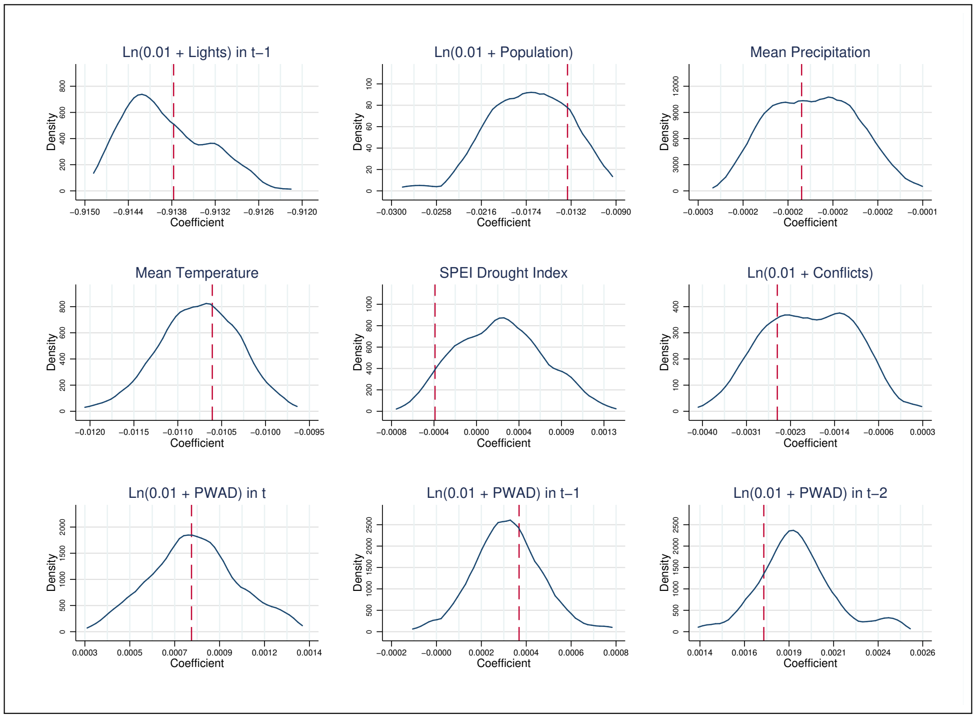


Figure 5: Distribution of Estimated Regression Coefficients Across 100 Simulated Random Grids

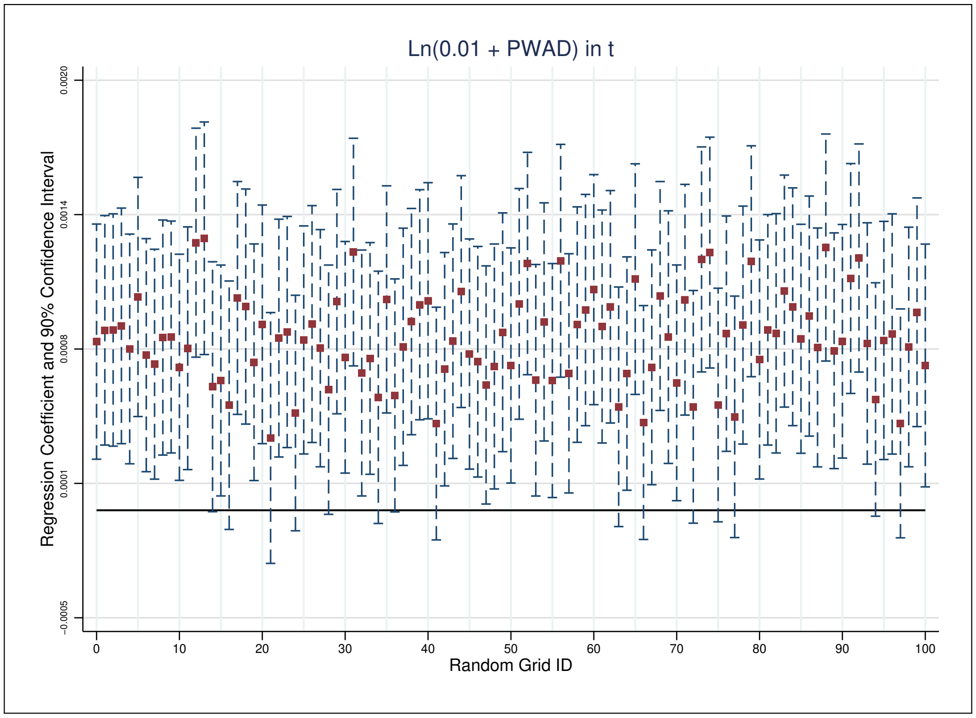


Figure 6: Range Plot of Variable ln$(0.01 + PWAD_{g,c,t})$ Across 100 Simulated Random Grids

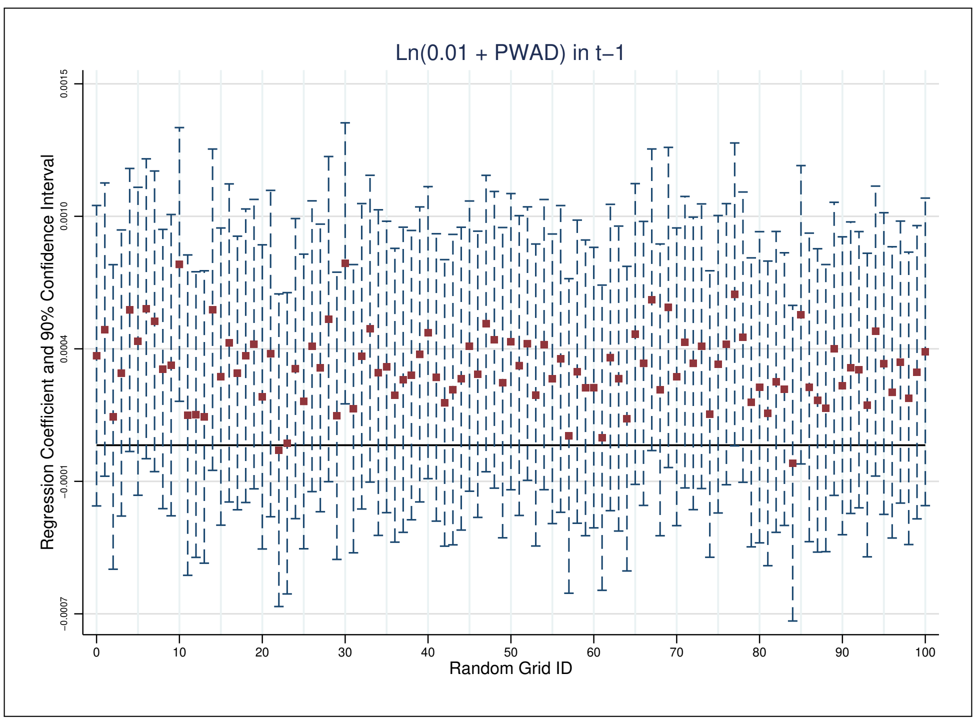


Figure 7: Range Plot of Variable ln$(0.01 + PWAD_{g,c,t-1})$ Across 100 Simulated Random Grids

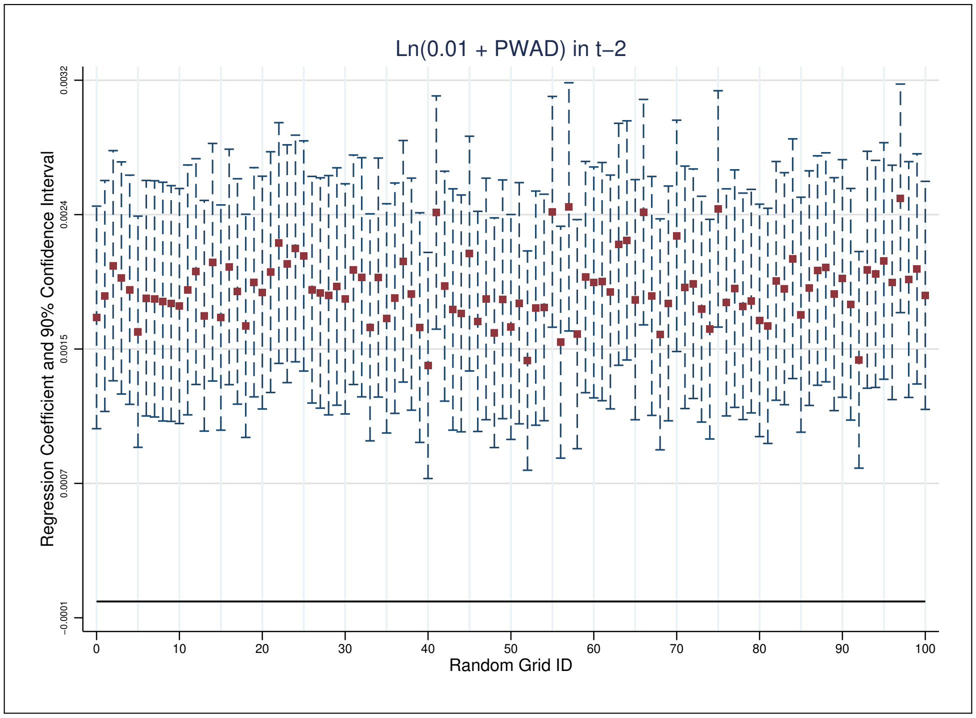


Figure 8: Range Plot of Variable $\ln(0.01 + PWAD_{g,c,t-2})$ Across 100 Simulated Random Grids

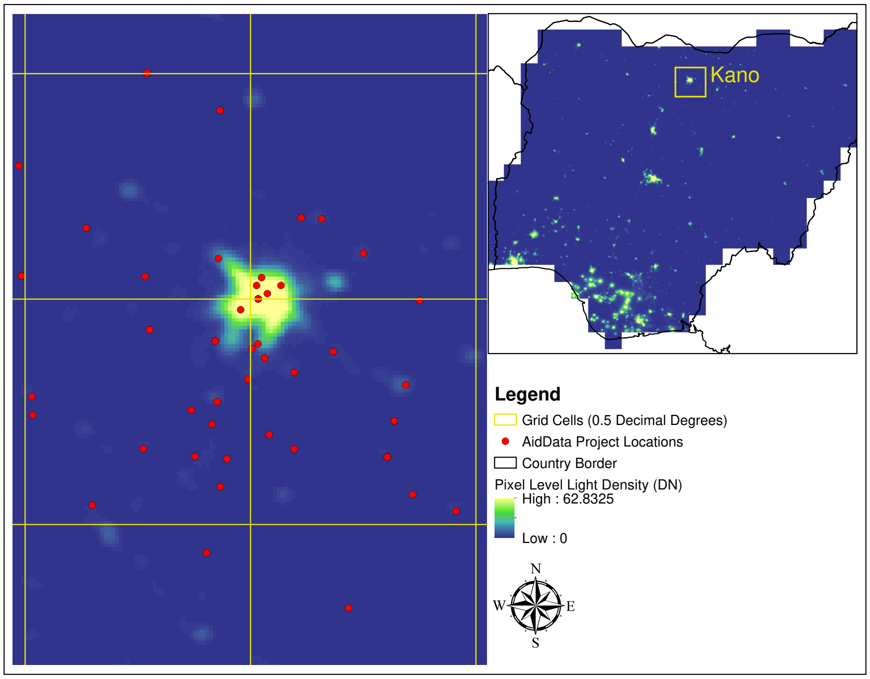


Figure 9: Pixel-level Light Density and AidData Project-Locations for the City Kano (Northern Nigeria)

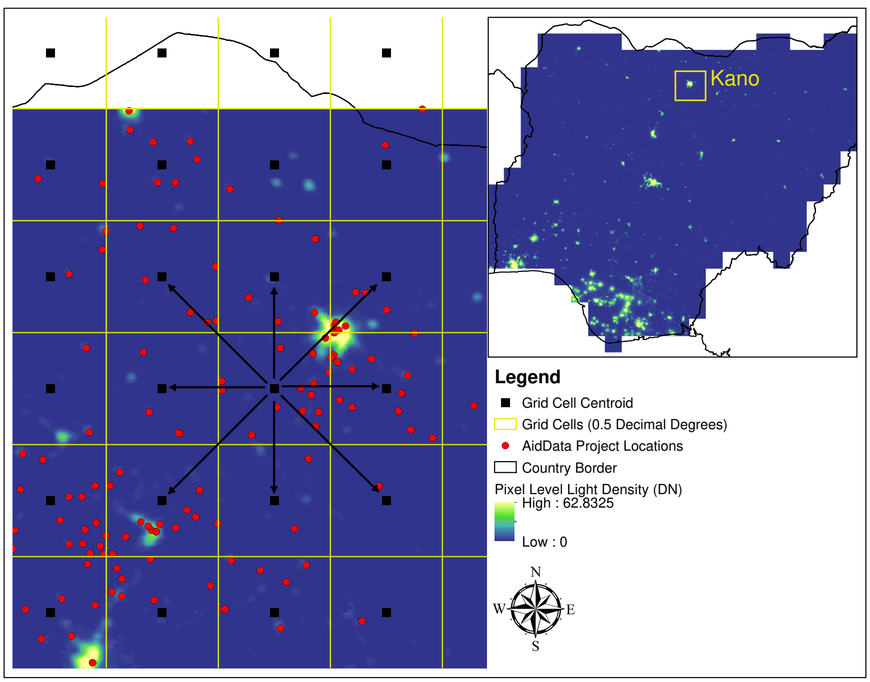


Figure 10: Illustration of Contiguous Grids From the Centroid of a Particular Grid

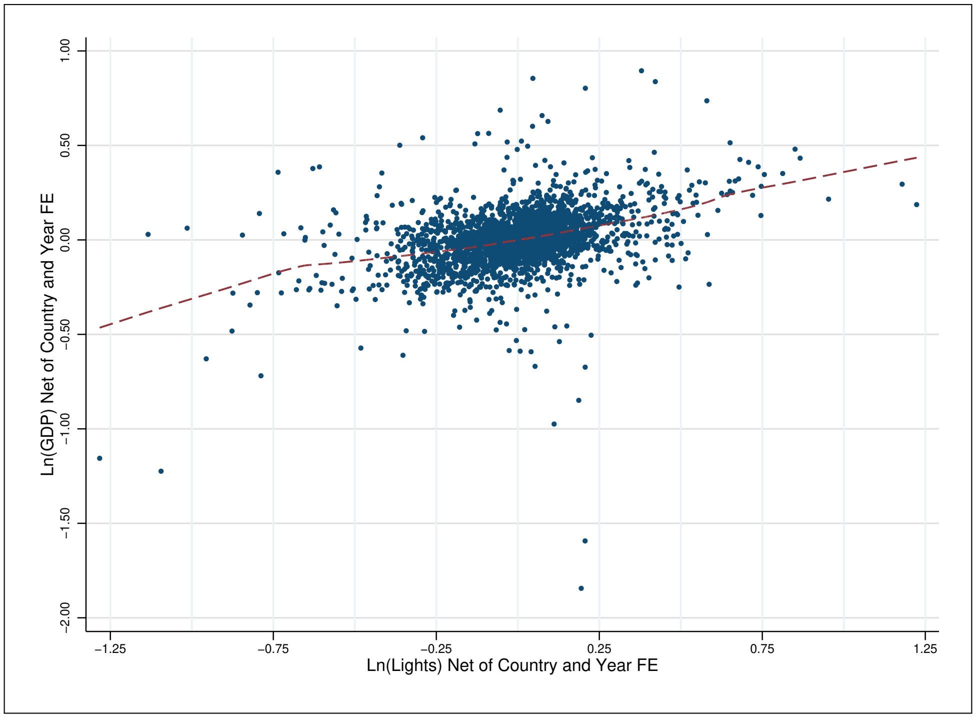


Figure 11: Relationship Between GDP and Night-Time Light Across Countries

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 8: Number of Foreign Aid Projects 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 AidData 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 9: 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 10: 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.

D Data Description and Sources

Dependent Variable

Satellite-measured Night-Time Light Growth. This variable is constructed from satellite night-time light images provided by the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Centre (NGDC) (NOAA-NGDC, 2015). The raw images are available at a spatial resolution of 30 arc seconds (approximately 0.925 kilometers at the equator) with a global coverage that span from -180 to 180 degrees longitude and from -65 to 75 degrees latitude, respectively. The data were collected by the US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) based on six different satellites during the period 1992 to 2013 with 12 co-temporal periods resulting in a total number of 34 satellite-year observations. The DMSP-OLS satellites have a night-time overpass typically occurring between 20:30 and 21:30 local time (Elvidge et al., 2001). Satellites are replaced at different points in time due to the fact that the optical sensors are subject to technical degradation over time. The data contains a digital number (DN) value ranging from 0 to 63 that is proportional to radiance (Elvidge et al., 1997):

$$Radiance \propto (DN)^{3/2} \times 10^{-10}\ W/cm^2/sr/\mu m.$$

A main limitation of the unprocessed satellite images is that the DN values are not radiometrically calibrated, which complicates the comparison of brightness values across different satellites and years. For this reason, we apply the method of inter-annual calibration to facilitate the comparison of DN values across different satellite-year observations, as outlined in Hsu et al. (2015). Specifically, the DN values of all satellite-year observations are calibrated to match the data range of a particular satellite reference year and area. We choose satellite DMSP-OLS F12 from 1999 as the reference year as it had the highest DN values. As the reference area, we use the boundaries of Los Angeles. The choice of Los Angeles as the reference area can be justified for two reasons. First as a developed US metropolis, Los Angeles underwent little change in its light characteristics over time. Second, it provides a wide range of possible data outcomes, ranging from high DN values in the city center to low DN values in suburban areas. Figure 12 illustrates the spatial distribution of pixel-level lights DN values of Los Angeles across 30 arc seconds grid cells from DMSP-OLS satellite F12 in the year 1999.

The inter-annual calibration approach is based on the following regression equation using pixel-level DN values within the boundaries of Los Angeles:

$$DN\left(F12, 1999\right)_p = \beta_0 DN\left(FSN, t\right)_p + \beta_1 \left[DN\left(FSN, t\right)_p\right]^2 + u\left(FSN, t\right)_p,$$

where FSN refers to the DMSP-OLS satellite F-series number (i.e., F10, F12, F14, F15, F16, and F18), t is the year of night-time light data collection (i.e., 1992 to 2013), and p is the unique pixel-level light density identifier of Los Angeles as the reference area. Thus, the variable $DN\left(FSN, t\right)_p$ is the pixel-level DN value collected by satellite series FSN in year t of pixel p. The term $u\left(FSN, t\right)_p$ is a pixel-level specific error term in the regression model. The idea of the inter-annual calibration approach is to adjust the DN values of a particular satellite F-series and year to match the corresponding data range of DMSP-OLS satellite F12 in the year 1999 (i.e., $DN\,(F12,1999)_p$). The quadratic specification allows for possible non-linearities in the relationship between $DN\,(F12,1999)_p$ and the various satellite-year observations. We omit the constant term from the regression equation to ensure that the predicted DN values from the fitted model are positive. Calculated DN values above the upper threshold (e.g., $DN > 63$) were set to 63.

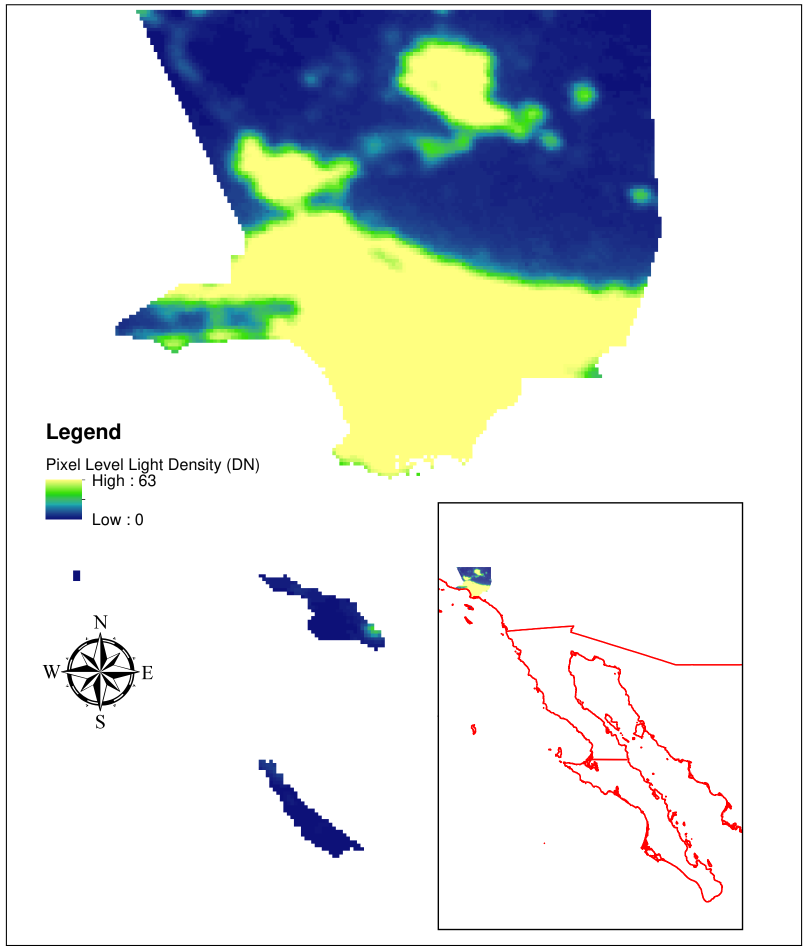


Figure 12: DMPS-OLS Satellite F12 Light Density in Year 1999 of Los Angeles

Table 11 reports the coefficient estimates from the inter-annual calibration approach across the different 34 satellite-year observations. The estimation sample in each regression model consists of 14,960 pixel-level DN values within the administrative boundaries of Los Angeles. Overall, the measure of fit in each regression equation indicates that the proposed calibration approach works quite satisfactorily, with squared correlation coefficients clearly exceeding 0.99 in each model specification. As a graphical illustration, Figure 13 depicts scatter plots between pixel-level DN values of DMSP-OLS satellite F12 in year 1999 on the vertical axis and the DN values of the various satellite-year observations on the horizontal axis. The solid line corresponds to the quadratic fit of the inter-annual regression approach and is drawn to facilitate comparison of the various pixel-level DN values. The figure reveals a quite significant variation of DN values across satellites and years.

An indication of successful inter-annual calibration would be the convergence of DN values for years where two satellite products are available. For this reason, we constructed a global Sum of Lights (SOL) index that refers to the sum of DN values across pixel-level lights density values within the borders of contemporary nation states. Figure 14 depicts the temporal evolution of the global SOL index across the different satellite F-series of the uncalibrated (i.e., raw) pixel-level DN images. This figure nicely illustrates that brightness values from two different satellite products are not comparable over time. For example, comparing satellite product DMSP-OLS F12 and F14 reveals that during the period 1997 to 1999, satellite series F12 had a much dimmer on-board calibration than satellite F12 during the same period. It is noteworthy that the DMSP-OLS satellite F15 indicates a sharp decline in global night-time light activity in the year 2003, even though DMSP-OLS F14 documents a slight rise in night-time light activity in the same year.

Figure 15 shows the evolution of the global SOL index, but this time using the DN values that have been derived from the inter-annual calibration approach. Reassuringly, the figure quite significantly reveals a convergence of DN values for years where two satellite products are available. In essence, the previous discussion indicates that the use of satellite night-time light images from the NOAA-NGDC (2015) database in panel data applications should be treated with some caution given the fact that the brightness values from two different satellite products are not comparable over time. Instead, we emphasize the merits of the inter-annual calibration approach that provides a simple tool to facilitate comparison of DN values across the various different satellite-year observations.

In the following, we outline the construction of the main dependent variable used in the empirical analysis. After successful completion of the inter-annual calibration approach, we construct a sum of lights index across 0.5 decimal degrees latitude $\times$ longitude grid cells. In years with two satellite images available, we used the simple average of both products. We denote this variable as $Light_{g,c,t}$ that refers to the SOL index of grid cell g in country c at year t. Analogous to cross-country economic growth regressions, we construct the annual logarithmic growth rate of the SOL index – i.e., $\triangle \ln(0.01 + Light_{g,c,t}) = \ln(0.01 + Light_{g,c,t}) - \ln(0.01 + Light_{g,c,t-1})$ – that we employ as the main dependent variable throughout the empirical analysis. Adding the small number 0.01 ensures that we include even those grid cells in the estimation sample that display no night-time light activity over time.

Table 11: Coefficient Estimates from the Inter-Annual-Calibration Approach of Pixel-Level Light DN Values

Dependent Variable: Pixel-level DN Values of DMSP-OLS Satellite F12 in Year 1999 of Los Angeles: $DN\left(F12, 1999\right)_p$

DMSP-OLS	Year of	$DN\left(F12, 1999\right)_p$		$\left[DN\left(FSN, t\right)_p\right]^2$		Number of Pixel-	Measure of Fit:
F-Series	Data Collection	Coeff.	Std. Err.	Coeff.	Std. Err.	Level Observations	Squared Correlation
F10	1992	0.9422***	(0.0037)	0.0009***	(0.0001)	14960	0.9999
F10	1993	1.2928***	(0.0029)	-0.0046***	(0.0000)	14960	0.9976
F10	1994	1.3111***	(0.0031)	-0.0049***	(0.0001)	14960	0.9973
F12	1994	1.1436***	(0.0032)	-0.0022***	(0.0001)	14960	0.9994
F12	1995	1.1346***	(0.0029)	-0.0021***	(0.0000)	14960	0.9995
F12	1996	1.2653***	(0.0036)	-0.0041***	(0.0001)	14960	0.9981
F12	1997	1.1779***	(0.0041)	-0.0029***	(0.0001)	14960	0.9991
F12	1998	1.1075***	(0.0031)	-0.0017***	(0.0001)	14960	0.9996
F12	1999	1	(N/A)	0	(N/A)	14960	1
F14	1997	1.6562***	(0.0044)	-0.0105***	(0.0001)	14960	0.9887
F14	1998	1.5517***	(0.0026)	-0.0088***	(0.0000)	14960	0.9923
F14	1999	1.5222***	(0.0024)	-0.0083***	(0.0000)	14960	0.9931
F14	2000	1.3620***	(0.0031)	-0.0057***	(0.0001)	14960	0.9966
F14	2001	1.5361***	(0.0031)	-0.0085***	(0.0001)	14960	0.9924
F14	2002	1.6438***	(0.0042)	-0.0103***	(0.0001)	14960	0.9894
F14	2003	1.4862***	(0.0031)	-0.0078***	(0.0001)	14960	0.9940
F15	2000	1.1593***	(0.0025)	-0.0025***	(0.0000)	14960	0.9993
F15	2001	1.2057***	(0.0024)	-0.0032***	(0.0000)	14960	0.9988
F15	2002	1.2511***	(0.0022)	-0.0040***	(0.0000)	14960	0.9984
F15	2003	1.7447***	(0.0028)	-0.0118***	(0.0000)	14960	0.9858
F15	2004	1.7449***	(0.0030)	-0.0118***	(0.0000)	14960	0.9858
F15	2005	1.7580***	(0.0030)	-0.0120***	(0.0001)	14960	0.9852
F15	2006	1.5419***	(0.0036)	-0.0086***	(0.0001)	14960	0.9923
F15	2007	1.6085***	(0.0047)	-0.0096***	(0.0001)	14960	0.9905
F16	2004	1.5432***	(0.0036)	-0.0086***	(0.0001)	14960	0.9926
F16	2005	1.7155***	(0.0036)	-0.0113***	(0.0001)	14960	0.9873
F16	2006	1.3517***	(0.0036)	-0.0056***	(0.0001)	14960	0.9966
F16	2007	1.2453***	(0.0034)	-0.0039***	(0.0001)	14960	0.9984
F16	2008	1.2575***	(0.0038)	-0.0041***	(0.0001)	14960	0.9982
F16	2009	1.4141***	(0.0037)	-0.0066***	(0.0001)	14960	0.9953
F18	2010	0.9560***	(0.0041)	0.0006***	(0.0001)	14960	1.0000
F18	2011	1.2682***	(0.0032)	-0.0043***	(0.0001)	14960	0.9981
F18	2012	1.1172***	(0.0037)	-0.0020***	(0.0001)	14960	0.9996
F18	2013	1.1787***	(0.0032)	-0.0029***	(0.0001)	14960	0.9991

Notes: This table reports coefficient estimates from the inter-annual calibration approach of pixel-level light density values using DMSP-OLS satellite F12 in the year 1999 as the base reference year and Los Angeles as the reference area. See the main text for additional details on data construction and estimation. The measure of fit refers to the squared correlation between the fitted and actual DN values of each satellite-year estimation sample.

Robust standard errors are reported in parentheses.

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

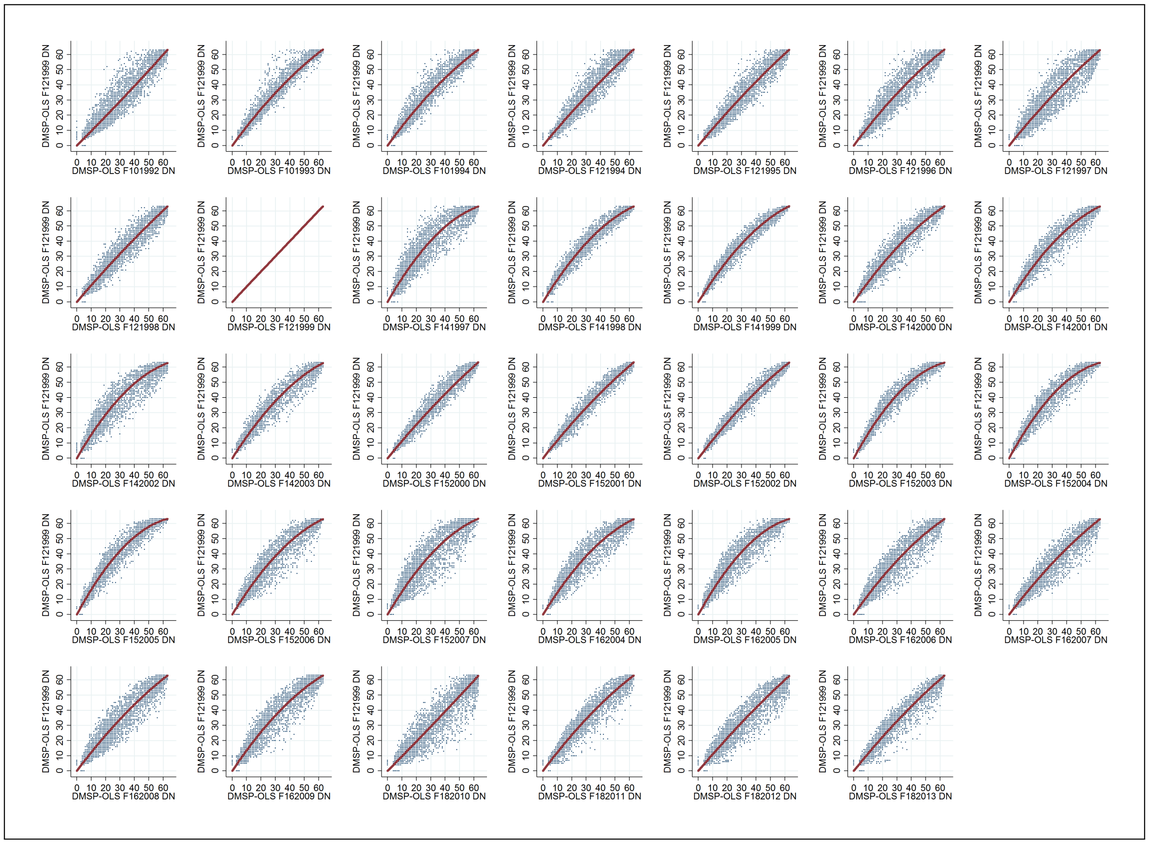


Figure 13: Scatterplot of Inter-Annual Calibrated DN Values for Los Angeles

Notes: This figure shows the results from the inter-annual calibration approach using DMSP-OLS F12 in 1999 as the base year and the administrative boundaries of Los Angeles as the reference area. The vertical axis depicts pixel-level Digital Number (DN) values of DMSP-OLS satellite F12 in year 1999 across 30 arc seconds grid cells within the boundaries of Los Angeles. The horizontal axis shows the corresponding pixel-level DN values across various satellite-year observations. The solid line refers to the quadratic fit of the inter-annual calibration approach. The number of pixel-level observations is 14,960. See the main text for additional details on data construction and estimation methodology.

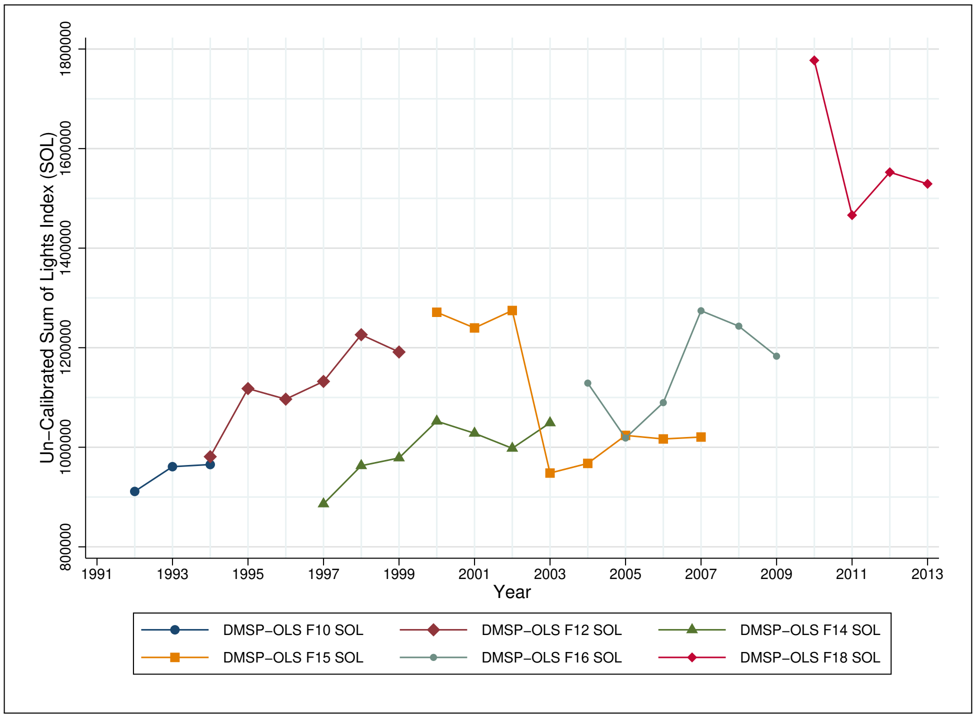


Figure 14: Un-Calibrated Global Sum of Lights Index Across Satellite Products

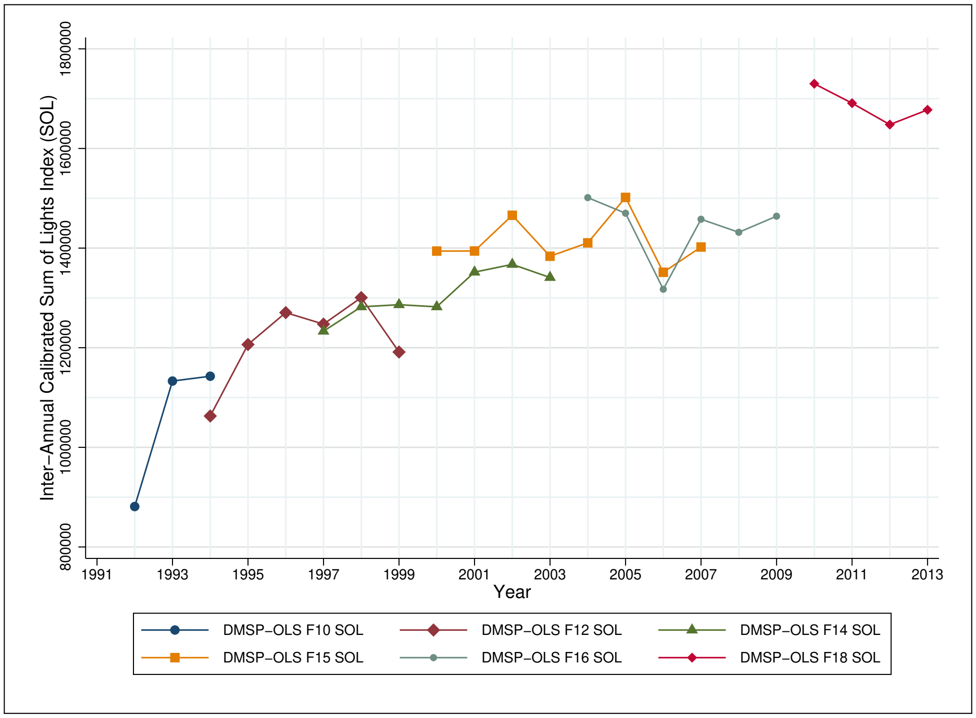


Figure 15: Calibrated Global Sum of Lights Index Across Satellite Products

Geo-Coded World Bank Foreign Aid Project Data

Indicator World Bank Foreign Aid Project. Indicator variable that takes value 1 for grid cells with World Bank foreign aid projects and 0 otherwise. The data on geocoded World Bank foreign aid projects approved for the years 1995 to 2014 with various levels of precision codes are provided by AidData (2016). See the main text for additional details on data construction and sources. The raw data are distributed by the AidData database and freely available online at http://aiddata.org/research-datasets.

Number of World Bank Foreign Aid Projects. This variable refers to the number of geocoded World Bank foreign aid project locations within 0.5 decimal degrees latitude $\times$ longitude grid cells. See the main text for additional details on data construction and sources. The raw data are distributed by the AidData database and freely available online at http://aiddata.org/research-datasets.

World Bank Project-Specific Annual Disbursement Flows. This variable refers to World Bank project-specific annual disbursement flows within 0.5 decimal degrees latitude $\times$ longitude grid cells. The data were constructed using the project-specific financial activity data from the World Bank (2016) Project and Operations web page. This database provides detailed information on World Bank foreign aid projects such as the donor, investment amount, and the actual date of the financial transaction. The data on project-specific disbursement flows were first aggregated across years and then converted to constant 2011 USD based on exchange rates data from the National Accounts Statistics of the United Nations (2016).

Since detailed financial activity data are only available at the project but not project-location level, a weighting scheme is needed to spatially distribute project-specific annual disbursement flows to project locations across grid cells and years. To accomplish this task, we use the number of project locations of each World Bank foreign aid project within 0.5 decimal degree grid cells as our preferred weighting scheme. See the main text for additional details on data construction and sources.

Socioeconomic, Demographic, and Conflict Factors

Population Size. This variable refers to the population size within 0.5 decimal degrees latitude $\times$ longitude grid cells. The raw data are distributed by the Gridded Population of the World, Version 3 (GPWv3) database 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 (CIESIN-FAO-CIAT, 2007). The method of linear interpolation is employed to calculate population count measures between each five-year interval. The data are freely available online from the Socioeconomic Data and Applications Center (SEDAC) hosted by the Center for International Earth Science Information Network (CIESIN) at Columbia University http://sedac.ciesin.columbia.edu/data/collection/gpw-v3.

Share of Urban Extent Area. This variable refers to the share of urban area within 0.5 decimal degrees latitude $\times$ longitude grid cells. The Global Rural-Urban Mapping Project, Version 1 (GRUMPv1) reports the share of urban area at a spatial resolution of 30 arc seconds (approximately 0.925 kilometers at the equator) based on combined information of night-time light activity and buffered settlement points. The raw data are distributed by the Socioeconomic Data and Applications Center (SEDAC) hosted by the Center for International Earth Science Information Network (CIESIN) in collaboration with the International Food Policy Research Institute (IFPRI), The World Bank, and Centro Internacional de Agricultura Tropical (CIAT), and are freely available online at http://sedac.ciesin.columbia.edu/data/set/grump-v1-urban-extents.

Linguistic Diversity. This variable refers to a measure of ethno-linguistic diversity, ranging from 0=low to 1=high, within 0.5 decimal degrees latitude $\times$ longitude grid cells using a slight variation of the Herfindahl-Hirschman concentration index. The index is constructed from the relative area inhabited by the various ethno-linguistic groups within 0.5 decimal degree grid cells. Information on the global distribution of ethno-linguistic groups is provided by the Global Mapping International (2010b).

Georeferenced Conflict Events. This variable refers to the number of georeferenced conflict events within 0.5 decimal degrees latitude $\times$ longitude grid cells. The UCDP Georeferenced Event Dataset (UCDP GED) presented in Sundberg and Melander (2013), provides detailed information on three types of organized violence (i.e., state-based conflict, non-state conflict, and one-sided violence), with a temporal and georeferenced spatial dimension. Each conflict event has been georeferenced according to 7 different precision codes referring to an exact location (precision code of 1), a maximum radius of about 25 km around a known location (2), a second-order administrative division (ADM2) (3), first-order administrative division (ADM1) (4), a linear feature (e.g., river, political border, or road line) (5), the whole country (6), and if the conflict event occurred in international waters or air space (7). In the empirical analysis, we use the number of all three types of conflict events with georeferenced precision codes of 3 and smaller to account for the local consequences of conflicts on grid-cell-specific socioeconomic outcomes (e.g., economic loss, forced migration, and famines). The raw data (accessed on 16/02/2017) is made available online by the UCDP system http://ucdp.uu.se/downloads/.

Climatic Factors

Temperature. This variable refers to the yearly average of monthly temperature values (in degrees Celsius) within 0.5 decimal degrees latitude $\times$ longitude grid cells. The raw data are distributed by the Climatic Research Unit (CRU) at the University of East Anglia as a gridded monthly time-series dataset with a spatial resolution of 0.5 decimal degrees latitude $\times$ longitude. The CRU TS Version 3.23 dataset has a global land coverage (excluding Antarctica) that comprises the period 1901 to 2014. The dataset includes six main climatic variables (e.g., mean temperature, diurnal temperature range, precipitation, wet-day frequency, vapor pressure and cloud cover) and an additional four variables that have been derived from these (e.g., minimum temperature, maximum temperature, frost-day frequency, and potential evapotranspiration). The various climatic variables were constructed from meteorological stations across the world with interpolated observations between station points. See Harris et al. (2014) for a more detailed discussion on the construction and sources of the various climatic variables. The monthly climatic dataset is freely available online at https://crudata.uea.ac.uk/cru/data/hrg/.

Precipitation. This variable refers to the yearly average of total monthly precipitation values (in millimeters) within 0.5 decimal degrees latitude $\times$ longitude grid cells. See the description of the *Temperature* variable for additional details on data construction and sources.

Share Area in Tropics. This variable refers to the share of land area in the tropics according to the Köppen-Geiger climatic classification within 0.5 decimal degrees latitude $\times$ longitude grid cells. The raw data are distributed as a raster file with a spatial resolution of 0.1 decimal degrees latitude $\times$ longitude and freely available online at http://people.eng.unimelb.edu.au/mpeel/koppen.html. See Peel et al. (2007) for a detailed discussion on the construction and sources of the Köppen-Geiger climatic map.

SPEI Drought Index. This variable refers to the standardized precipitation evapotranspiration index (SPEI), as outlined in greater detail by Vicente-Serrano et al. (2010a). The calculation of the SPEI drought index is based on monthly precipitation (P) and potential evapotranspiration (PET) data. Specifically, the SPEI refers to the difference between precipitation and potential evapotranspiration at various time scales (e.g., 3, 6, 12, 18, and 24 months) involving the following 3 calculation steps:

(1) The first step requires the calculation of the PET (measured in millimeters) index. The climatology literature proposes various approaches in calculating potential evapotranspiration, whose practical feasibility depends on the availability of meteorological data, such as solar radiation, temperature, wind speed, and relative humidity. Due to its simplicity, Vicente-Serrano et al. (2010a) initially proposed the use of the Thornthwaite (1948) equation which only requires meteorological data on monthly-mean temperature. However, this approach was abandoned in the later construction of their SPEI database in favor of the more sophisticated Penman-Monteith method (Beguería et al., 2014). This methodology defines PET as the potential evapotranspiration of a reference crop with an assumed height of 0.12 meters above the surface that resembles the potential evaporation of growing green grass that is sufficiently watered, as outlined in the Food and Agricultural Organization of the United Nations (FAO) (Allen et al., 1998). The FAO Penman-Monteith method of PET is defined as

$$PET = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} U_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)}, \tag{8}$$

where PET refers to the reference evapotranspiration [mm day^{-1}], R_n is the net radiation at the crop surface [MJ m^{-2} day^{-1}], G is the soil heat flux density [MJ m^{-2} day^{-1}], T is the mean daily temperature [°C], U_2 is the measured (or estimated) wind speed [m s^{-1}], e_s is the saturation vapor pressure height [kPa], e_a is the actual vapor pressure [kPa], Δ is the slope of the vapor pressure curve [kPa °C^{-1}], and γ is the psychometric constant [kPa °C^{-1}]. It is assumed that all the meteorological variables are measured at 2 meters height above the ground surface. However, wind speed is typically measured at 10 meters height. To adjust wind speed observations to the standard 2 meters height, a logarithmic conversion function of the form $U_2(z = 10) = U_{10} \frac{\ln(128)}{\ln(6.78 \times 10 - 5.42)}$ is used, where U_{10} is the measured wind speed at 10 meters height [m s^{-1}] and $z = 10$ is the height of the measurement above ground surface [m] (Allen et al., 1998).

The PET data are constructed and distributed by the Climatic Research Unit (CRU) of the University of East Anglia (Harris et al., 2014). In cases of missing climatology data (e.g., dewpoint temperature, saturation water pressure, and solar radiation), Allen et al. (1998) recommend the construction of the missing observations using gridded data on monthly (mean, maximum, and minimum) temperature, vapor pressure, cloud cover, and wind speed to proceed with the calculation of the FAO Penman-Monteith equation.

(2) The calculated difference D between the P and PET values for a given year y and month j is aggregated at different time scales k (e.g., 3, 6, 12, 18, and 24 months). The chosen time scale has the advantage of identifying drought conditions related to different hydrological subsystems. Shorter time scales reflect drought series related to soil water content and changes in river discharge, medium time scales identify drought series related to reservoir storages and changes in water content of rivers, and long time scales can identify drought conditions related to variations in groundwater storage. Specifically, the monthly mean temperature values are accumulated by the use of a rectangular kernel function, where the available set of months were given equal weights according to the following expression

$$X_{y,j}^{k} = \begin{cases} \sum\limits_{l=13-k+j}^{12} D_{y-1,l} + \sum\limits_{l=1}^{j} D_{y,l} & if \;\; j < k, \\ \sum\limits_{l=j-k+1}^{j} D_{y,l} & if \;\; j \geq k, \end{cases} \tag{9}$$

where $D_{y,l} = (P_{y,l} - PET_{y,l})$ is the aforementioned difference between precipitation and potential evapotranspiration (expressed in millimeters) in a given month and year. In cases where the assumption of equal weights might be too restrictive, a Gaussian kernel is recommended where the weights decrease non-linearly across months (Beguería et al., 2014).

(3) In the final step, a log-logistic distribution was fitted to the $D_{y,l}$ values, whose distributional parameters were estimated through the use of Probability Weighted Moments (PWMs) and the L-moment methodology (Hosking, 1990). The cumulative distribution function of the log-logistic distribution is given according to

$$F(D) = \left[1 + \left(\frac{\alpha}{D-\gamma}\right)^{\beta}\right]^{-1}, \tag{10}$$

where α, β, and γ are scale, shape, and origin parameters of the log-logistic distribution. The SPEI values are then calculated as the standardized values of $F(D)$, with mean 0 and a standard deviation of 1. Positive SPEI values correspond to a trend of relative wetness in comparison to the time period under investigation, whereas negative values correspond to a trend towards a drier climate.

The global SPEI database is presented in Vicente-Serrano et al. (2010b) and Beguería et al. (2014), with a spatial resolution of 0.5 decimal degrees latitude $\times$ longitude and a monthly time dimension. The SPEI values are calculated at time scales ranging from 1 to 48 months and the current version 2.5 (accessed on 31/08/2017) is made freely available online at http://digital.csic.es/handle/10261/153475.

Topographic Factors

Elevation. This variable refers to the mean elevation value (in meters above the sea level) within 0.5 decimal degrees latitude $\times$ longitude grid cells. The raw data are distributed by the National Oceanic and Atmospheric Administration (NOAA) and US National Geophysical Data Center, TerrainBase, release 1.0 (CD-ROM), Boulder, Colorado. The spatial resolution of the elevation data is 30 arc seconds (approximately 0.925 kilometers at the equator). The data are part of the the Center for Sustainability and the Global Environment (SAGE) at the University of Wisconsin and freely available online at http://nelson.wisc.edu/sage/data-and-models/atlas/maps.php?datasetid=28&includerelatedlinks=1&dataset=28.

Standard Deviation of Elevation. This variable refers to the standard deviation of the mean elevation value within 0.5 decimal degrees latitude $\times$ longitude grid cells. See the description of the *Elevation* variable for additional details on data construction and sources.

Range of Elevation. This variable refers to the range of the mean elevation value (i.e., the difference between the maximum and minimum elevation value) within 0.5 decimal degrees latitude $\times$ longitude grid cells. See the description of the *Elevation* variable for additional details on data construction and sources.

Microgeographic Factors

Distance to Capital City. This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to the country's capital city. The corresponding country's capital city latitude and longitude coordinates are available from the CIA *The World Factbook* database at https://www.cia.gov/library/publications/the-world-factbook/index.html.

Distance to Nearest Settlement This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to the next largest settlement with an estimated population size of at least 100,000 in year 2000. Information on geocoded settlement points is provided by the Global Rural-Urban Mapping Project, Version 1 (GRUMPv1) database. The raw data are distributed by the Socioeconomic Data and Applications Center (SEDAC) hosted by the Center for International Earth Science Information Network (CIESIN) in collaboration with the International Food Policy Research Institute (IFPRI), The World Bank, and Centro Internacional de Agricultura Tropical (CIAT) and freely available online at http://sedac.ciesin.columbia.edu/data/set/grump-v1-urban-extents.

Distance to Border. This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to the country's national border. The country shape files from the Global Mapping International (2010a) database were used to identify the national borders of contemporary states.

Distance to Coast. This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to the coastline. The global coastline shape file is distributed by the Global Mapping International (2010a).

Distance to River. This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to the major sea-navigable river. Geocoded data on the location of rivers and lakes is provided by the Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG) and distributed by the National Oceanic and Atmospheric Administration (NOAA) agency at https://www.ngdc.noaa.gov/mgg/shorelines/gshhs.html.

Distance to Power Transmission Line. This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to nearest power transmission line. Data on the location of power transmission lines are provided by the Global Mapping International (2010a).

Distance to Railroad. This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to the railroad line. Data on the location of railroad lines are provided by the Global Mapping International (2010a).

Distance to Road. This variable refers to the minimum geodesic distance (in kilometers) from the centroid of the grid cell to the road line. Data on the location of road lines are provided by the Global Mapping International (2010a).

Length of Railroad. This variable refers to the total railroad length (in kilometers) within 0.5 decimal degrees latitude $\times$ longitude grid cells. Data on the location of railroad lines are provided by the Global Mapping International (2010a).

Length of Road. This variable refers to the total road length (in kilometers) within 0.5 decimal degrees latitude $\times$ longitude grid cells. Data on the location of road lines are provided by the Global Mapping International (2010a).

Land Area. This variable refers to the land area (in square kilometers) within 0.5 decimal degrees latitude $\times$ longitude grid cells.

Absolute Latitude. This variable refers to the absolute latitude coordinate of the grid cell centroid in decimal degrees.

Mineral Resources

Number of Diamond Mines. This variable refers to the number of diamond mines within 0.5 decimal degrees latitude $\times$ longitude grid cells. Data on the location of diamond mines are provided by the Peace Research Institute Oslo (PRIO) and is freely available online at https://www.prio.org/Data/Geographical-and-Resource-Datasets/Diamond-Resources/. See Gilmore et al. (2005) for a detailed discussion on data construction and sources of the diamond mines database.

Number of Gemstone Deposits. This variable refers to the number of gemstone deposits within 0.5 decimal degrees latitude $\times$ longitude grid cells. The following gemstones are included in the dataset: ruby, sapphire, emerald, aquamarine, heliodor, moganite, goshenite, nephrite, jadeite, lapis lazuli, opal, tourmaline, periodit, topaz, pearl, garnet, zircon, spinel, amber, and quartz. Data on the worldwide location of gemstone deposits are freely available online at http://www.svt.ntnu.no/iso/Paivi.Lujala/home/GEMDATA.htm. See Lujala (2009) for additional details on data construction and sources.

Land Use Factors

Cropland Coverage. Global agricultural lands data on cropland and pasture in the year 2000 at 5 arc minutes (0.083333333 decimal degree latitude $\times$ longitude grid cells) spatial resolution (≈ 10 km at the equator) are provided by Ramankutty et al. (2008). This dataset provides information on the fraction of land allocated to cropland and pasture. The data are constructed by combining cross-country agricultural inventory data in each administrative unit i compiled from national census data with two satellite-derived land cover classification scheme products. The basic methodology for the derivation of the combined cropland and pasture land maps is based on two main calculation steps (the interested reader is referred to Ramankutty et al. (2008) for a more detailed discussion of data construction). In the first step, the authors used a linear relationship between the fraction of combined satellite-derived land cover classes ($\lambda_{j,i}$) against each component in the fraction of cropland (cf_i) and pasture land (pf_i) within each administrative unit i, respectively:

$$cf_i = \sum_{j=1}^{n_\lambda} (\alpha_j \times \lambda_{j,i}) + \varepsilon_{c,i} \quad (11)$$

$$pf_i = \sum_{j=1}^{n_\lambda} (\beta_j \times \lambda_{j,i}) + \varepsilon_{p,i}, \quad (12)$$

where $\lambda_{j,i}$ is, again, the fraction of the combined satellite-derived land cover class j in administrative region i, n_λ is the total number of land cover classes in the combined satellite-derived dataset, and $\alpha_j, \beta_j \in [0,1]$ with $\alpha_j + \beta_j \leq 1$ are the unknown coefficients to be estimated. The main idea of this estimation approach is to find those land cover classes that show a strong empirical relationship with the agricultural inventory data and to use this information to construct a spatially disaggregated map for cropland and pasture land at the 5 arc minutes spatial resolution level. Specifically, the authors tried to minimize the following objective function LSE using weighted least squares (WLS) to estimate the unknown regression coefficients for each of the preselected six geographic regions separately:

$$LSE = \sum_{i=1}^{n_i} \left[(\varepsilon_{c,i})^2 + (\varepsilon_{p,i})^2 \right], \quad (13)$$

where n_i is the number of observations in geographic region i. Moreover, the authors employed a stepwise regression method with backward selection in order to identify those land cover classes that are statistically significant. The estimated coefficients from this regression were then used to construct the fraction of cropland and pasture land within each 5 arc minutes latitude $\times$ longitude grid cell, ($cf_{x,y}$) and ($pf_{x,y}$), respectively:

$$\widehat{cf}_{x,y} = \sum_{j=1}^{n_\lambda} (\widehat{\alpha}_j \times \lambda_{j,x,y}) \quad (14)$$

$$\widehat{pf}_{x,y} = \sum_{j=1}^{n_\lambda} \left(\widehat{\beta}_j \times \lambda_{j,x,y}\right), \quad (15)$$

where (x, y) refer to the corresponding latitude $\times$ longitude grid cell coordinates.

To account for the uncertainty in the parameter estimates, Ramankutty et al. (2008) performed a bootstrap procedure with 1,000 replications and calculated the mean fraction of cropland and pasture land in each 5 arc minutes grid cell:

$$\widehat{cf}_{x,y}^{mean} = \frac{1}{1000} \sum_{k=1}^{1000} \sum_{j=1}^{n_\lambda} (\widehat{\alpha}_j(k) \times \lambda_{j,x,y}) \quad (16)$$

$$\widehat{pf}_{x,y}^{mean} = \frac{1}{1000} \sum_{k=1}^{1000} \sum_{j=1}^{n_\lambda} \left(\widehat{\beta}_j(k) \times \lambda_{j,x,y}\right), \quad (17)$$

where $\widehat{\alpha}_j(k)$ and $\widehat{\beta}_j(k)$ are the corresponding bootstrap estimates from step $k = 1, 2, ..., 1000$.

Finally, the second step in data construction deals with adjusting the grid cell cropland and pasture estimates to match with the agricultural inventory data within each administrative unit:

$$Cropland_{x,y}^{mean} = \mu cf_{x,y} \times \widehat{cf}_{x,y}^{mean} \quad (18)$$

$$Pasture_{x,y}^{mean} = \mu pf_{x,y} \times \widehat{pf}_{x,y}^{mean}, \quad (19)$$

where $\mu cf_{x,y}$ and $\mu pf_{x,y}$ are grid-cell-specific correction factors for cropland and pasture land, respectively.

The data on cropland coverage are used to construct the mean value, standard deviation, and range of the fraction of cropland within 0.5 decimal degree grid cells across 5 arc minutes cropland pixel-level values. The raw data on cropland and pasture land coverage are distributed by the EarthStat database and freely available online at http://www.earthstat.org/data-download/.

Land Suitability for Agriculture. This variable refers to a geospatial indicator, ranging from 0=low to 1=high, of land suitability for agriculture within 0.5 decimal degrees latitude $\times$ longitude grid cells. This index has been derived from Ramankutty et al. (2002) by combining existing relationships between climatic (e.g., growing degree days and moisture) and soil characteristics (carbon density and soil acidic/alkaline composition). The raw data have a spatial resolution of 0.5 decimal degrees latitude $\times$ longitude and are part of the Center for Sustainability and the Global Environment (SAGE) at the University of Wisconsin. The data are freely available online at http://nelson.wisc.edu/sage/data-and-models/atlas/maps.php?datasetid=19&includerelatedlinks=1&dataset=19.

Additional Geo-Spatial Indicators

Recodification Fixed Effects. A set of indicator variables that takes a value of 1 for grid cells with no night-time light activity, population, or with positive population size but no night-time light activity.