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Target at the Right Level: Aid, Spillovers and Growth in Sub-Saharan Africa

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Abstract
This article uses spatial analysis to investigate international aid effectiveness and aid spillovers at the sub-national level from World Bank aid projects in 3,764 second-order administrative divisions (ADM2) in 48 countries in Sub-Saharan Africa over the period of 1995-2014. By isolating the direct effects of aid flows in a given location, and separating them from time-invariant local characteristics, we are able to test both the direct effects of aid as well as the spillover effects from neighboring aid-receiving locations. In the empirical analysis, using geocoded aid data at various disaggregation levels together with nightlights data as a proxy for economic activity, we control for the aggregation bias that has plagued previous research on aid effectiveness. The use of nightlight data also helps deal with the measurement and data quality problems in aid recipient countries. Our identification strategy controls for simultaneity, reverse-causality and attenuation bias as well as country-specific heterogeneity using a two-stage instrumental variable (IV) approach with precipitation and temperature data used as IVs in the first stage. The empirical results reveal three previously undocumented findings on aid effectiveness. First, we find that aid at the local level (ADM2) promotes economic growth at an economically and statistically significant level. Second, we uncover significantly positive aid spillovers across adjacent localities (ADM2). Third, aid flows at more aggregate levels (ADM1 and country level) have the opposite effect and reduce economic growth. Interestingly, the net effect of all aid variables is near zero and is within the range of coefficient estimates reported at the country level by previous papers. These results are robust to a rich battery of sensitivity tests.

JEL codes: *O1; O4; O55; F35*

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1. Introduction

The growth and development effects of international aid have been a source of intense debate in economics for decades. Questions such as whether aid helps spur growth, reduce poverty, promote capital accumulation, build human capital and good institutions, which can enable takeoff through big push, among others, have been at the center of most of this literature (Rosenstein-Rodan, 1943; Burnside and Dollar, 2000; Hansen and Tarp, 2001; Collier and Dollar, 2002; Easterly, 2003, 2006; Dalgaard et al., 2004; Banarjee, 2007; Rajan and Subramanian, 2008). The theoretical literature that spurred interest in aid effectiveness goes back to debates on “big-push” and multiple equilibria that were pioneered by Rosenstein-Rodan (1943, 1961), Nurkse (1953), Myrdal (1957), Rostow (1959), and Chenery and Strout (1966). Accordingly, foreign aid, by relaxing foreign exchange and savings gaps as well as poverty traps, was seen as a way of overcoming barriers to industrialization and capital accumulation in less developed countries (as is supported by Harrod-Domar type models), allowing them to reach a stable and high-level equilibrium of development with a rising capital-labor ratio in modern (i.e. industrial) sector and shrinking labor surplus in the traditional sector (i.e. agricultural).[1] This earlier literature had a major come back in the 1980s, partly influenced by a growing attention in popular culture to the plight of developing countries in Africa. The Live Aid concerts in 1985, for example, were organized simultaneously in many cities around the world and were broadcasted in 150 countries to raise funds for famine relief in Ethiopia. 20 years later in 2005, Live 8 concerts, which were timed to precede the G8 summit in Scotland, had a similar aim: to fight poverty in less developed countries. Perhaps partly because of the growing public attention and pressure, G8 countries in that summit promised to double aid to developing countries by 2010, reaching $50 billion, half of which was earmarked for Africa. In the same summit, there was also agreement for debt cancellation to heavily indebted poor countries.

[1] For a review of this literature, see Addison et al. (2017).

The empirical work on aid effectiveness that boomed in the 1980s and thereafter was heavily influenced by this growing public awareness and celebrity activism by groups such as U2 to increase aid to less developed countries. However, despite a significant amount of research, a consensus is yet to emerge on aid effectiveness as existing studies report positive, negative and insignificant effects. On the positive side, Dalgaard et al. (2004), Clemens et al. (2012), and Askarov and Doucouliagos (2015b), among others, report positive effects of foreign aid on investment, capital accumulation and growth. There is also a rich literature arguing that aid effectiveness is conditional on a variety of country and donor specific factors, including: absorptive capabilities of aid-receiving countries (Burnside and Dollar, 2000); distribution and concentration of aid and poverty levels (Collier and Dollar, 2002), climate and geographical location (Dalgaard et al., 2004); the level of fiscal centralization (Lessmann and Markwardt, 2012); and motivations and objectives of donors (Aldasoro et al., 2010; Younas, 2008; Barthel et al., 2014). In contrast, Easterly (2003) and Easterly et al. (2004) question aid effectiveness, either conditional or unconditional, and argue that most aid to Africa has been ineffective in stimulating growth. In fact, they argue that the net effect appears to be negative. Furthermore, Roodman (2007, 2015) finds that the positive association between aid and growth that are reported in previous studies is not robust and is quite sensitive to the contemporaneous endogeneity between aid and growth. In the same vain, Rajan and Subramanian (2008) and Werker et al. (2009) find little evidence on aid effectiveness. Furthermore, in their meta study of 543 comparable estimates of aid effectiveness reported in 97 papers, Doucouliagos and Paldam (2009) find no evidence that aid, either conditionally or unconditionally, spurs growth. They also show that, despite a lack of robust evidence on aid effectiveness, 74% of papers published on the topic report positive results, likely reflecting the unwillingness of research community to “publish negative results” (p. 433). Thus, the debate continues, and in fact, is alive more than ever.[2] Burnside and Dollar (2000) has received over 1,200 citations in Google Scholar since 2015 (out of a total of 5,475 citations) and there are over three million articles on aid and growth in Google Scholar (as of September 28, 2019).

In this paper we contribute to this long-running debate on aid effectiveness by addressing three issues that are of paramount importance for the internal validity of testing aid-growth relationship. First, previous studies on aid effectiveness paid only limited attention to the aggregation bias as they tested aid effectiveness using only macro and aggregate data even though aid is allocated through many projects in distinct localities and in an uneven and heterogeneous manner. It is highly likely that aggregating the total amount of aid over different localities with different characteristics causes measurement error and produces biased estimates. Furthermore, aid disbursements through central governments are more likely to suffer from what Easterly (2006) calls "feedback and accountability" problem as aid agencies and government bureaucracy share the responsibility together, which makes monitoring the allocated tasks much more difficult. They are also much less likely to allocate aid based on a bottom up approach that relies on feedback from aid-recipients themselves. Furthermore, measurement error for national income and other development indicators is likely to be higher at the national level, especially in countries that are in need of aid more (Jerven, 2013). Missing observations and sample selection bias in aid datasets at the national level also produce biased results (Breitwieser and Wick, 2016). Therefore, if aid is effective in stimulating growth at all, it

[2] See, for example, the debate on aid effectiveness surrounding the Millennium Villages Project of Jeffrey Sachs in Sub-Saharan Africa. The project was promoted as an answer to the U.N. Millennium Goals "to eradicate extreme poverty and hunger". However, even after all the scrutiny this project has received, there is still no consensus over its success. While Sachs and his team argue that the project was a success (Sanchez et al., 2007; Pronyk et al., 2012), others disagree (Nature, 2012; Munk, 2013; Wanjala and Muradian, 2013).

will be easier to detect at the micro level through local aid projects than aggregate disbursements at the national level.

Second, and equally important, we know little about aid spillovers. Unlike macro-level cross-country studies, which typically assume country independence and within-country homogeneity, we expect aid to have economic effects not only in the aid-receiving locations themselves but also in neighboring locations. In theory, aid flows to neighboring localities can have both positive and negative spillovers, leaving the net effect ambiguous. Aid flows attract (as well as distract) resource movements across different places, which can affect economic performance outside the recipient location. At the sub-national level, individuals enjoy more economic interactions with each other than at the country level as barriers to entry and exit are much lower, allowing for a greater degree of resource and factor mobility and knowledge dissemination.[3] Through income effects aid flows can increase effective demand for goods and services, and labor from neighboring regions, which will boost local economic growth and employment. Increasing capital accumulation, particularly in physical infrastructure such as roads, sanitation, irrigation networks, water access, and health care, is also expected to have significant positive externalities on neighboring regions. Through aid flows in neighboring localities, people can also gain know-how, expertise and human capital through their interactions with aid providers or better access to schooling (Askarov and Doucouliagos, 2015a). There can also be negative spillovers such as brain drain through emigration of skilled workers to aid-receiving regions, increased cost of living, rising crime rates, crowding out of local producers because of increased supply of goods through aid that are distributed below their marginal costs. Increasing socio-political conflicts caused by disputes over aid allocation,

[3] Askarov and Doucouliagos (2015a) is the only paper we are aware of that examines aid spillovers. In their country-level macro analysis, they report a positive growth effect in aid-recipient countries but a negative spillover effect in others.

or growing rent-seeking networks also stand out among other negative externalities (Lenkins and White, 2011). Thus, ignoring potential spillovers causes overestimating or underestimating the effects of aid.

Third, methodological problems are rampant in a large part of the aid effectiveness literature, especially regarding the direction of causality, and endogeneity and self-selection problems (Roodman, 2007, 2015; Nunn and Qian, 2014; Addison et al., 2017). These problems are further compounded because of poor data quality and measurement issues in aid recipient countries (Jerven, 2013; Breitwieser and Wick, 2016).

In this paper we try to address all three issues in our examination of aid effectiveness and aid spillovers at the sub-national level in Sub-Saharan Africa, which is home to most of the least developed countries (LDCs) with a heavy reliance on foreign aid. First, using variation in nightlights as a proxy for economic growth together with geo-coded aid flows, we focus on local growth effects of aid at different disaggregation levels. The use of nightlight data also helps deal with the measurement and data quality problems in aid recipient countries. Second, by isolating the direct effects of aid flows in a given location, and separating them from time-invariant local characteristics, we test spillover effects from neighboring aid-receiving locations. Third, we address the identification issue by controlling for the reverse causality and endogeneity bias between aid and growth using a two-stage instrumental variable (IV) approach with precipitation and temperature data used as IVs for growth in the first stage. In the empirical analysis, we use geo-coded data from World Bank for aid projects in 3,764 second-order administrative divisions (ADM2, which is equivalent to a U.S. county) in 48 countries in Sub-Saharan Africa over the period of 1995-2014. Additionally, we employ geographic information systems (GIS) methods to establish neighborhood weight matrices for potential spillovers.[4] The empirical results reveal

[4] To the best of our knowledge, Dreher and Lohmann (2015) is the only paper that examines aid effectiveness at a subnational level. Overall, they report mixed and inconclusive results, partly driven by regional heterogeneity. We

three previously undocumented findings on aid effectiveness. First, we find that aid at the local level (i.e. ADM2) promotes economic growth at an economically and statistically significant level. Second, we uncover significantly positive aid spillovers across adjacent localities at the ADM2 level. Third, aid flows at more aggregate levels (i.e. the first-level administrative areas, ADM1, and the country-level) have the opposite effect and reduce economic growth. Interestingly, the net effect of these four aid variables is near zero and is within the range of coefficient estimates reported at the country level by most previous papers. These results are robust to a rich battery of sensitivity tests.

The remainder of the paper is organized as follows. Section 2 describes the empirical methodology and introduces the data. Section 3 presents the main results, followed by robustness checks in section 4. Section 5 concludes.

2. Empirical Analysis

2.1 Model Specification

We adopt a standard growth model in Eq. (1) to examine aid effectiveness and aid spillovers at the subnational level.[5]

$$Growth_{ijt} = \alpha_0 + \alpha_1 * Light_{ijt-1} + \beta_1 * Aid_{ijt-1}^{ADM2} + \beta_2 * Aid_{-ijt-1}^{ADM2} + \beta_3 * Aid_{ijt-1}^{ADM1} +$$

$$\beta_4 * Aid_{ijt-1}^{Country} + \gamma' X_{ijt-1} + \delta_i + \delta_t + \varepsilon_{i,t} \qquad (1)$$

differ from their work in four dimensions. First, we account for spillovers from other aid-receiving localities. Second, we disaggregate aid flows into four groups, ADM1, ADM2, ADM2 in neighboring localities, and country level. Third, we focus on Sub-Saharan Africa, which helps with identification because of inter-regional heterogeneity. Fourth, our identification strategy allows us to establish a causal effect and as it tackles with the endogeneity and reverse causality problems.

[5] Note that unlike Dreher and Lohmann (2015), we use a dynamic growth model here, which controls for path dependency and convergence dynamics.

where i refers to subnational unit ADM2 in aid-recipient country j; t is the time period, measured by four-year averages.[6] δ_i is ADM2 fixed effects and controls for time-invariant but ADM2-specific factors. The use of ADM2 fixed effects also controls for any time-invariant structural causes of nightlight intensity variation across ADM2s, and allows us to focus on within-ADM2 variation over time. δ_t is time fixed effects and controls for cross-section invariant but time specific effects such as commodity price shocks. ε is the error term. We lag control variables by one period to partially alleviate the simultaneity problem and also to capture any delayed effects of aid over time.

$Growth_{ijt}$ is the average logarithmic growth rate in annual nightlight density per capita at the ADM2 level. We discuss this variable further in Section 2.2.

$Light_{ijt-1}$ is the average (log) level of (one plus) the nightlight density per-capita at time *t-1* as a proxy for income per capita in ADM2 i. If there is (conditional) convergence (divergence), we expect α_1<0 (α_1>0), which means faster (slower) growth in poorer ADM2s.

Aid_{ijt-1}^{ADM2} is the (log) level of (one plus) total amount of aid per-capita (in current USD) received in ADM2 at time *t-1*.

Aid_{-ijt-1}^{ADM2} is the (log) level of (one plus) total amount of aid per-capita (in current USD) received by i's neighbors at *t-1*. Total aid received by each neighbor of i, [–i], is calculated by the average total aid received by adjacent ADM2s. For tractability, we make some simplifying assumptions here: (i) aid spillovers are limited to those ADM2s within a country's borders as resource and factor movements are much more limited across than within countries; and (ii) spillovers exist only across adjacent neighbors given that resource and factor movements are expected to decay in the distance between aid receiving regions. We later test the sensitivity of

[6] The period averages are over 1995-1998, 1999-2002, 2003-2006, 2007-2010, and 2011-2013 where 1995 is the first year for aid projects in the dataset. We also use nightlight data for the period of 1991-1994 to gain an additional period as we use the lagged values of aid in Eq. (1).

our findings to these assumptions in the robustness section. As discussed earlier, the net effect of aid spillovers is ambiguous as there are both positive and negative externalities from aid.

Aid_{ijt-1}^{ADM1} is the (log) level of (one plus) average aid per-capita received per ADM2 at the ADM1 level. It is calculated by taking the average aid received by all ADM2s in a specific ADM1, excluding aid directly targeted to *i*. It controls for the growth effect of aid given at a larger administrative unit.

$Aid_{ijt-1}^{Country}$ is the (log) level of (one plus) average aid per-capita received per ADM2 at the country level, excluding the direct aid given at ADM1 and ADM2 levels. It is equal to the average of the sum of all aid given at the country level divided by the number of all ADM2s. We should note that the precision levels of aid variables, Aid_{ijt-1}^{ADM2}, Aid_{-ijt-1}^{ADM2}, Aid_{ijt-1}^{ADM1}, and $Aid_{jt-1}^{country}$ are mutually exclusive and collectively exhaustive.[7]

As discussed earlier, the effect of four *Aid* variables on *Growth* is indeterminate. To the extent that aid flows have a net positive effect on growth, we expect positive coefficients for $\beta_1 - \beta_4$. However, if the negative effects are stronger because of increasing corruption, rent-seeking, socio-political conflicts, misallocation of resources and distorted relative prices, or lower productivity, we expect to find negative coefficients for the β's. Or, given that money is fungible, if aid is used to substitute for government expenditures in a given location, the net effect can be zero. The same is true if aid flows are used for inefficient, corrupt or unproductive projects with low social and private rates of return. Our identification strategy allows us to separate some of these effects based on the assumption that targeted aid at more disaggregated levels is easier to monitor, making the donors and recipients more accountable. The fungibility problem is also

[7] The aid variables at the ADM2 level are with precision levels 1-3. Aid at the ADM1 level is with precision level 4, and aid at the country level is with precision levels 5-8. More details are in the Appendix. The correlation between these four aid variables ranges between 0.11 and 0.35.

expected to be weaker for targeted aid projects at the local level than aid disbursements at the national level. Performance outcomes are also easier to be identified at the local level given the heterogeneous nature of aid disbursements as well as aid expenditures. Last but not least, Eq. (1) allows us to control for the possibility that aid flows to a particular locality can have different effects in the aid recipient locations and its neighbors through various spillovers.

$X_{ijt-1}$is a vector of control variables at the country level and includes the following: General government final consumption expenditure, *GovExp*, which is the level of government expenditure as a percentage of GDP in country *j*. Depending on crowding-in vs. crowding-out effects, *GovExp* can have a positive or negative effect on growth. Inflation rate, *Inflation*, which is the percentage change in GDP deflator in country *j*, can have a negative effect depending on the size of distortions it creates. It can also grease the wheels, facilitating faster growth. Trade openness, *Openness*, is the percentage share of exports and imports in GDP in country *j*. *Openness* can increase growth and through channels such as economies of scale, competition and productivity gains.

2.2 Estimation Methodology

The main coefficient estimates of interest in Eq. (1) are β_1, β_2, β_3, and β_4 as they reveal the direction and significance of aid effectiveness and aid spillovers at the sub-national level. However, as is well recognized in previous research we have a serious problem of endogeneity here, including simultaneity and reverse causality, as the growth performance of a country may also affect its aid inflows, leading to biased results. For example, donors may use aid as a reward (punishment) for countries with good (bad) economic performances, or, allocate more aid to those that are struggling the most on humanitarian grounds such as fighting famine or alleviating poverty. Because aid in the previous period can be taken as predetermined in the current period, lagging aid variables, as we do in Eq. (1), can partially help alleviate the simultaneity problem. However, if there is serial correlation in aid disbursements, as is very likely, aid flows in one period will be correlated with aid flows in the next, with the latter being potentially correlated with current period growth.

The use of an IV approach can help address the simultaneity problem. However, finding good instruments for aid that are correlated with the aid variable but uncorrelated with the error term is notoriously hard. Boone (1996) and Burnside and Dollar (2000) use population size in recipient countries as an instrument for aid. However, Clemens et al. (2012) show that population size is a weak IV as it cannot explain much variation in aid flows. Rajan and Subramanian (2008) and Lessmann and Markwardt (2012) use historical, political and language connections between donors and recipients as IVs for aid. And yet these variables are defined only at the country level and cannot be used at the sub-national level. Hansen and Tarp (2001), Lessmann and Markwardt (2012) and Askarov and Doucouliagos (2015) apply further lagged aid variables such as *t-2* or *t-3* to build exclusion restrictions, but serial correlation problem persists in this type of IV approach. Therefore, to address these issues, we follow Brückner (2013) and adopt a two-step approach to isolate the exogenous part of aid in the aid-growth relationship. First, we regress aid on growth, using annual average precipitation and air temperature as IVs.[8] Next, we remove the endogenous part of aid flows based on the estimated regression coefficients, and then use the residual "uncontaminated" aid as an instrument in the aid-growth regression. Thus, we regress aid on growth to capture the potential effects of growth on aid in Eq. (2) using two-stage least squares (2SLS).

$$Aid_{ijt-1} = \tau_1 * Growth_{ijt} + \delta_i + \delta_t + \epsilon_{ijt} \qquad (2)$$

where Aid_{ijt-1} is a vector of (log) level of (one plus) aid per capita variables and includes Aid_{ijt-1}^{ADM2}, Aid_{-ijt-1}^{ADM2}, Aid_{ijt-1}^{ADM1}, and $Aid_{ijt-1}^{Country}$. $Growth_{ijt}$ is the growth rate of nightlight density per capita in ADM2 *i* and country *j* at time *t*. δ_i and δ_t are ADM2 and time fixed effects.

[8] Unlike Brückner (2013), we did not use the international commodity prices as an IV as they do not vary across ADM2s (or even countries) and therefore are absorbed by the ADM2 and time fixed effects.

We use air temperature and precipitation in location *i* at time *t* as IVs for $Growth_{ijt}$. Agricultural production is mostly controlled by climatic factors, particularly precipitation and temperature. Changes in precipitation and temperature affect soil fertility, timing of planting, and growth of plants with significant consequences for agricultural production. The dependence on rainfall and temperature is even higher in Sub-Saharan Africa partly because of lack of modern water and soil management and irrigation techniques, which make crop planting and harvesting more sensitive to climatic factors, and partly because of its geographical, socio-economic and demographical characteristics. Particularly, rain-fed agricultural production that is managed mostly by small-scale subsistence farmers with limited technological and financial resources, and limited access to information and basic infrastructure such as roads and irrigation networks, make African agriculture and household incomes very sensitive to climate (Dell et al., 2014; Pereira, 2017). According to World Bank, over 55% of labor force was employed in agriculture in Sub-Saharan Africa in 2016, and agricultural sector accounted for a staggering 92% of all freshwater withdrawals in that year (World Bank, 2019). Therefore, we expect rainfall and temperature conditions to affect income growth contemporaneously (Dell et al, 2014). The exclusion restriction for the IVs here is that current weather conditions should not affect any lagged aid flows. These instruments vary by ADM2 and year, allowing us to capture variation in *Growth*. After capturing the potential endogeneity by τ_1, we estimate the adjusted aid series in Eq. (3), which is assumed to be exogenous to $Growth_{ijt}$, and can be used as IVs for *Aid* in Eq. (1):

$$Aid_{ijt-1}^{*} = Aid_{ijt-1} - \tau_1 * Growth_{ijt} \tag{3}$$

2.3 Data

The dependent variable in Eq. (1), *Growth*, is measured at the subnational level from 3,764 aid recipient ADM2s in 48 Sub-Saharan African countries.[9] As discussed earlier, one major issue that plagued previous work on aid effectiveness is the use of aggregate growth and aid data at the national level. In addition to the aggregation bias, the use of national data creates other problems as national income statistics in low-income countries, especially in those that need the aid the most, are not reliable. As argued by Jerven (2013), for example, serious data reporting problems and errors for GDP measurement are widespread in many African countries that make empirical work particularly difficult. However, there is simply no reliable subnational income series that could replace national data in most countries. Therefore, following recent literature on economic growth, we use the nightlight intensity as a consistent, reliable and robust proxy to measure local economic activity (Elvidge et al., 2001, 2009; Sutton and Costanza, 2002; Henderson et al., 2012; Hodler and Raschky, 2014; Donaldson and Storeygard, 2016).[10]

The nightlight data are available from the US Air Force Defense's Meteorological Satellite Program, which monitors earth through its satellites, each moving around the world

[9] Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Cape Verde, Comoros, Congo, Rep, Congo (Dem. Rep.), Côte d'Ivoire, Eritrea, Equatorial Guinea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, São Tomé and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe.

[10] Growth rates based on income and nightlights can differ as the income elasticity of lights may be different than one, and the light-output ratio may change overtime. Also, nightlights are measured by different satellites in different years, effecting sensor quality and mechanics. In addition, sensor sensitivity is likely to diminish by age. Cloud cover, humidity and other weather conditions can also affect light diffusion. However, by using the growth rate of nightlight density, we difference out the location-specific fixed effects. Any remaining time, satellite or location specific factors are controlled by the use of ADM2 fixed effects and year fixed effects. The residual part is then treated as a measurement error. For an extensive discussion of using nightlight data as a measure of income and growth, see Henderson et al. (2012) and Donaldson and Storeygard (2016).

orbit 14 times a day (NOAA, 2015). The data, which are available for 1992-2013, cover the intensity of nightlights on earth between 65-degree South and 75-degree North and include most of the inhabited areas for human economic activities. The nightlights dataset uses 30 arc-second pixels (1/120th of a degree of latitude and longitude, approximately 0.86 square kilometers at the equator) to represent the yearly average light intensity on earth. Pixels are on a scale from 0 to 63, with 0 no light and 63 the highest lights intensity.[11]

We use the longitude and latitude data to match aid projects to particular locations at ADM1 and ADM2 levels using the Global Administrative Areas database (2015), which provides boundaries at different administrative levels for each country. Each administrative unit is depicted as a polygon with descriptive information about that unit. ADM1 regions are subnational units below the national borders such as counties or municipalities while ADM2 locations are those that are below the ADM1 regions.

Our main control variable is the geocoded aid flows from the World Bank Geocoded Research Release database (Version 1.3, Level 1) provided by AidData (2017). The dataset for Sub-Saharan Africa covers aid projects in 3,764 ADM2s in 48 countries over the period of 1995-2014.[12] Each aid project includes information on the longitude and latitude of the location as well as on the precision level, which determines the target location. Our aid variable includes the sum of aid disbursements in 21 different activities.[13] As shown in Table 1, while the mean level of aid at the ADM2 level is \$220,933, it displays a high level of variation with a standard deviation of \$946,819. Likewise, the (average per ADM2) aid levels at ADM1 and country levels

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[11]The online Appendix provides further details on the processing procedures of spatial data.

[12] For details of the dataset, see Tierney et al. (2011). The data does not separate different types of aid such as humanitarian or infrastructure aid.

[13] In constructing the aid variable at ADM2 level for a given year, we divided the total amount of aid disbursement of an aid project by its duration. For further details, see the Appendix.

are $81,441 and $7,071, respectively (current prices). The average aid a neighbor of an aid receiving ADM2 location receives is $228,552. Overall, we observe a high level of heterogeneity in aid distribution across different aggregation levels and locations, causing a high level of coefficient of variation.

<Insert Table 1 Here>

Figures 1-3 show geographic distribution of aid projects across Africa at different administrative levels for the period analyzed, including ADM2, ADM1 and country level. In the empirical analysis we take advantage of the high level of variation at the ADM2 level, compared to ADM1 and country level. We should also note that aid projects are clustered among certain geographic regions such as Western and Eastern Africa and are relatively absent in Northern and Southern Africa. These graphs also reveal a high level of within and between country heterogeneity in the distribution of aid projects, which provide further justification for using a sub-national analysis to examine aid effectiveness. Figures 2 and 3 for the ADM1 and country level aid projects make the inter-regional differences even more obvious both within and across countries.

<Insert Figures 1-3 Here>

Figure 4 shows the average annual growth rate of nightlight density in Sub-Saharan Africa at the ADM2 level between 1992 and 2013. Similar to the case with aid flows, Figure 4 reveals a significant level of growth heterogeneity both within and between countries. If we were to use aggregate data at the national level, as most previous studies have done, we would have missed this heterogeneity in growth rates as well as in the distribution of aid projects in Sub-Saharan Africa.

<Insert Figure 4 Here>

We use annual averages of monthly mean surface air temperatures, and monthly total precipitation to match the frequency of the aid data. Both variables are from the Center for Climatic Research at the University of Delaware (version 4.01) and are depicted as continuous pixels across the world for 1900-2014. The geocoded population data are from Center for International Earth Science Information Network Version 4 (CIESIN, 2015) and from the Centro Internacional de Agricultura Tropical (CIAT, 2015). Like nightlights data, population data are depicted as pixels, with each pixel attached with the population count in that pixel. The population data is available only every five years (1990, 1995, 2000, 2005, 2010, 2015) and we use linear interpolation to fill in the gaps in the data series.[14] Country level data on government expenditures, inflation, and trade openness are from World Development Indicators of the World Bank (World Bank, 2019).

3. Empirical Results

Table 2 presents regression results from Equation (2) where we tackle the issue of endogeneity and reverse causality. In column (1) we test the appropriateness of our IVs by regressing growth on air temperature and precipitation and find that they are statistically significant at the 1% level, both individually and jointly. The results suggest that air temperature has a positive and precipitation has a negative effect on growth, which are consistent with those reported in Dell et al. (2012) and Wood and Mendelsohn (2014).[15] In Columns (2)-(5) we show regression results where Aid_{ijt-1}^{ADM2}, Aid_{-ijt-1}^{ADM2}, Aid_{ijt-1}^{ADM1}, and $Aid_{ijt-1}^{Country}$ are the dependent variables, and temperature and precipitation are IVs for growth. Using parameter estimates for τ in Eq. (2), we remove the simultaneity effect from growth to (lagged) aid variables in columns (2)-(5). While the coefficient estimates themselves are not the main focus here, we should note that we find

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[14] Given the slow change in population, we assumed a linear trend and calculated the slope of population against time, and then based on the estimated slope, interpolated population for the missing years.

[15] While we know that increasing temperatures tend to increase crop yields, the effects of precipitation are not clear. First, because many sub-Saharan African countries have rainforest climate, where the nutritious soil is accumulated on the top; increasing precipitation can wash the nutrients away and reduce the productivity of the soil (Sachs, 2001). Second, increasing moisture, cloud cover or spreading of pests can lower crop yields and therefore growth rates, especially in countries that lack the necessary infrastructure to deal with these problems.

growth rate of this year to be a significant predictor of aid disbursements last year at all four levels of aid flows at the 10% level. Thus, the failure to remove the causal effect of growth on aid may explain some of the conflicting findings in literature. We should also note that the IVs for growth in the first stage pass the over-identification test in all specifications.

<Insert Table 2 Here>

Table 3 shows the second-stage estimates from Eq. (1) where we introduce aid variables at the ADM2, ADM1 and country level one by one in columns (1)-(5), and then altogether in column (6). All sets of regressions include a full set of ADM2 and year fixed effects and are estimated by 2SLS. When introduced alone in Column (1) we find a significantly positive effect (at 1% level) of Aid_{ijt-1}^{ADM2}, suggesting that aid flows to local districts at the ADM2 level have significant growth enhancing effects. This positive effect is also economically significant, a 1% increase in aid per capita is predicted to increase next year's growth rate per capita by 1.06 percentage points, which is a quarter of the average growth rate (4.3%) in a given ADM2 in our sample during the period analyzed. In column (2), we introduce the average aid received by adjacent neighbors of *i*, Aid_{-it-1}^{ADM2}, to examine the spillover effects. Unlike Askarov and Doucouliagos (2015a), who report a negative spillover effect in transition economies at the country level, we find that there are indeed positive and significant spillovers from aid-receiving localities to their neighbors in Sub-Saharan Africa. This growth effect is also economically significant and is almost half the size of the direct effects of aid to a given ADM2. After controlling for the spillover effect, the coefficient estimate of Aid_{ijt-1}^{ADM2} drops only marginally and remains significant, both statistically and economically. Thus, without this spillover effect, we would have underestimated the aid effectiveness.

<Insert Table 3 Here>

In column (3) we introduce Aid_{ijt-1}^{ADM1} by itself, which controls for the effects of aid received per ADM2 at the ADM1 level. The results suggest that aid received at ADM1 level is negatively associated with economic growth in a given ADM2. In other words, aid targeted at more aggregate levels is likely to harm local economic growth, which is consistent with the findings from previous literature on aid pessimism (Doucouliagos and Paldam, 2009). In column (4) when we include all three aid variables, Aid_{ijt-1}^{ADM2}, Aid_{-ijt-1}^{ADM2}, and Aid_{ijt-1}^{ADM1}, we continue to find a positive and significant growth effect of aid at the ADM2 level together with positive and significant aid-spillovers from adjacent regions. And yet, aid at the ADM1 level, Aid_{ijt-1}^{ADM1}, still shows an economically and statistically significant negative effect on growth. These findings may also help reconcile the seemingly inconsistent findings in the literature. In column (5) we introduce $Aid_{ijt-1}^{Country}$, which measures average aid at the country level per ADM2. Similar to the effect of aid at the ADM1 level, aggregate aid flows at the country level has a significantly negative effect on local growth in a given ADM2. Column (6), which is our benchmark specification, includes all four aid variables at the same time. Confirming findings in columns (1) - (5), all aid variables retain their sign and significance levels while the size of coefficient estimates decreases slightly. The total effect of aid targeted at ADM2 level together with spillovers from aid-receiving adjacent regions is now equal to 1.448, which is quite significant both statistically and economically. In contrast, if we sum the coefficient estimates of all aid variables in column (6), the net effect becomes 0.005, which is near zero and not significant, either statistically or economically. This estimate is almost identical to the findings of Doucouliagos and Paldam (2009), who report a coefficient close to zero in their meta-analysis of 40 papers on aid effectiveness. Overall, the results suggest that aid targeted at the local level tends to promote local growth, while aid targeted at more aggregate levels is likely to hurt it.

Turning to other control variables, we find that lagged (log) level of dependent variable, *Light* has a negative and significant effect on growth, suggesting a within-country conditional convergence in light density. Furthermore, we find that total government expenditure in GDP (*GovExp*) and inflation rate (*Inflation*) are negatively associated with local economic growth. In contrast, trade openness has a positive effect on local growth. Across all sets of regressions both the Cragg-Donald Wald F statistic and Kleibergen-Paap rk Wald F statistic are greater than the critical values provided by Stock and Yogo (2005), indicating that the instruments have good explanatory power to explain the endogenous aid variables.

To the best of our knowledge, these are the very first statistical estimates of aid effectiveness, including spillovers, at different disaggregation levels. These results are also consistent with the findings from earlier studies that report negative or insignificant effects of country level aid flows. Boone (1996), for example, shows that aid flows at the national level are likely to increase the size of the government without promoting investment or human capital development. In their study of effects of aid on road projects in Vietnam, Van de Walle and Mu (2007) also show that targeted aid is easier to monitor and audit and therefore is less likely to be misappropriated for other government projects. Likewise, Svensson (2000) and Asongu (2012) show that foreign aid provides rent-seeking opportunities and is associated with higher corruption. Among other possible reasons for aid effectiveness at the local level, we should also consider higher local community participation in a bottom-up rather than top-down approach, which helps channel aid to more effective and locally needed *and* wanted projects, given that local communities have better knowledge about local conditions, needs and capabilities (Feeney, 1998). The bottom-up approach in aid and development policy design is also likely to increase community appropriation of aid projects, making them more effective and durable (Easterly, 2008).

4. Extensions and Sensitivity Analysis

In this section we perform a rich battery of robustness tests to examine the sensitivity of our findings to sample selection and specification error. Using the baseline results of Column (6) in Table 3, we first examine the issue of outliers in Table 4. In column (1) we present results after dropping observations with growth rates below and above the 1st and 99th percentiles. Given that we use nightlight densities as a proxy for growth, our results might be affected by unstable or extreme nightlight observations, caused by faulty satellite images or remote sensing processing. While the use of ADM2 and year fixed effects help reduce this bias, removing these outliers can help reduce the noise in the data further and improve both the accuracy and the precision of our point estimates. After dropping these observations on higher and lower ends of the tail, we continue to find similar results to those reported before: aid targeted at the ADM2 level has a significantly positive growth effect while the opposite is the case for aid flows at the ADM1 and country levels. We also continue to find a significantly positive spillover effect from aid flows in neighboring regions. One major difference from earlier results, however, is that the size of coefficient estimates drops significantly and becomes very close to those previous papers that reported positive effects from aid to growth at the country level (Doucouliagos and Paldam, 2009; Clemens et al., 2012). A 1 percent increase in *Aid* at ADM2 level, for example, now increases local growth by 0.146 percentage points, rather than 0.757 as reported in column (6) of Table 3. Likewise, the spillover effect from adjacent ADM2 is now 0.134 rather than 0.691. Considering that the average growth rate at ADM2 level is 4.3%, these are still economically significant magnitudes.

<Insert Table 4 Here>

In column (2) we tackle the zero nightlights issue. About 10% of observations contain zero nightlights per capita, indicating that economic activities in those locations are insufficient to emit any light that is detectable by the satellites. Concerned by the potential underestimation of aid effectiveness resulting from this undetectability problem, we exclude observations with zero nightlight density from the sample. The results in column (2) confirm our earlier findings as all aid variables have very similar coefficient estimates to those in the baseline regression of column (6) in Table 3 and are statistically significant at 1% level.

The opposite of zero nightlight issue is the abnormally high nightlights that are caused by accidents or other incidences, producing extreme light emissions. For example, gas flares, which are often observed in petroleum production fields, tend to produce highly intensified lights with little observable economic activity. Another possible cause is forest fires, which emit significant light density but are hardly qualified to serve as proxies for human economic activities. To address these issues, in columns (3) and (4) we drop observations that are at the top 1% and 5% of the nightlight per capita, respectively. The regression results again confirm our earlier findings. We also note that coefficient estimates move closer as we exclude outliers at the higher end of the distribution in columns (1), (3) and (4), suggesting that extremely high nightlight densities rather than zero nightlights are pushing the coefficients on aid effectiveness upwards. In columns (5) and (6) we exclude those ADM2s that receive aid the most, particularly those in the 99^{th} and 95^{th} percentiles. However, excluding these aid outliers had only a marginal effect on our earlier findings, leaving our main conclusions intact. Last but not least, we excluded one country at a time from the sample and found almost identical results as before. These results are reported in the online Appendix.

Next, in Table 5 we test the sensitivity of our results to measurement error and omitted variable bias. In our benchmark estimations we used 4-year averages to limit the effects of business cycles and short-term shocks as well as the delayed effects of aid on economic growth. However, not all variables in our dataset have continuous four-year observations for the full period analyzed and if we restricted the sample to a balanced panel we would have too few observations. Therefore, in columns (1) and (2) of Table 5 we test the sensitivity of our findings to the number of observations included in the four-year averages. In column (1) we first restrict the sample to include no less than 2 observations for each of the four-year periods and continue to find similar results to those before. One noticeable difference, however, is that the size of coefficient estimates are now doubled, suggesting that our earlier estimates could be the lower rather than the upper bound for aid effectiveness. In column (2) we repeat the same exercise but this time limiting the sample to those with no less than three observations for each four-year window. Our findings again remain unchanged with the exception that the coefficient estimates are now significantly larger for all four aid variables.

<Insert Table 5 Here>

In the data we observe that average values for each of the four aid-variables increase significantly from the first four-year period (1995-1998) to the second one (1999-2002).[16] In addition to a trend increase in aid flows to Africa, another possible reason for this is the missing observation problem if aid flows were not recorded properly during the earlier years of the sample. As we use lagged aid to explain current economic growth, the regression estimates in the second period may suffer from this bias. To check for this possibility, in column (3) we drop the first four-year observations from the sample and still find similar results. In column (4) we test the sensitivity of our results to the assumption that aid spillovers are limited only to those adjacent ADM2 locations within a country's borders. Once we drop this assumption and consider all adjacent locations that receive aid, independent of country borders, we expect the spillover effects to be weaker, as national borders impose physical barriers of entry and exit. Results in column (4) confirm our earlier findings and also show that aid spillovers are not confined to localities within a given country but across border as well, even if at a lower level. As a falsification test, we also generated random adjacent neighbors within a country to see if the spillover effects diminish over physical territory. The (unreported) results show that the spillover effects become more than 20 times smaller. The results are again reported in the Appendix.

Next, in column (5) we expand our main specification by including a control variable for the level of institutional development at the country level (Burnside and Dollar, 2000). We measure institutional development by the International Country Risk Guide index (ICRG), which is a composite variable of institutional development in 12 subcategories, including government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in politics, religious tensions, law and order, ethnic tensions, democratic

[16] The mean of (log) aid variables, Aid_{ijt-1}^{ADM2}, Aid_{-ijt-1}^{ADM2}, Aid_{ijt-1}^{ADM1}, $Aid_{ijt-1}^{country}$, are 1.448, 3.323, 2.687 and 1.612 during 1995-1998 but are 2.938, 5.436, 5.131 and 2.676 during 1999-2002, respectively.

accountability, and bureaucracy quality. *ICRG* ranges from 0 to 100, with higher scores representing better institutional development. The results in column (5) are quite similar to those before and confirm the significantly positive effect of country-level institutional development on growth.[17] In the Appendix, we repeated this exercise by replacing *ICRG* with another proxy of institutional development, *PolityIV* scores from the Polity IV project, and confirmed these findings.

In equation (1) we tested the effect of foreign aid on per capita income growth, measured by growth rate of nightlights per capita in a given ADM2. However, an increase in economic activity per person can result from an increase in total income (i.e. total nightlights) or a decrease in population, or both. To separate these two effects and identify which one is more important in Sub-Saharan Africa, in column (6) we replace the nightlights per capita growth with total nightlights growth. The results confirm our earlier findings as all aid variables retain their sign and significance levels. However, the magnitudes of coefficients are smaller than in Table 3. The negative effects of aid at more aggregate levels are also reduced substantially. In column (7) we replaced the aid variables with an aggregate measure of aid, which is the sum of aid disbursements at all levels. This exercise also allows us to compare our results with the wider research on aggregate aid flows. The regression estimates suggest that the effect of total aid flows on local growth at ADM2 level is negative and economically much smaller. This finding also provides further support to our method of using disaggregated aid data to measure aid effectiveness. In other words, the previously reported negative or insignificant effects of aid on growth could be caused by the aggregation bias.

Next, we repeated the growth regression by running growth per capita on ADM1-time and country-time fixed effects and recovered the residuals. These residuals capture those parts

[17] In the Appendix, we repeat all robustness tests including the ICRG variable and find similar results.

of growth that cannot be explained by any time variant ADM1 or country specific effects. Next, we included these residuals in our main growth equation and repeated the same exercise as in Table 3. The results in column (8) are similar to those before. We also repeated this exercise to reproduce Table 3 and reported in the Appendix. The results were again very similar. Finally, we dropped one country at a time from the sample (with and without institutional development index, *ICRG*) and repeated the regression analysis. The (unreported) results confirm our previous findings and are available in the Appendix.

5. Conclusion

This article revisits the debate on aid effectiveness using a sub-national analysis in Sub-Saharan Africa. We argue that previous studies on aid effectiveness have suffered from an identification bias as they focused mostly on aggregate aid and economic growth while paying scant attention to aid spillovers and economic growth at the local level. Furthermore, most earlier studies have failed to address the reverse causality and endogeneity problems, which are of paramount importance for the internal validity of estimated relationship between foreign aid and growth.

In this paper we tackled the aggregation bias by using aid data at the subnational level, which allowed us to examine aid effectiveness at different levels of disaggregation within a country. Furthermore, our use of nightlights data made it possible to analyze the effectiveness of targeted-aid on economic activity at the subnational level. Using precipitation and temperature information as IVs for economic activity together with a two-step estimation method, we addressed the endogeneity and reverse causality problems. After dealing with the identification and estimation issues, the empirical results revealed that aid targeted at the local level (i.e. ADM2) promotes local economic growth, while aid received at more aggregate levels (i.e. ADM1 and country level) have the opposite effect. We also uncover robust evidence that there are significantly positive aid spillovers across adjacent locations, both within and across a country's borders. We confirm these findings using a rich battery of sensitivity tests. Overall, our analysis shows that micro scale interventions can be effective in stimulating economic growth in Sub-Saharan Africa.

Our findings have significant policy implications. If the objective of international aid is to promote local economic growth, we should then focus more on targeted aid projects rather than others at the national level. Aid at more aggregate levels might be misappropriated for other purposes and can create reek seeking and corruption, reducing overall aid effectiveness. Aggregate aid disbursements are also notoriously hard to monitor for performance targets, creating serious accountability problems for both donors and aid recipients. Our analysis, therefore, suggests that donors, who often prefer mega projects at the country level with more visibility and glamor, should instead focus their efforts to targeted local projects, which will increase the potential for feedback from local communities and allow experimentation to test what works best. Furthermore, we suggest that when considering aid effectiveness, policy makers, international aid institutions and individual donors need to consider aid spillovers between neighboring regions. To increase such spillovers, policy makers can consider ways of reducing barriers to goods and resource movements and knowledge dissemination. Furthermore, given the high level of competition among different aid projects for funding, showing the effectiveness of each dollar spent can increase the likelihood of receiving future aid disbursements.

Finally, we should note that our analysis does not necessarily address the criticism that targeted aid programs undermine “big push” type aid efforts that aim larger scale structural transformation in developing countries. Building infrastructure, developing physical and human capital, institutional development, macroeconomic stability, poverty reduction and health care, and speeding up industrialization and developing dynamic comparative advantage remain among top goals of development economists. The all-at-once approach that is more recently advocated by Millennium Villages can also be consistent with our findings as long as the aid programs are targeted to specific projects. We expect future research to expand our analysis by taking into account other determinants of aid effectiveness at the local level, including the types of aid, characteristics of donors, and varieties of targeted development programs.

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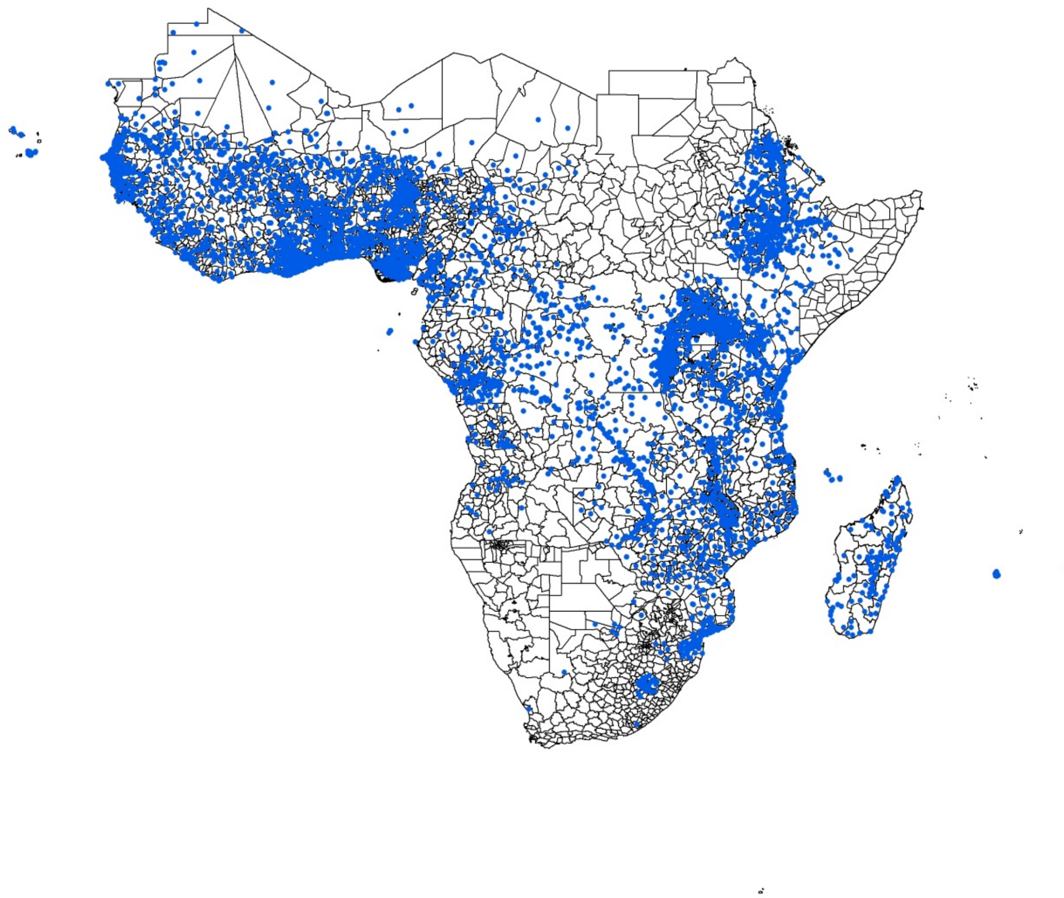
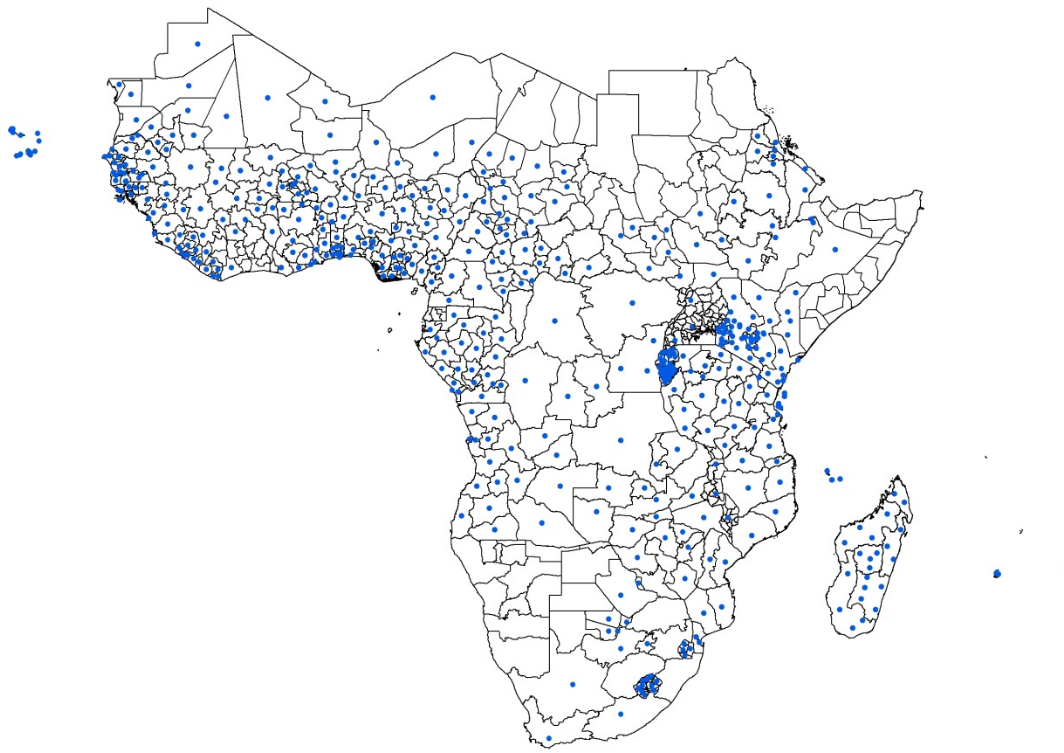
Figure 1: Aid Projects at ADM2 Level in Sub-Saharan Africa



Notes: This map shows ADM2 boundaries and aid projects at ADM2 level. The ADM2 boundaries are drawn as polygons and aid projects at ADM2 level are depicted as points.

Source: Authors' calculations.

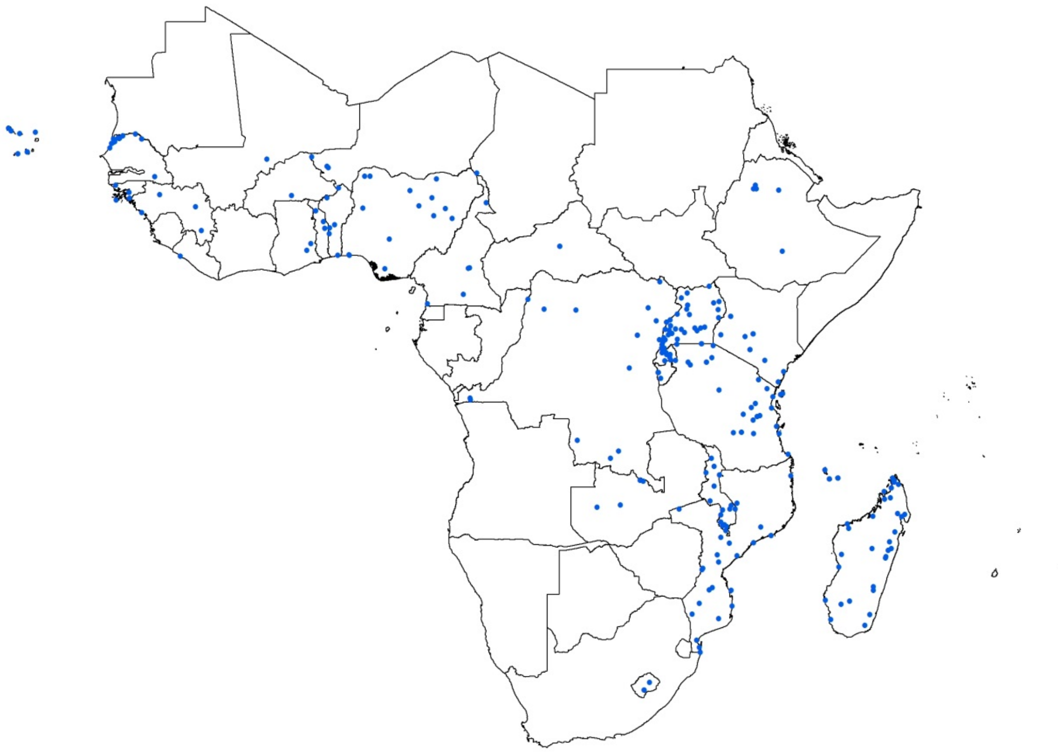
Figure 2: Aid Projects at ADM1 Level in Sub-Saharan Africa



Notes: This map shows ADM1 boundaries and aid projects at ADM1 level in Sub-Saharan Africa. ADM1 boundaries are drawn as polygons and aid projects at ADM1 level are depicted as points.

Source: Authors' calculations.

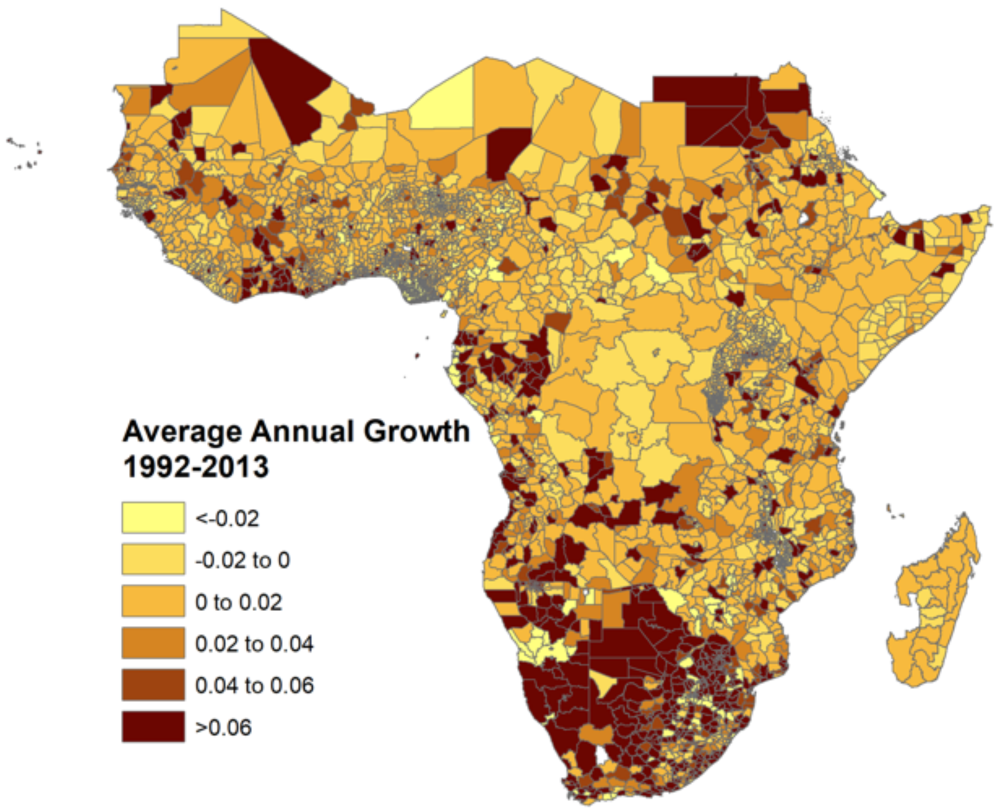
Figure 3: Aid Projects at Country Level in Sub-Saharan Africa



Notes: This map shows country boundaries and aid projects at country level in Sub-Saharan Africa. Country boundaries are drawn as polygons and aid projects at country level are depicted as points. Dots outside the continent are for island locations.

Source: Authors’ calculations.

Figure 4: Average annual growth of nightlight per capita at the ADM2 level in Sub-Saharan Africa



Notes: The data shows average annual growth rate of nightlight density per capita (in decimals) at the ADM2 level. Missing observations are caused by the lack of population data for a given location.

Table 1: Summary statistics

	N	Mean	Std. Dev.	Min	Max	Median
Aid_{ijt-1}^{ADM2}	11,619	220,933	946,819	0	2.885e+07	0
Aid_{-ijt-1}^{ADM2}	11,619	228,552	568,713	0	1.221e+07	43,771
Aid_{ijt-1}^{ADM1}	11,619	81,411	211,936	0	3.420e+06	10,621
$Aid_{jt-1}^{country}$	11,619	7,071	19,379	0	134,349	0
$Growth_{ijt}$	11,619	0.043	0.735	-16.08	18.65	0
$Light_{ijt-1}$	11,619	0.028	0.096	0	2.398	0.002
$Population_{,t-1}$	11,619	181,433	224,339	26.92	11,619	124,968
$Temperature_{it-1}$	11,548	24.39	3.894	5.858	11,548	25.65
$Precipitation_{it-1}$	11,548	88.33	45.95	0.460	11,548	83.664
$GovExp_{it-1}$	11,533	13.75	4.917	6.388	11,533	13.697
$Inflation_{it-1}$	11,458	12.21	8.878	-0.718	11,458	8.918
$Openness_{it-1}$	11,605	66.80	28.47	27.37	11,605	59.810
$ICRG_{it-1}$	11,619	55.97	9.908	38.40	11,619	56.65

Notes: The data refer to four-year averages that are used in the regression analysis. Aid_{it-1}^{ADM2} and Aid_{-it-1}^{ADM2}refer to the amount of aid received by ADM2 and by ADM2's neighbors, respectively. Aid_{it-1}^{ADM1} is the average aid received by ADM2s at the ADM1 level (total aid divided by the number of ADM2s in a given ADM1, excluding the amount of aid received at ADM2 level). $Aid_{it-1}^{country}$is the average aid received by ADM2 at the country level, excluding the amount of aid received at ADM2 and ADM1 levels. All aid variables are measured in current US dollars (dividing by average population will give per capita numbers). *Growth* is the growth rate of light density per capita. *Light is* the logarithm of lagged (one plus) light density per capita. *Population* is total population count. *Temperature* and *Precipitation* are air temperature and precipitation levels. *GovExp* is government final consumption expenditure as a share of GDP, *Inflation* is the average annual inflation rate, *Openness* is share of total trade in GDP, *Fiscal* is the fiscal surplus as a share of GDP, and *ICRG* is the institutional development index.

Table 2: Simultaneity analysis

	(1)	(2)	(3)	(4)	(5)
	$Growth_{ijt}$	Aid_{ijt-1}^{ADM2}	Aid_{-ijt-1}^{ADM2}	Aid_{ijt-1}^{ADM1}	$Aid_{ijt-1}^{Country}$
$AirTemp_{ijt}$	0.057***				
	(0.021)				
$Precipitation_{ijt}$	-0.002***				
	(0.0006)				
$Growth_{ijt}$		-21.180*	-14.680*	23.190*	11.850*
		(12.040)	(8.592)	(13.070)	(6.843)
Obs.	22,584	15,056	15,056	15,056	15,056
Number of ADM2	3,764	3,764	3,764	3,764	3,764
ADM2 FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
F-statistics	0.000	0.000	0.000	0.000	0.000
Hansen	-	0.518	0.167	0.130	0.878

Notes: 2SLS estimates using robust standard errors in parentheses. ***, **, and * refer to p<0.01, p<0.05, p<0.1, respectively. All regressions here and thereafter include an unreported constant variable. *ADM2 FE* and *Year FE* are ADM2 and year fixed effects. *Hansen* is Hansen's J-statistics. *F-statistics* and *Hansen* are reported by their p-values. For other variable definitions, refer to Table 1.

Table 3: Effect of aid on growth

	(1)	(2)	(3)	(4)	(5)	(6)
Aid_{ijt-1}^{ADM2}	1.060***	0.936***		0.788***		0.757***
	(0.163)	(0.146)		(0.114)		(0.106)
Aid_{-ijt-1}^{ADM2}		0.486***		0.694***		0.691***
		(0.077)		(0.100)		(0.098)
Aid_{ijt-1}^{ADM1}			-0.931***	-1.217***		-1.070***
			(0.131)	(0.172)		(0.148)
$Aid_{ijt-1}^{Country}$					-0.801***	-0.373***
					(0.111)	(0.055)
$Light_{ijt-1}$	-22.79***	-21.45***	-33.25***	-34.55***	-30.44***	-36.46***
	(4.051)	(4.275)	(4.530)	(4.268)	(4.141)	(4.324)
$GovExp_{jt-1}$	-0.242***	-0.318***	0.016	-0.313***	-0.041***	-0.328***
	(0.039)	(0.052)	(0.011)	(0.049)	(0.009)	(0.049)
$Inflation_{jt-1}$	-0.049***	-0.068***	-0.025***	-0.107***	0.041***	-0.083***
	(0.009)	(0.012)	(0.005)	(0.017)	(0.006)	(0.013)
$Openness_{jt-1}$	0.0160***	0.022***	0.005**	0.029***	-0.001	0.028***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Obs.	13,242	13,242	13,242	13,242	13,242	13,242
Number of ADM2	3,327	3,327	3,327	3,327	3,327	3,327
ADM2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald	430.580	173.155	564.382	71.799	1188.415	55.145
Kleibergen-Paap	46.301	22.090	54.862	17.179	63.818	13.600
Stock-Yogo	5.53	3.63	5.53	na	5.53	na

Notes: The dependent variable is *Growth.* The results are based on 2SLS with robust standard errors in parentheses. ***, **, and * refer to p<0.01, p<0.05, p<0.1, respectively. ADM2 FE and Year FE are ADM2 and year fixed effects. *Cragg-Donald* and *Kleibergen-Paap* are Cragg-Donald Wald F-statistic and Kleibergen-Paap rk Wald F-statistic. *Stock-Yogo* is Stock and Yogo (2005) critical values.

na is not available. For other variables, refer to Tables 1 and 2.

Table 4: Robustness tests: Excluding outliers

	(1)	(2)	(3)	(4)	(5)	(6)
	1th<Growth<99th	Light>0	Light<99th	Light<95th	Aid<99th	Aid<95th
Aid_{ijt-1}^{ADM2}	0.146***	0.830***	0.416***	0.168***	0.777***	0.948***
	(0.008)	(0.120)	(0.045)	(0.016)	(0.110)	(0.139)
Aid_{-ijt-1}^{ADM2}	0.134***	0.847***	0.381***	0.155***	0.698***	0.753***
	(0.008)	(0.122)	(0.041)	(0.015)	(0.099)	(0.111)
Aid_{ijt-1}^{ADM1}	-0.212***	-1.175***	-0.593***	-0.245***	-1.076***	-1.237***
	(0.011)	(0.166)	(0.062)	(0.023)	(0.150)	(0.178)
$Aid_{ijt-1}^{Country}$	-0.072***	-0.418***	-0.205***	-0.084***	-0.385***	-0.382***
	(0.006)	(0.064)	(0.024)	(0.009)	(0.058)	(0.061)
$Light_{jt-1}$	-15.72***	-36.05***	-29.07***	-30.69***	-36.51***	-38.40***
	(1.319)	(4.370)	(3.310)	(2.180)	(4.362)	(4.621)
$GovExp_{jt-1}$	-0.062***	-0.506***	-0.179***	-0.073***	-0.331***	-0.423***
	(0.005)	(0.078)	(0.022)	(0.008)	(0.051)	(0.067)
$Inflation_{jt-1}$	-0.017***	-0.093***	-0.045***	-0.018***	-0.086***	-0.112***
	(0.002)	(0.016)	(0.006)	(0.002)	(0.014)	(0.018)
$Openness_{jt-1}$	0.005***	0.027***	0.015***	0.006***	0.029***	0.037***
	(0.001)	(0.006)	(0.003)	(0.001)	(0.005)	(0.007)
Obs.	13,052	10,725	13,161	12,835	12,855	11,645
Number of ADM2	3,309	2,800	3,310	3,238	3,304	3,166
ADM2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald	248.339	44.314	91.839	213.694	52.399	40.854
Kleibergen-Paap	111.396	12.926	24.575	33.789	13.363	12.489
Stock-Yogo	na	na	na	na	na	na

Notes: The dependent variable is *Growth.* 2SLS estimates with robust standard errors in parentheses. ***, **, and * refer to p<0.01, p<0.05, p<0.1, respectively. ADM2 FE and Year FE are ADM2 and year fixed effects. F-statistics is reported by its p-values. For other variable definitions, refer to Tables 1 and 2.

Table 5: Robustness tests: Alternative model specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	n≥2	n≥3	Drop first period aid	Cross-border	ICRG	Total lights	Aggregate aid	ADM1 & Country-time FE
Aid_{ijt-1}^{ADM2}	1.246***	1.426***	0.696***	0.913***	0.649***	0.052***		0.414***
	(0.195)	(0.242)	(0.092)	(0.130)	(0.074)	(0.009)		(0.050)
Aid_{-ijt-1}^{ADM2}	1.617***	1.764***	0.659***	0.286***	0.606***	0.060***		0.387***
	(0.245)	(0.291)	(0.098)	(0.043)	(0.069)	(0.008)		(0.047)
Aid_{ijt-1}^{ADM1}	-2.528***	-2.820***	-1.141***	-0.996***	-0.945***	-0.063***		-0.599***
	(0.370)	(0.447)	(0.145)	(0.141)	(0.104)	(0.012)		(0.070)
$Aid_{ijt-1}^{Country}$	-1.432***	-1.472***	-0.180***	-0.338***	-0.234***	-0.037***		-0.150***
	(0.253)	(0.288)	(0.034)	(0.051)	(0.031)	(0.005)		(0.021)
$Aid_{jt-1}^{Aggregate}$							-0.111***	
							(0.015)	
$Light_{jt-1}$	-34.37***	-35.71***	-51.41***	-36.39***	-30.27***	-0.778***	-19.77***	-18.76***
	(5.322)	(5.907)	(5.221)	(4.427)	(3.482)	(0.019)	(4.587)	(2.353)
$GovExp_{jt-1}$	-1.758***	-1.956***	-0.137***	-0.244***	-0.385***	-0.035***	-0.003	-0.247***
	(0.270)	(0.327)	(0.027)	(0.039)	(0.048)	(0.007)	(0.003)	(0.032)
$Inflation_{jt-1}$	0.057*	0.064*	-0.089***	-0.066***	-0.069***	-0.005***	0.006***	-0.046***
	(0.033)	(0.037)	(0.015)	(0.011)	(0.009)	(0.002)	(0.001)	(0.006)
$Openness_{jt-1}$	0.220***	0.277***	0.034***	0.021***	0.015***	0.0004	-0.008***	0.011***
	(0.039)	(0.056)	(0.006)	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)
$ICRG_{jt-1}$					0.031**	0.029***	0.012***	0.015*
					(0.014)	(0.003)	(0.002)	(0.009)
Obs.	5,219	4,892	9.981	13,242	11,386	11,386	8,570	11,386
Number of ADM2	1,893	1,823	3,327	3,327	2,863	2,863	2,445	2,863
ADM2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald	13.668	10.893	45.126	63.213	56.911	32.941	6.3e+04	56.911
Kleibergen-Paap	11.816	9.947	16.218	13.068	21.690	10.722	3903.438	21.690
Stock-Yogo	na	na	na	na	na	na	5.53	na

Notes: 2SLS estimates with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. $Growth_{ijt}$ is the dependent variable in all the columns. Column (2) and Column (3) only include the 4-year window with no less than 2 and 3 observations to make the average. Column (3) drops the observations using the first period aid. Column (4) allows spillovers for adjacent regions across country borders. Column (5) adds ICRG score as a control for institutional development. Column (6) replaces nightlight per capita growth with nightlight growth. Column (7) replaces aid variables with an *Aggregate* aid variable, which is the sum of aid disbursements at all four levels. In Column (8) the dependent variable is growth residuals from the regression where we regressed the growth rate on ADM1-time and country-time fixed effects.