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Aid and Growth at the Regional Level

by Axel Dreher and Steffen Lohmann

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I N T E R N A T I O N A L M O N E T A R Y F U N D

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Research Department and Strategy, Policy, and Review Department

Aid and Growth at the Regional Level*

Prepared by Axel Dreher and Steffen Lohmann

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Abstract

This paper brings the aid effectiveness debate to the sub-national level. We hypothesize the non-robust results regarding the effects of aid on development in the previous literature to arise due to the effects of aid being insufficiently large to measurably affect aggregate outcomes. Using geo-coded data for World Bank aid to a maximum of 2,221 first-level administrative regions (ADM1) and 54,167 second-level administrative regions (ADM2) in 130 countries over the 2000-2011 period, we test whether aid affects development, measured as nighttime light growth. Our preferred identification strategy exploits variation arising from interacting a variable that indicates whether or not a country has passed the threshold for receiving IDA's concessional aid with a recipient region's probability to receive aid, in a sample of 478 ADM1 regions and almost 8,400 ADM2 regions from 21 countries. Controlling for the levels of the interacted variables, the interaction provides a powerful and excludable instrument. Overall, we find significant correlations between aid and growth in ADM2 regions, but no causal effects.

JEL Classification Numbers: F35, O19, O47

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1 Introduction

Consider Malawi's recent World Bank-sponsored Rural Land Development Project. In line with its objectives, the project succeeded in increasing the incomes of about 15,000 poor rural families in the project districts.¹ Overall, the Bank's Independent Evaluation Group (IEG) rates around 75 percent of the World Bank's projects as successful.² Still, these projects do not seem to measurably increase economic growth at the country level, as indicated by the lack of robustness in empirical studies on the effectiveness of foreign aid.³ This striking disparity between micro-level effectiveness and macro-level ineffectiveness is persistent in the empirical literature and has been coined the micro-macro paradox in foreign aid (Mosley, 1987).

We argue that the previous literature's focus on country- rather than regional-level growth in incomes is one important reason for the lack of a robust effect of aid on growth.⁴ While Malawi's World Bank project may increase the incomes of people in some of the targeted areas, it is unlikely that the increase in incomes is sufficiently large to be measurable at the country level. This arguably holds when we consider the total of Malawi's projects. According to data from AidData, total geo-coded aid inflows to Malawi amounted to almost 5.3 billion US dollars over the 2004-11 period (Peratsakis et al., 2012; Rajlakshmi, 2013).⁵ However, the regional allocation of this aid is not uniform across Malawi. For instance, the North receives fewer projects than the South, and aid projects cluster in densely populated areas.⁶ While these projects may fail to measurably promote growth in all of Malawi, the effects of aid might well be discernable at a more disaggregated level.

The lack of evidence on aid effectiveness at the regional level is due to the dearth of available data and the methodological problems in measuring the causal effect of aid below the country-level. With data availability increasing as a consequence of AidData's (and selected recipient countries') geo-coding efforts of aid projects,⁷ some recent studies have looked at the regional allocation of aid. However, with the exception of two studies focusing on Malawi,⁸ aid's effect on

¹See http://ieg.worldbankgroup.org/Data/reports/PPAR-75556-P132257-Malawi_Land_Dvlpmt.pdf (accessed March 16, 2014). The project was approved in 2004, and closed in 2011.

²See Dreher et al. (2013).

³E.g., Rajan and Subramanian (2008); Doucouliagos and Paldam (2009); Bjørnskov (2013); Roodman (2015).

⁴Another reason, of course, is the lack of a credible identification strategy. We return to this below.

⁵This represents around 80 percent of total World Bank commitments there. It amounts to 16 percent of Malawi's GDP over the same period.

⁶See AidData's blog entry on Malawi of April 19, 2012, <http://aiddata.org/blog/where-are-donors-working-in-malawi-a-new-dataset-sheds-light> (accessed March 19, 2014).

⁷See Strandow et al. (2011) and AidData (2015).

⁸See Rajlakshmi (2013) and Dionne et al. (2013).

growth has so far not been analyzed at the sub-national level.⁹ With geo-coded data on World Bank aid now being made available, we are able to conduct such an analysis.¹⁰

The lack of systematic empirical evidence on the effectiveness of aid below the country-level is an important gap in the literature. As we explain in detail in section 2, we aim to fill this gap by making use of geo-coded data for 1,662 World Bank aid projects in 2,221 first-level administrative regions (ADM1) and 54,167 second-level administrative regions (ADM2) in 130 countries that were approved over the 2000-2011 period.¹¹ We test whether and to what extent disbursements of this aid and the number of World Bank projects affect development, measured as nighttime light growth. Given that we are the first to investigate the regional effectiveness of aid in promoting growth for a large sample of recipient countries, we start by replicating two prominent identification strategies from the country-level literature as closely as possible. First, we follow the recent analysis of Clemens et al. (2012), who address the potential endogeneity of aid by removing country-specific factors that do not vary over time, allowing for a time lag between the disbursement of aid and growth, and focusing on aid that they assume is particularly likely to affect growth in the short-run – so-called early-impact aid. Second, we rely on Brückner (2013), who suggests using, *inter alia*, rainfall growth and its square to purge aid of that part that is driven by changes in GDP per capita. As we explain below, these approaches cannot fully address concerns regarding the endogeneity of aid, and thus not necessarily allow us to identify a causal effect. What is more, rainfall turns out to be weak as an instrument for growth in our sample in most specifications.

Our own approach to identify the causal effect of aid on growth is closely connected to recent innovations in the country-level literature on aid effectiveness. We rely on Galiani et al. (2014), who instrument aid inflows with the income threshold of the International Development Association (IDA) for eligibility to the World Bank’s concessional aid. This instrument could arguably be correlated with growth for reasons other than aid (Dreher and Langlotz, 2015). We overcome this problem by interacting the indicator of whether or not a country has crossed the IDA’s threshold for receiving concessional aid with a recipient region’s probability to receive aid, following recent identification strategies in the country-level literature on aid effectiveness (Werker et al., 2009; Ahmed, 2013; Nunn and Qian, 2014; Chauvet and Ehrhart, 2014; Dreher

⁹Chauvet and Ehrhart (2014) employ the World Bank’s Enterprise Surveys to examine how aid affects the growth of firms in 29 developing countries. While they do not use geo-coded aid, this allows them to combine country-level and firm-level characteristics, potentially mitigating reversed causality.

¹⁰Of course, we would like to test the effectiveness of aid from a larger sample of donors. Such data are not available for a worldwide sample.

¹¹ADM1 regions are the governmental units directly below the nation state; ADM2 regions are those below the ADM1 level.

and Langlotz, 2015).¹² Controlling for the levels of the interacted variables, the interaction provides a powerful and excludable instrument.

According to our results (shown in section 3), aid and nighttime light growth are significantly correlated at the second-level administrative areas (ADM2) level, but not at the larger first-level administrative areas (ADM1) level. Specifically, when we do not employ instruments, lagged aid shows a positive and significant correlation when region-fixed effects are not included in the specification, but a negative correlation otherwise. Purging aid of its endogenous component relying on rainfall growth and its square, we find the instruments to be weak in most specifications. The exception is at the ADM2 level, where we find a negative effect of aid on growth in our region-fixed effects specification. However, given the strong identifying assumption that this result relies on, we advise caution in interpreting it. When we employ our preferred instrument – the interaction of the probability to receive aid with having passed the IDA income threshold – in a sample of 478 ADM1 regions and almost 8,400 ADM2 regions in 21 countries, we find no effect of aid on development.

We conclude that there is no robust evidence showing that aid increases growth and discuss implications for future research in the final section of the paper.

2 Data and Method

The literature on the allocation and effectiveness of foreign aid below the country-level is scarce, mainly due to a lack of geo-coded data on aid, relevant outcomes, and adequate control variables. A number of datasets exist however which allow testing for sub-national determinants and consequences of aid. The dataset covering the largest number of countries has recently been provided by AidData (2015) in collaboration with the World Bank and consists of 3,534 geo-coded World Bank projects spread over 141 countries, approved over the 2000-2011 period.¹³ AidData also provides geo-coded information on projects from the African Development Bank (AfD) approved in the 2009-2010 period.¹⁴ Dreher et al. (2014) provide geo-coded data on Chinese aid to Africa,

¹²Werker et al. (2009) rely on an interaction between oil prices and Muslim majority countries to instrument for oil-producing donors' aid, Ahmed (2013) and Dreher and Langlotz (2015) interact donor-level political fractionalization (which induces increases in donors' aid budgets) with the probability of a recipient country to get aid, while Nunn and Qian (2014) interact the probability to receive aid with US wheat production (to instrument for food aid from the United States). Chauvet and Ehrhart (2014) interact donor government revenue with cultural and historic distance between the donor and the recipient.

¹³See Findley et al. (2011) for a detailed description of an earlier – partial – release of these data.

¹⁴The World Bank- and AfD-data have been used in a number of aid allocation studies. Öhler and Nunnenkamp (2014) use an earlier subset of these data to study what determines the allocation of aid across a sample of 27 recipient countries over the 2005-2011 period. Variants of these data have also been used to study the determinants of aid allocation in Nunnenkamp et al. (2012) for India, Jablonski (2014) for Kenya, and Powell and Findley (2012) for six Sub-Sahara African recipient countries. Zhang (2004) relies on data provided by the World Bank to investigate the determinants of World Bank project allocation across Chinese provinces.

for the 2000-2012 period.¹⁵ Cambodia and Malawi share detailed information on the regional allocation of the aid they receive from a large number of donors.¹⁶

For this project, we make use of AidData’s geo-coded data for World Bank projects – the only data available for a worldwide sample of countries over a reasonably long period of time. The raw dataset contains the project’s date of approval, the (anticipated) date of termination, and the amounts committed to and disbursed in the project over its entire duration. To calculate project-specific annual disbursements, we link the project database to the Bank’s documentation of project-specific financial flows, including the precise date of project disbursements.¹⁷ We transform these disbursements into constant 2011 US\$. A second variable of interest is the number of active projects per region rather than amounts of aid. This variable is frequently used in the literature trying to quantify the effects of World Bank involvement, as it might more adequately measure other components that accompany a project, like technical advice or program conditions, than do the amounts of aid alone (Boockmann and Dreher, 2003).

AidData covers projects that have been approved over the 2000-2011 period, comprising total commitments of nearly 370 bn US\$. For each project, detailed information on its locations is recorded, with different degrees of precision: Some projects are implemented in a limited geographical area, such as a village or city. Others are realized at more aggregate levels, such as a municipality, a district or greater administrative region. As described in detail in Findley et al. (2011) and Strandow et al. (2011), the geo-coding is implemented by experienced coders in a double-blind process. Information on project locations come from various World Bank sources, most importantly project-specific planning or implementation documents. In a next step, coordinates of these locations are extracted from geographic online services providing names and coordinates of administrative divisions, populated areas, and other places of interest. Obviously, the coding precision reflects the sectoral composition of aid. Projects in sectors such as “Finance” or “Public Administration, Law, and Justice” are geo-coded predominantly at the national scale, while projects in sectors like “Transportation” are typically assigned to more

¹⁵Their results show that African regions where the current leader of a country was born receive substantial increases in aid from China, but – controlled for region-fixed effects – not from the World Bank.

¹⁶Öhler (2013) uses these data to investigate whether and to what extent donors coordinate at the regional level in Cambodia; Rajlakshmi (2013) and Dionne et al. (2013) investigate the allocation of projects from 30 donor agencies in Malawi.

¹⁷These data are available at the World Bank’s project website (<http://www.worldbank.org/projects>) per project, but not in aggregate form. We downloaded these data and aggregated disbursement flows on a yearly basis, treating negative disbursements as zero. In contrast to Dionne et al. (2013) we therefore do not need to estimate actual disbursements based on commitments or make restrictive assumptions on the spread of financial flows over the duration of a project. We provide our disbursement data at <http://aiddata.org/replication/worldbankdisbursements>.

precise locations.¹⁸

In total, close to 48 percent of all project locations geo-coded by AidData are assigned to a distinguishable subnational location. Since this paper focuses on sub-national projects' effects on sub-national growth, we exclude projects that are nation-wide in scope, for which no or unclear information on location is provided, and projects that are directly allocated to a government entity, as these cannot be attributed to specific regions.¹⁹

We use the available project information on longitude and latitude of respective locations to match the aid projects to the respective country's first and second Administrative Regions (ADM1 and ADM2) using data from the Global Administrative Areas (GADM) database.²⁰ ADM1 regions are the governmental units directly below the nation state, such as counties, regions, provinces, municipalities, or districts, among others, depending on the particular country (see Figure 1 for the African continent). ADM2 regions are those regions that are directly below the ADM1 level, like districts, municipalities, and communes. Regarding the matching to ADM1 regions, 77 percent of the projects were implemented in more than one region, without information on the share of aid disbursements going to the particular sites. For ADM2 regions, this concerns 88 percent of the projects. Following the previous literature (e.g., Dionne et al., 2013), we assume that aid (disbursements and number of projects) is allocated in proportion to the size of an area's population.²¹

Population data are taken from CIESIN/CIAT's "Gridded Population of the World" (CIESIN, 2005). These data are available for a worldwide grid of 2.5 arc-minutes resolution for the years 2000, 2005, and 2010. We calculate population size per administrative region by taking its mean population density and multiplying it with the area size provided in the GADM file. We use linear interpolation for the missing years, given that population changes slowly over time. Figure 1 shows the sum of aid disbursements per-capita over the whole 2000-2011 period for ADM1 regions of Africa. The figure illustrates the wide range of aid-receipts at the regional

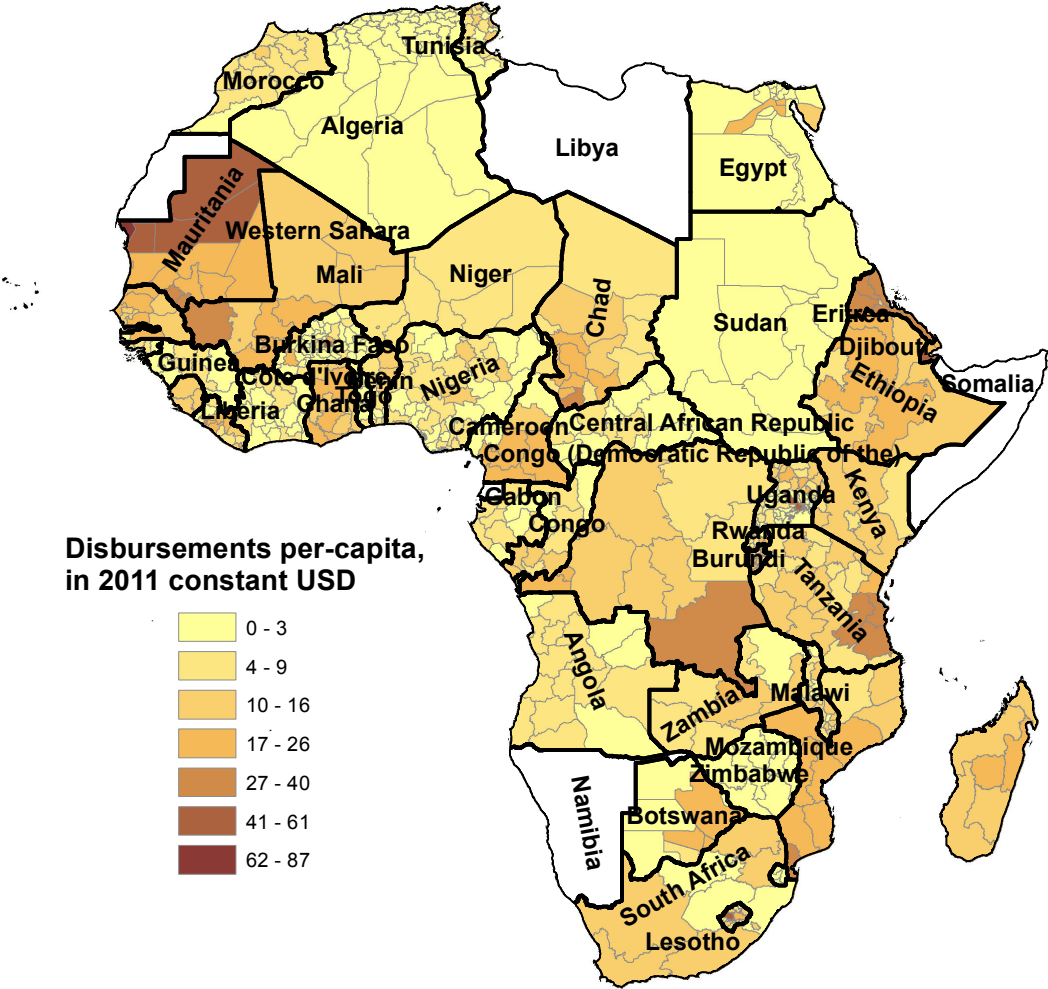
¹⁸The "Tamil Nadu Road Sector Project" in India as one typical infrastructure project, for example, aims to promote the core road network of Tamil Nadu through upgrading existing state highways, maintaining smaller state roads, and institutional strengthening. In the dataset, twelve geo-coded locations are assigned to the project of which six correspond to an exact location, such as a village or town, five to ADM2 regions, and one to an ADM1 region. Malawi's "Rural Land Development Project," introduced above, in turn could only be assigned more broadly to five smaller administrative divisions.

¹⁹In the empirical analysis, any potential country-wide effects of these flows are absorbed through the inclusion of country-period fixed-effects.

²⁰See <http://www.gadm.org>.

²¹23% (12%) of the projects are located in one ADM1 (ADM2) region exclusively, 37% (25%) have locations in between 2-5 regions, 21% (19%) in 6-10 regions, and 18% (44%) in at least 10 regions. We test robustness by dividing aid amounts and numbers equally per project location, as in Dreher et al. (2014). Our conclusions are not affected by this.

Figure 1: Location-specific World Bank disbursements in Africa, ADM1 regions, 2000-2011



Notes: Total disbursements calculated based on AidData (2015). Disbursements for projects in multiple ADM1 regions are divided according to a region's share in population.

level within some (but not all) African countries, emphasizing the importance of investigating the effects of aid at the regional level.²²

As is common in the literature on aid effectiveness, we average our data to smooth changes over the business cycle. We follow Galiani et al. (2014) and build averages over three years. This is useful for our preferred identification strategy below, as donors commit funds to the IDA in so-called replenishment rounds that span these three-year periods.²³ Our reduced-form empirical models are at the region-period level:

$$\begin{aligned} Growth_{i,t} = & \alpha + \beta Aid_{i,t-1} + \delta DEV_{i,2000} + \zeta POP_{i,t-1} + \theta POPGROWTH_{i,t} \\ & + \rho AREA_i + \mu DIST_i + \eta_{c,t} + \epsilon_{i,t} \end{aligned} \quad (1)$$

$$Growth_{i,t} = \alpha + \beta Aid_{i,t-1} + \zeta POP_{i,t-1} + \theta POPGROWTH_{i,t} + \eta_{c,t} + \lambda_i + \epsilon_{i,t}, \quad (2)$$

where i denotes regions and c countries. $Growth_{i,t}$ measures region i 's average annual growth rate in nighttime light over period $t - 1$ to t . $Aid_{i,t-1}$ denotes the natural logarithm of annual per-capita aid disbursements in constant 2011 US\$ or – alternatively – the number of projects per capita with ongoing disbursements to the region in the previous period.²⁴ All regressions include fixed effects for each country in each period ($\eta_{c,t}$). Model (1) in addition controls for $DEV_{i,2000}$ – the (logged) level of a region's development (measured in nighttime light) at the beginning of our sample period, to control for conditional growth convergence. It includes POP and $POPGROWTH$, which are the logarithm of a region's population size and its population growth rate, $AREA$, reflecting the size of the administrative region, and $DIST$, measuring the (logged) shortest distance from the region's center to the country's capital. It is sometimes argued that population and area size affect growth, either negatively due to less diversified economies and higher exposure to external risk or positively, due to increases in productivity (Easterly and Kraay, 2000). Regarding distance to the country's capital, we hypothesize more distant regions to experience lower rates of growth.

²²For they can be clearly identified as outliers in partial leverage plots, we remove the upper and lower 1th-percentiles of all aid variables from the sample.

²³Specifically, we average data over the periods 2000-02, 2003-05, 2006-08, 2009-11, matching the IDA's replenishment rounds. We also include light data for the year 2012 to gain an additional "period," given that aid enters the regressions with a lag.

²⁴We add 0.01 before we take logs to avoid losing observations without disbursements or projects. Note that we also take the number of projects in per-capita terms. Our conclusions hold, however, when taking the absolute number of projects per region. We follow Galiani et al. (2014) and include logged aid rather than the level of aid along with its square, as do, e.g., Clemens et al. (2012). The reason is that we mostly rely on results from instrumental variable estimation but only have one instrument for two endogenous variables in case we include aid squared. Taking the log allows for a decreasing marginal effect of aid (but does not allow its effect to change sign).

Model (2) includes fixed effects for regions λ_i in addition to those for country-periods, and therefore excludes control variables that do not vary over time at the regional level. Model (1) consequently identifies the potential effect of aid exploiting variation between regions (and over time), while Model (2) exploits within-region variation over time exclusively. While being more conservative than Model (1), this comes with the disadvantage of few three-year-period observations per region, which makes the identification of significant effects less likely. The error term is $\epsilon_{i,t}$, and we cluster standard errors at the regional level.

Our measure of development relies on nighttime light data as an approximation of regional economic activity. Such data have been introduced to the literature in Elvidge et al. (1997) and Sutton and Costanza (2002), and are frequently used in the recent economics literature (probably most prominently in Henderson et al., 2012). Nighttime light is a practical source of data for regional economic activity when official data on GDP are unavailable or where official statistics might be prone to measurement error or manipulation (Chen and Nordhaus, 2011).²⁵ Particularly in the developing world, uncertainty about official GDP estimates can be enormous (Henderson et al., 2012; Jerven, 2013).²⁶ A substantial number of studies has show the correlation between nightlight and GDP to hold at the sub-national level, for regions of varying size and levels of development.²⁷

Since a large part of economic activity comes in the form of consumption and production using light in the evenings, nighttime light intensity can be considered a meaningful reflection of human economic activity. A range of studies have established a strong empirical relationship between nighttime light intensity and GDP both over time and across regions. Recently, Henderson et al. (2012) document a high correlation between changes in nighttime light intensity and GDP growth at the country-level while Doll and Morley (2006) and Hodler and Raschky (2014) provide similar regional-level evidence. Further research also finds strong positive associations between nighttime light intensity and public infrastructure indicators (Michalopoulos and Papaioannou, 2014) as well as composite wealth indices from Demographic and Health Surveys (DHSs) (Noor et al., 2008; Michalopoulos and Papaioannou, 2013), both at the national and the subnational

²⁵Since nighttime light data are not directly relevant to governments, they are less likely to be systematically targeted by policy interventions.

²⁶See <http://qz.com/139051/nigerias-economy-is-about-to-grow-40-in-one-day/#139051/nigerias-economy-is-about-to-grow-40-in-one-day> for a case from Nigeria (accessed March 19, 2014).

²⁷See Doll and Morley (2006); Bhandari and Roychowdhury (2011); Hodler and Raschky (2014); Mveyange (2015); Olivia and Stichbury (2015). Any structural differences between regions that do not vary over time across regions will be captured by region-fixed effects in our preferred estimations.

level.²⁸

We use satellite images from the National Oceanic and Atmospheric Administration (NOAA, nd), providing information on nighttime light activity for the 1992-2012 period. Images are taken in the evenings, for a global grid in 30 arc-minutes resolution, and measured on a 0-63 scale (with larger values indicating more activity). The data remove background noise and exceptional events such as fires. They are, however, not directly comparable over time. The reason is that the data included in our sample are generated with three different satellites and consequently different sensors. What is more, sensors deteriorate with time, so that images from periods too far apart might hardly be comparable (Elvidge et al., 2014). We therefore rely on recalibrated data provided by Elvidge et al. (2014) at the country-year level, and adjust our regional nighttime light data according to a region's share in total light.²⁹ Figure 2 compares yearly totals of nighttime light intensity values for the regions in our sample with the recalibrated data. As can be seen, the recalibration method smoothes nighttime light substantially, both between satellites and in the years where data are generated by the same satellite, but where sensor sensitivity changes over time.

Our proxy for regional development is calculated as the growth rate of (recalibrated) mean nighttime light intensity in a region and year. We removed the upper and lower 5th-percentiles from the sample, which can be clearly identified as outliers in partial leverage plots based on our baseline specification.³⁰ Figure 3 shows the resulting growth in average nighttime light intensity over the 2000/02-2003/05 period for Africa at the ADM1 level. Table A.1 in the Appendix shows the sources and definitions of all variables, while Table A.2 reports descriptive statistics.

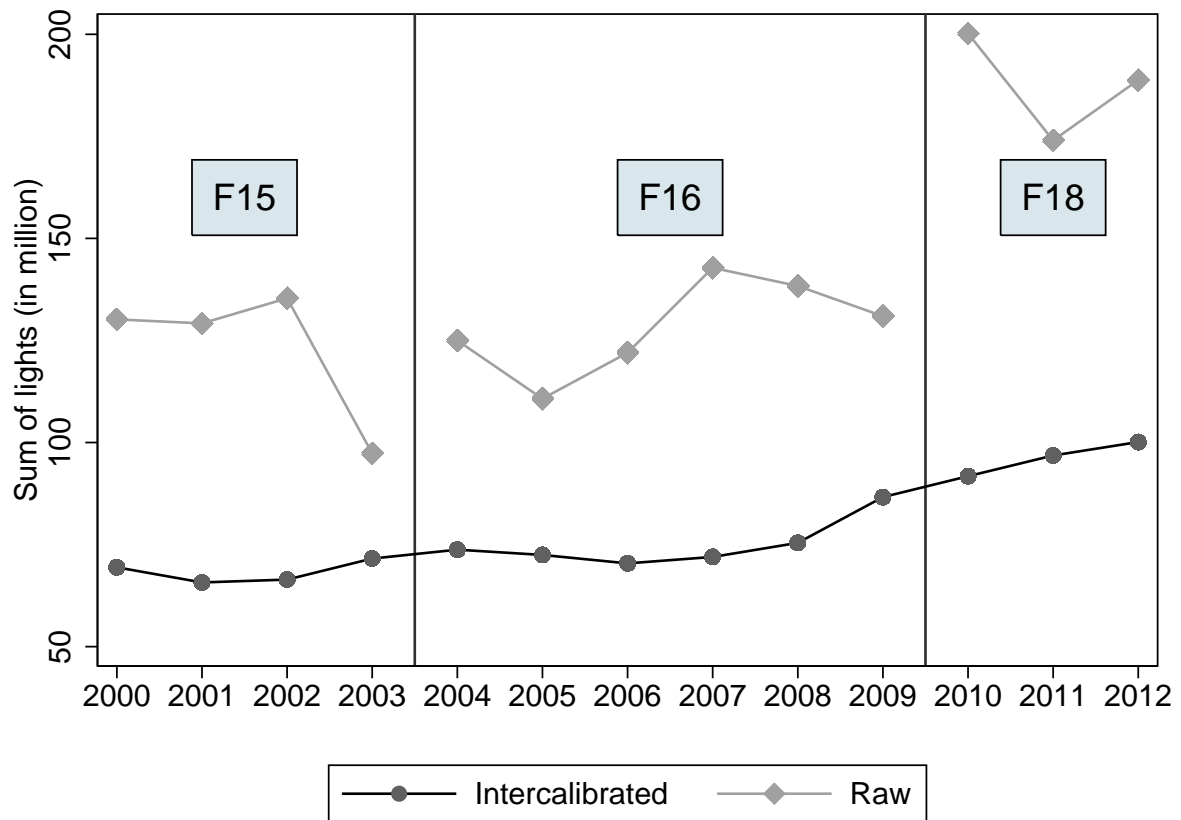
The scarce literature on the sub-national determinants of aid effectiveness provides interesting evidence on the correlates of aid projects on the regional level, but fails to convincingly address

²⁸Possibly, certain World Bank projects, particularly those aiming at infrastructure development, affect this measure through opening up construction sites lit at night. While such sources of light might be the result of economic activity as in any aid effectiveness study, i.e., that of increasing investment, we also check whether our results are robust to the exclusion of those parts of aid. In a sensitivity analysis, we drop projects assigned to the transportation sector (which, however, accounts for the largest share of projects). With the exception of the OLS regressions for ADM2 regions, where the coefficient loses significance, the results remain similar. For this reason and since the identification of construction projects is inexact to some extent – the datasets only allows the identification of a broader sector – we refrain from overemphasizing this channel.

²⁹The method relies on reference to a base area where nighttime light can be assumed to vary little over time, with the data range of other areas adjusted in accordance.

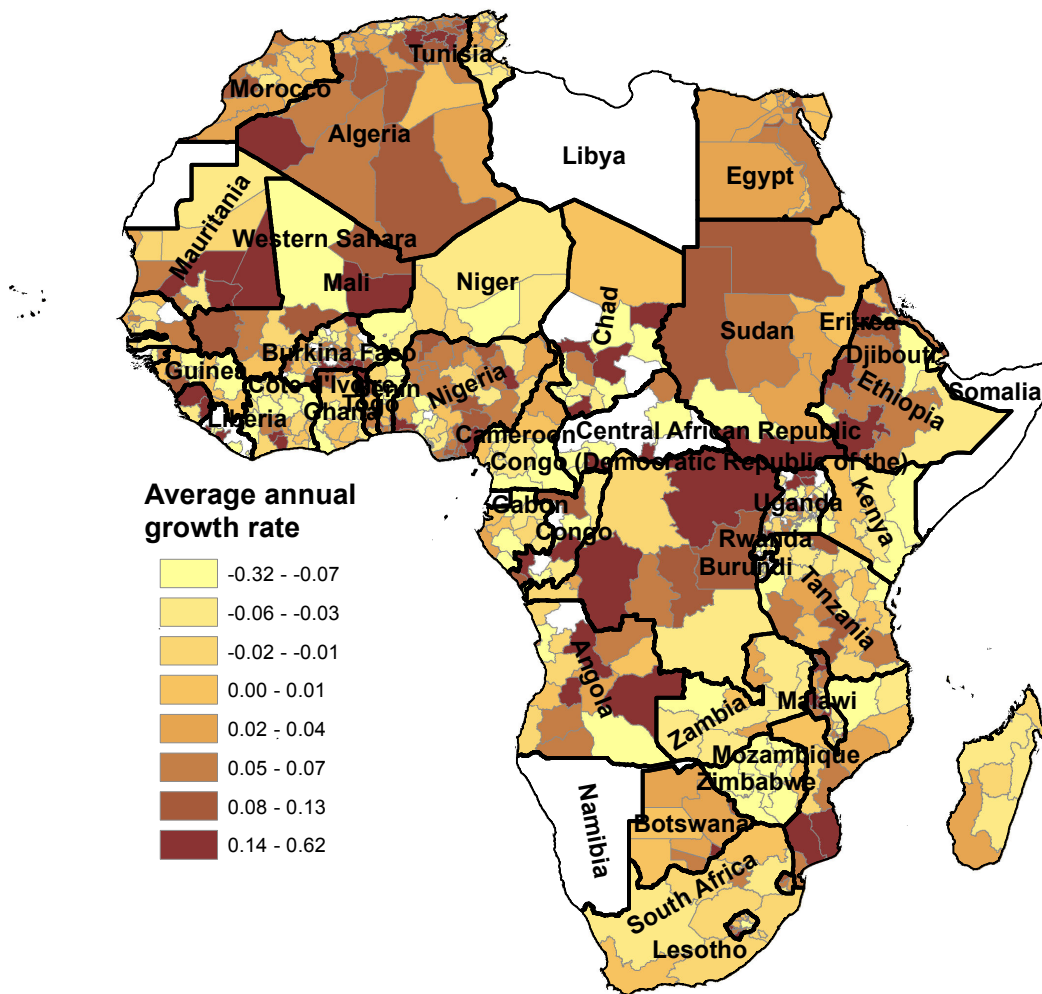
³⁰Our results depend on this to some extent. When we do not remove outliers the correlation between aid and growth tends to be more negative.

Figure 2: Raw versus intercalibrated nighttime light, 2000-2012



Notes: The vertical axis shows the annual sum of nighttime light pixel values throughout our sample period for different satellites (F15/F16/F18). Intercalibrated data are based on adjustment factors taken from Elvidge et al. (2014), according to a region's share in total light.

Figure 3: Regional growth in Africa, ADM1 regions, 2000-2002 to 2003-2005



Notes: Growth in average nighttime light intensity (in percent) based on NOAA Version 4 DMSP-OLS Nighttime Lights Time Series. Data have been calibrated based on Elvidge et al. (2014).

causality.³¹ We present results using three different identification strategies.³² First, we broadly follow Clemens et al. (2012), not using any instrument for aid, but allowing aid to affect growth with a time lag, and removing influences that do not vary over time (across countries and, in our case, across regions). Clemens et al. categorize all aid into one of two categories, so-called early- and late-impact aid.³³ Early-impact aid contains those types of aid that can reasonably be expected to affect growth in the short-term, like budget support and program aid and certain categories of project aid (e.g., infrastructure investment or support for production in transportation, agriculture and industry). We use the sector classification included in AidData’s project database to characterize a project based on the major sector that it is assigned to.³⁴ This identification strategy would be unable to identify a causal effect of aid to the extent that donors (or recipients) are selective and allocate more aid to the regions they expect will use the aid more effectively.

Second, we follow the approach of Brückner (2013). Brückner addresses the endogeneity of aid by instrumenting for changes in per capita GDP with data on rainfall growth and its square and international commodity price shocks in his aid allocation equation. He then uses that part of aid that is not driven by GDP per capita growth as an instrument to identify the causal effect of aid on per capita GDP. We broadly follow this approach at the regional level, using data on rainfall from the Global Precipitation Climatology Centre (GPCC) of the German Weather Service (Schneider et al., 2011).³⁵ We do not include commodity price shocks because they do not vary across regions and are therefore absorbed by our country-period fixed effects. The

³¹Rajlakshmi (2013) is the only study we are aware of that tries to address the endogeneity of aid below the sub-national level. Rajlakshmi investigates the allocation and effectiveness of geo-coded aid projects from 30 agencies in Malawi over the 2004-2011 period. He identifies his instruments for the aid effectiveness regressions based on the significance of the variables included in his aid allocation regressions. The endogeneity of aid for the outcome variables included in the aid allocation equation is not addressed; what is more, the exclusion restriction of the instruments used in the aid effectiveness regressions is unlikely to hold (regional dummies and an indicator for rural regions are likely to affect disease severity via channels other than aid). His Propensity Score Approach is based on few variables and is thus likely to suffer from unobserved heterogeneity between the treatment and control group.

³²Alternative strategies to identify the effect of development aid on economic growth can broadly be grouped along three lines (see Dreher et al., 2014). The first relies on instruments related to the size of the population in the recipient country. The second uses internal instruments – the lagged levels and differences of aid – and estimates system GMM regressions. The third relies on insight from the literature on the allocation of aid and uses proxies for political connections between the donors and recipients as instruments. As Bazzi and Clemens (2013) show, the first two strategies are unlikely to allow the identification of causal effects, as both population and lagged values of aid are likely to have direct effects on growth. While political connection-based instruments might be more likely to be excludable, Dreher et al. (2014) show that political motives influence the effectiveness of aid, so that the effect of politically motivated aid (the Local Average Treatment Effect) cannot be generalized to represent the effect of aid more broadly.

³³This measure has however been shown not to be a robust predictor of growth (Rajan and Subramanian, 2008; Bjørnskov, 2013; Roodman, 2015).

³⁴Early-impact aid includes agriculture/fishing/forestry, energy/mining, access to finance, industry/trade, information/communications, and transportation. Late-impact aid includes education, health and other social services, public administration, and water and sanitation.

³⁵See ftp://ftp.dwd.de/pub/data/gpcc/html/fulldata_v6_doi_download.html (accessed March 19, 2014). These data are available over the 2000-2010 period.

identifying assumption is the absence of a direct effect of rainfall growth on aid, other than via its impact on incomes. As holds for Clemens et al. (2012), Brückner’s identifying assumption might easily be violated.

Our third strategy connects to recent work on aid effectiveness at the country-level, which we are convinced could most plausibly identify a causal effect of foreign aid at the regional level (in case there is any). Our approach builds on Galiani et al. (2014), who instrument aid inflows with passing the IDA’s threshold for receiving concessional aid. As Galiani et al. explain, donors pledge their contributions for three-year periods. The IDA threshold is updated annually, and amounts to a GNI per capita of US\$1,215 in the Bank’s fiscal year 2015. Countries that pass the threshold are likely to see a substantial reduction in IDA lending, though they do not become ineligible for IDA aid immediately (Galiani et al., 2014). Of course, the decrease in IDA aid might be replaced by increases in other donors’ aid, in our case, those of the International Bank for Reconstruction and Development (IBRD), in particular. However, Galiani et al. (2014) show that other donors reduce their aid in line with IDA aid, rather than substituting for it.³⁶ They also show that after a country crosses the IDA-threshold, IDA aid to GNI drops by 92 percent, on average. As can be seen in Figure 4, the pattern described in Galiani et al. (2014) is prevalent in our data as well. On average, IDA-aid per capita decreases by 75 percent between the year before we assume the threshold effect to materialize (i.e., six years after the threshold has been passed) and the year thereafter. The figure also shows that the decrease in IDA aid is not systematically offset by corresponding increases in IBRD funding.

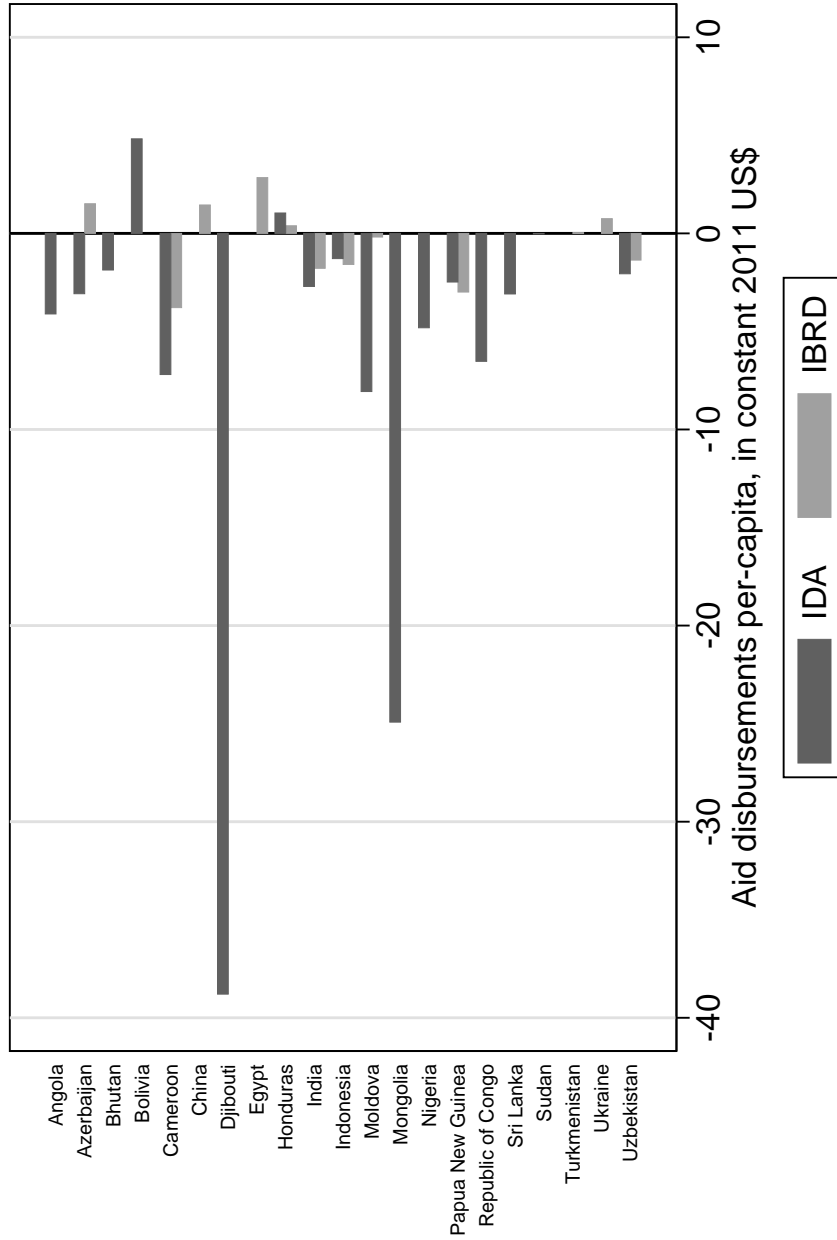
The IDA income-threshold – even if it would be fully exogenous from a recipient country’s perspective – could arguably be correlated with growth for reasons other than aid (Dreher and Langlotz, 2015).³⁷ As Galiani et al. (2014) explain, countries could pass the income threshold due to a large positive shock that is reversed in later years.³⁸ We overcome this potential shortcoming by interacting the indicator of whether or not a country has passed the IDA threshold with a recipient region’s probability to receive aid, following recent innovations in the country-level literature on aid effectiveness (Werker et al., 2009; Ahmed, 2013; Nunn and Qian, 2014; Dreher and Langlotz, 2015). As Nunn and Qian (2014, pp. 1632, 1638) explain, the resulting regressions resemble difference-in-difference approaches, where – in our application of the method – we

³⁶For more details on the relation between IDA aid and the income threshold, see Galiani et al. (2014). Knack et al. (2014) provide the years that countries crossed the IDA-threshold. Galiani et al. find that DAC aid decreases by 59 percent after a country crosses the threshold.

³⁷Of course, to the extent that aid-dependent countries are less likely to cross the threshold – “cooking their books” – it might well be endogenous to aid; see Kerner et al. (2014) and Galiani et al. (2014) who come to opposite conclusions on whether or not manipulation takes place.

³⁸They employ alternative instruments using a smoothed income trajectory to rule out the effect of shocks and find similar results however.

Figure 4: Change in location-specific disbursements after IDA income threshold crossing



Source: own calculations based on AidData (2015)

Notes: The graph shows the countries' average difference in region-specific aid disbursements between the period prior to the year when the IDA-threshold effect is assumed to take place (i.e., six years after the income threshold is passed) and one year later.

compare regular aid recipients to irregular recipients as the recipient’s IDA status changes.³⁹ While we report results employing the other two identification strategies described above in order to be comparable with the existing literature at the country-level, we base our conclusions mainly on this, preferred, approach. This comes at the cost of dismissing a large number of countries from the sample, as we prefer to implement our identification strategy only for countries that crossed the IDA-threshold at a point in time that is covered by our sample. The resulting number of countries included here is 21, referring to 478 ADM1 and almost 8,400 ADM2 regions.⁴⁰

Our assumed timing broadly follows the previous literature. Countries are considered as IDA graduates after having been above the income threshold for three consecutive years (Galiani et al., 2014). Galiani et al. therefore expect decreases in aid disbursements to take effect in the next replenishment period rather than instantaneously and lag the instrument by one three-year period. We add an additional three-year period lag, given that commitments are on average disbursed with a delay, broadly in line with the timing suggested in Dreher et al. (2014).⁴¹ Note that ten countries passed the threshold in the last or second-to last period in our sample. We follow Galiani et al. (2014) and keep them in the sample, even though the instrument will be zero for these countries throughout the sample period due to using the instruments in lags. We calculate the probability of receiving aid as the number of years in all years that a region has received any World Bank aid prior to when we assume the IDA-threshold effect to take place (i.e., six years after the income threshold is passed).⁴²

The next section reports our results.

3 Results

Table 1 shows the results for our first set of regressions at the ADM1 level, broadly following Clemens et al. (2012). When region-fixed effects are excluded, nighttime light growth decreases with the level of nighttime light in 2000 at the one-percent level of significance, indicating within-country convergence in development. At the five-percent level, growth increases with the

³⁹We tested for differences in growth across regions with a high compared to regions with a low probability to receive aid prior to passing the threshold and did not find significant differences. As do Galiani et al. we only consider countries that crossed the threshold from below for the first time in constructing the instrumental variable. In our sample, only Bolivia passed the threshold twice. Our results are robust to using the second crossing instead of the first.

⁴⁰This compares to 35 countries in Galiani et al. (2014).

⁴¹Results are qualitatively similar when using a one-period lag.

⁴²The main analyses in Ahmed (2013) and Nunn and Qian (2014) calculate the probability to receive aid over the whole sample period. Our second-stage results are similar when we follow this approach. The resulting first stage for ADM1 regions is substantially weaker however.

size of the regional population but is unaffected by population growth. More distant and smaller regions grow less, at the one-percent level of significance.

Note that we have to exclude nighttime light in 2000, region size, and distance to the capital when we control for region-fixed effects, as they do not vary over time. In these specifications (Model 2 above), population is no longer significant at conventional levels, arguably due to its low variation over time within region (aggravated by using linear interpolation to derive the yearly data).

Columns 1 and 2 of Table 1 report results for (log) aid disbursements. As can be seen, aid has no significant effect on growth. This holds regardless of whether region-fixed effects are excluded (column 1) or included (column 2).⁴³ The insignificant effect is easy to explain. To the extent that aid is fungible, it might simply substitute for government expenditures that would have flown to the region in the absence of any aid. The true effect of aid on growth in that particular region would then indeed be zero.⁴⁴ Another potential reason for the insignificant coefficient of aid is reversed causality, even in the presence of lags. If crises and aid are persistent, higher aid might be the effect of lower growth, biasing the coefficient of aid downwards.⁴⁵ The coefficient might then turn out to be insignificant, even if the true effect of aid is positive. Third, the low number of periods and the resulting lack of variation might challenge the identification of aid's effect on growth. And finally, of course, the insignificant coefficient could reflect the absence of an effect of aid on growth, even if the aid is not diverted to other regions.

Columns 3 and 4 of Table 1 replicate the analysis replacing aid disbursements with the number of aid projects with positive disbursements, while columns 5-8 show regressions that separate early-impact from late-impact aid, following Clemens et al. (2012). The results show insignificant coefficients of aid in all specifications.

Table 2 replicates the analysis focusing on the smaller ADM2 regions. If our hypothesis that more disaggregated analysis facilitates identification of significant effects holds true, we would expect stronger effects here compared to the results in Table 1 above. To the contrary, focusing

⁴³We separately included aid from the concessional International Development Association (IDA) and the less concessional loans from the International Bank for Reconstruction and Development (IBRD). The coefficients are not significant at conventional levels. We also separated projects that have been successfully evaluated by the Bank's Independent Evaluation Group from those that have been not. Excluding region-fixed effects, growth is negatively correlated with unsuccessful projects, at the ten-percent level of significance.

⁴⁴Recipient governments might use their additional budgetary leeway to finance their own pet projects in other regions – projects that cannot be identified and evaluated, but which potentially increase growth in the regions that get them. The same holds to the extent that positive spillovers increase growth in other regions, even absent any growth effects in the region that receives the aid.

⁴⁵As Roodman (2015) shows, the procedure applied in Clemens et al. (2012) fails to remove contemporaneous endogeneity.

Table 1: OLS and Region-Fixed Effects, ADMI, 2000-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
(Log) Total aid, t-1	0.0003 (0.0007)	0.0001 (0.0011)						
(Log) No. of projects, t-1			0.0006 (0.0011)	0.0009 (0.0018)				
(Log) Early-impact aid, t-1					-0.0006 (0.0007)	-0.0017 (0.0011)		
(Log) Late-impact aid, t-1					0.0006 (0.0008)	0.0004 (0.0012)		
(Log) No. of early-impact projects, t-1							0.0001 (0.0012)	-0.0013 (0.0019)
(Log) No. of late-impact projects, t-1							0.0006 (0.0011)	0.0005 (0.0019)
(Log) Nighttime light in 2000	-0.0142*** (0.0019)		-0.0145*** (0.0019)		-0.0141*** (0.0020)		-0.0147*** (0.0020)	
(Log) Size of population, t-1	0.0038** (0.0019)	0.0502 (0.0526)	0.0040** (0.0019)	0.0569 (0.0529)	0.0041** (0.0019)	0.0548 (0.0531)	0.0043** (0.0019)	0.0736 (0.0531)
Population Growth	0.0870 (0.1085)	0.9221 (1.0902)	0.0903 (0.1088)	1.0924 (1.0960)	0.0865 (0.1073)	0.9565 (1.1025)	0.1211 (0.1083)	1.2207 (1.1004)
(Log) Area	-0.0056*** (0.0020)		-0.0059*** (0.0020)		-0.0058*** (0.0020)		-0.0060*** (0.0020)	
(Log) Distance to capital	-0.0052*** (0.0012)		-0.0052*** (0.0012)		-0.0052*** (0.0012)		-0.0053*** (0.0012)	
Region-FE	No	Yes	No	Yes	No	Yes	No	Yes
Country-Period-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	130	130	130	130	130	130	130	130
Number of regions	2221	2221	2214	2214	2219	2219	2213	2213
R2	0.29	0.47	0.29	0.47	0.29	0.47	0.29	0.47
Observations	8541	8541	8519	8519	8469	8469	8470	8470

Notes: OLS and region-fixed-effects regressions (FE). Dependent variable: Growth in nighttime light. All variables are averaged over 3-year-periods. Standard errors, clustered at the region-level, in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: OLS and Region-Fixed Effects, ADM2, 2000-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
(Log) Total aid, t-1	0.0006** (0.0003)	-0.0012** (0.0005)						
(Log) No. of projects, t-1			0.0016*** (0.0004)	-0.0011 (0.0008)				
(Log) Early-impact aid, t-1					0.0011*** (0.0003)	-0.0005 (0.0006)		
(Log) Late-impact aid, t-1					-0.0004 (0.0004)	-0.0016** (0.0007)		
(Log) No. of early-impact projects, t-1							0.0025*** (0.0006)	-0.0004 (0.0010)
(Log) No. of late-impact projects, t-1							0.0001 (0.0006)	-0.0023** (0.0011)
(Log) Nighttime light in 2000	0.0272*** (0.0006)		0.0273*** (0.0006)		0.0271*** (0.0006)		0.0272*** (0.0006)	
(Log) Size of population, t-1	-0.0058** (0.0006)	-0.1234** (0.0149)	-0.0060*** (0.0006)	-0.1220*** (0.0150)	-0.0057*** (0.0006)	-0.1249*** (0.0150)	-0.0058*** (0.0006)	-0.1207*** (0.0151)
Population Growth	0.1293*** (0.0404)	-0.1448 (0.2762)	0.1324*** (0.0406)	-0.1707 (0.2777)	0.1326*** (0.0407)	-0.2097 (0.2782)	0.1294*** (0.0405)	-0.1558 (0.2789)
(Log) Area	0.0227*** (0.0007)		0.0228*** (0.0007)		0.0226*** (0.0007)		0.0227*** (0.0007)	
(Log) Distance to capital	-0.0014** (0.0005)		-0.0015*** (0.0005)		-0.0013** (0.0005)		-0.0014** (0.0005)	
Region-FE	No	Yes	No	Yes	No	Yes	No	Yes
Country-Period-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	130	132	130	132	130	132	130	132
Number of regions	54165	54167	54104	54106	54055	54057	54016	54018
R2	0.14	0.47	0.14	0.47	0.14	0.47	0.14	0.48
Observations	195886	195893	195803	195808	194064	194071	194249	194253

Notes: OLS and region-fixed-effects regressions (FE). Dependent variable: Growth in nighttime light. All variables are averaged over 3-year-periods. Standard errors, clustered at the region-level, in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

on smaller regions will make it less likely to identify statistically significant effects if the main reason for the lack of significant coefficients of aid is fungibility, and aid is more likely to be diverted to areas close to the intended region. The results are strikingly different compared to Table 1. First, note that with the exception of the distance to the country's capital there are substantial changes for all control variables. Growth increases with the level of nighttime light in the year 2000, the region's size and population growth (in the case where the region-fixed effects are excluded from the regression), but decreases with the size of its population, all at the one-percent level of significance.

As shown in column 1, when we do not control for region-fixed effects, growth significantly increases with aid disbursements at the five-percent level. Conversely, when we include them – in column 2 – growth decreases with aid, also at the five-percent level of significance. The coefficient of column 1 shows that an increase in per capita aid by ten percent increases nighttime light growth by 0.006 percentage points. With average disbursements in our sample amounting to US\$ 2.39 and an average population of 2.4 million, this amounts to additional aid in the order of US\$ 0.58 million. The corresponding decrease in growth according to column 2 is almost twice as high. These numbers compare to an increase of 0.35 percentage points in GDP per capita growth following a one-percentage point increase in the aid to GNI-ratio according to the country-level results in Galiani et al. (2014) and an increase of 0.2 percentage points in Clemens et al. (2012).

The results for aid broadly hold when we replace disbursements with the number of projects in columns 3 and 4, though the negative coefficient in the fixed effects specification is no longer significant at conventional levels.

Columns 5-8 separate early-impact aid from late-impact aid, as suggested in Clemens et al. (2012). The results are indeed substantially more positive for early-impact aid compared to late-impact aid. When we exclude region-fixed effects, growth increases with early-impact aid (columns 5 and 7), with a coefficient roughly twice as high as those of total aid disbursements and 50 percent larger regarding the number of projects, while late-impact aid has no significant effect.⁴⁶ When we include the region-fixed effects, however, early-impact aid is insignificant at conventional levels, while late-impact aid is negatively correlated with growth (columns 6 and 8). Potentially, the negative side effects associated with aid – like Dutch Disease effects, deteriorating governance etc. – materialize immediately, while the potential positive longer term growth-effects of late-impact aid are yet to be realized, rendering the short-term net effect

⁴⁶A Wald test on equality of both coefficients has a p-value of 0.006.

negative.

It is instructive to compare these results with regressions at the country level. As reported in Table A.3 in the Appendix, the results show no significant effect of World Bank aid on nightlight growth in any specification, in line with the results reported for ADM1 regions in Table 1 above, but in stark contrast to the results at the ADM2 level. This is contrary to results from similar country-level specifications in Clemens et al. (2012). Arguably, the reason is that World Bank aid alone (rather than aid from all donors) is insufficiently large to measurably affect growth at the country level, while such an effect can more easily be identified at the regional level. We conclude from this comparison that a sufficiently fine-grained analysis can indeed lead to significant results where the application of analogous methods at the country level does not. This leads us to expect that a regional analysis of aid by a larger number of donors, comprising larger amounts than World Bank aid alone, would produce more robust conclusions than can be found in the current literature. Of course, the identified coefficients do not necessarily represent a causal effect of aid, to the extent that the identifying assumptions proposed by Clemens et al. (2012) are violated.

Table 3 turns to our first set of instrumental variables regressions, purging aid of its endogenous component. In line with Brückner (2013), we therefore regress nighttime light growth on annual rainfall growth and its square. Columns 1 and 2 focus on ADM1 regions, excluding and including region-fixed effects, respectively. As can be seen, the rainfall variables are completely insignificant in both regressions, and therefore unsuitable as instruments in this sample. Columns 3 and 4 turn to the ADM2 level instead. Again, rainfall growth and its square are insignificant when we do not control for region-fixed effects (in column 3). However, rainfall growth and its square are jointly significant at the one-percent level once we include region-fixed effects (in column 4). We find nightlight growth to decrease with rainfall growth at the one-percent level, but to increase with its square (at the five-percent level).⁴⁷ In what follows, we apply Brückner's methodology to this specification only, acknowledging that the instruments lack power in our other specifications.

Columns 5 and 6 show the corresponding second stage regressions for aid disbursements and the number of World Bank projects, respectively. The coefficient of growth in this second stage is then used to predict the amount of aid that is due to decreasing growth. The growth-driven part of aid is subtracted from all aid to a particular region and period, and the resulting variable – those parts of aid that are not endogenous to nighttime light growth – is used as an instrument

⁴⁷This is contrary to the results in Brückner (2013), who finds that growth increases with rainfall growth, but decreases with its square.

Table 3: 2SLS estimates using rainfall as IV, 2000-2011

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ADM1 Growth OLS	ADM1 Growth FE	ADM2 Growth OLS	ADM2 Growth FE	ADM2 Aid 2SLS (FE)	ADM2 Projects 2SLS (FE)	ADM2 Growth 2SLS (FE)	ADM2 Growth 2SLS (FE)
Rainfall Growth	-0.0458 (0.0373)	-0.0752 (0.0529)	-0.0227 (0.0189)	-0.0684*** (0.0245)				
(Sq.) Rainfall Growth	0.3203 (0.3441)	0.8921 (0.5825)	0.1602 (0.1801)	0.5956** (0.2745)				
(Log) Total aid, t-1							-0.1195*** (0.0033)	
(Log) No. of projects, t-1								-0.1499*** (0.0051)
Growth in nighttime light						1.9445* (1.0724)		
(Log) Nighttime light in 2000	-0.0169*** (0.0026)		0.0097*** (0.0014)					
(Log) Size of population, t-1	0.0057*** (0.0026)	0.0052 (0.0847)	0.0039*** (0.0014)	-0.1715*** (0.0330)	0.7898* (0.4546)	0.3705* (0.2240)	-0.1807*** (0.0371)	-0.1628*** (0.0323)
Population Growth	0.0082 (0.1326)	-1.9754 (3.6931)	0.1912*** (0.0677)	-0.0068 (1.4284)	-0.7126 (7.7137)	-0.9461 (3.3804)	-0.1266 (1.3845)	-0.1900 (1.2293)
(Log) Area	-0.0094*** (0.0028)		0.0104*** (0.0017)					
(Log) Distance to capital	-0.0076*** (0.0017)		0.0039*** (0.0012)					
Region-FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Country-Period-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	119	119	119	119	119	119	119	119
Number of regions	1811	1811	12179	12179	12179	12166	12179	12166
R2	0.32	0.55	0.20	0.53	-0.16	0.07	-0.25	0.00
Observations	5182	5182	34474	34474	34474	34359	34474	34359
First stage F-stat.					8.03	7.59	8720.89	17022.09

Notes: OLS, 2SLS and corresponding region-fixed-effects regressions (FE). Dependent variables indicated in column head: Growth in nighttime light (*Growth*), Log of per-capita aid disbursements plus 0.01 (*Aid*), Log of per-capita project count plus 0.01 (*Projects*). All variables are averaged over 3-year-periods. Standard errors, clustered at the region-level, in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

for total aid in the growth regressions reported in columns 7 and 8. The F-statistics on the excluded instruments are shown at the bottom of the table. As can be seen, they are reasonably high, but slightly below the rule-of thumb value of 10 in the aid regressions (columns 5 and 6) and easily exceed 10 in the growth regressions (columns 7 and 8). The results of the aid effectiveness regressions show a large and highly significant negative effect of aid on growth. The coefficients imply that an increase in per capita aid by ten percent decreases growth by 1.1 percentage points, while a corresponding increase in the number of projects decreases growth by 1.4 percentage points. These effects are an order of magnitude larger compared to those above. However, due to the strong identifying assumptions we take these results as suggestive rather than definitive.

Tables 4 and 5 turn to our preferred specification, focusing on ADM1 and ADM2 regions respectively. Columns 1-4 replicate the main specifications of Table 1 for the greatly reduced sample of countries that crossed the IDA-threshold at any time during our analyzed period. The OLS results for the resulting 478 regions from 21 countries are very similar compared to Tables 1 and 2. As in the larger sample, there is no significant effect of aid on growth in ADM1 regions (Table 1). Growth in ADM2 regions increases with aid when we do not control for region-fixed effects, but decreases with aid otherwise (Table 2). This holds for aid disbursements and the number of World Bank projects, the only substantive difference to the larger sample above being that the negative correlation between project numbers and growth is now significant at the five-percent level in the fixed effects specification.

Columns 5 and 6 show the first-stage regressions of our 2SLS approach. When we explain aid with the interaction of the probability of receiving aid and the IDA-income threshold indicator, we find it to be negative and highly significant in all four regressions. When we exclude region-fixed effects (in column 5), we control for the probability of receiving aid; including region-fixed effects (column 6), the probability of receiving aid is captured by the regional dummies. In any case, the IDA-graduation indicator is captured by the country-period fixed effects. The F-statistic on the excluded instrument indicates strong power. At the ADM1 level, the coefficients of columns 5 and 6 of Table 4 imply that passing the IDA threshold reduces aid by 70 percent when comparing a region with a probability of receiving aid of 45 percent (first quartile of the probability's distribution) to a region with a probability of 85 percent (third quartile). The corresponding effect at the ADM2 level is 72 percent (Table 5).

The results for the corresponding second-stage regressions in columns 7 and 8 show that aid is completely insignificant once its endogeneity is taken account of. This holds for the formerly positive correlation excluding region-fixed effects for the analysis at the ADM2 level, as well

Table 4: 2SLS estimates based on the IDA income threshold crossing, ADM1, 2000-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Growth OLS	Growth FE	Growth OLS	Growth FE	Aid OLS	Aid FE	Growth 2SLS	Growth 2SLS (FE)	Projects OLS	Projects FE	Growth 2SLS	Growth 2SLS (FE)
Pr(Aid) * Above IDA threshold					-3.0510*** (0.6232)	-3.1773*** (0.7065)			-1.9108*** (0.3913)	-1.9161*** (0.4268)		
(Log) Total aid, t-1	-0.0007 (0.0017)	-0.0033 (0.0030)					0.0033 (0.0117)	0.0028 (0.0133)			0.0075 (0.0185)	0.0040 (0.0217)
(Log) No. of projects, t-1			0.0002 (0.0026)	-0.0040 (0.0049)								
(Log) Nighttime light in 2000	-0.0156*** (0.0036)		-0.0157*** (0.0037)		0.0101 (0.0471)		-0.0158*** (0.0036)		0.0096 (0.0373)		-0.0158*** (0.0036)	
(Log) Size of population, t-1	0.0077** (0.0037)	-0.0312 (0.1579)	0.0072** (0.0037)	-0.0364 (0.1572)	0.0442 (0.0737)	1.2615 (1.9264)	0.0073** (0.0036)	-0.0411 (0.1515)	-0.0203 (0.0499)	-0.2065 (1.0464)	0.0073** (0.0036)	-0.0365 (0.1497)
Population Growth	0.2132 (0.3009)	-3.2020 (2.1845)	0.2084 (0.3003)	-3.2889 (2.1545)	7.3338 (7.4279)	70.3194*** (24.1650)	0.1899 (0.3095)	-3.5401 (2.2551)	7.9195 (4.8184)	22.0263* (13.0336)	0.1485 (0.3301)	-3.3943 (2.1344)
(Log) Area	-0.0055 (0.0036)		-0.0057 (0.0036)		-0.0056 (0.0600)		-0.0059 (0.0036)		-0.0251 (0.0402)		-0.0057 (0.0036)	
(Log) Distance to capital	-0.0007 (0.0024)		-0.0006 (0.0023)		0.0151 (0.0564)		-0.0007 (0.0023)		-0.0008 (0.0421)		-0.0006 (0.0022)	
Pr(Aid) in region before IDA crossing					5.9329*** (0.1908)				4.0051*** (0.1827)			
Region-FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country-Period-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	21	21	21	21	21	21	21	21	21	21	21	21
Number of regions	478	478	478	478	478	478	478	478	478	478	478	478
R2	0.23	0.20	0.23	0.20	0.71	0.60	0.23	0.19	0.77	0.63	0.22	0.20
First stage F-stat.					23.97	20.23			23.85	20.15		
Observations	1858	1858	1872	1872	1858	1858	1858	1858	1872	1872	1872	1872

Notes: OLS, 2SLS and corresponding region-fixed-effects regressions (FE). Dependent variables indicated in column head: Growth in nighttime light (*Growth*), Log of per-capita aid disbursements plus 0.01 (*Aid*), Log of per-capita project count plus 0.01 (*Projects*). Pr(Aid) calculated as mean incidence of aid disbursements to a region before six years past the crossing of the IDA income threshold. All other variables are averaged over 3-year-periods. Standard errors, clustered at the region-level, in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: 2SLS estimates based on the IDA income threshold crossing, ADM2, 2000-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Growth OLS	Growth FE	Growth OLS	Growth FE	Aid OLS	Aid FE	Growth 2SLS	Growth 2SLS (FE)	Projects OLS	Projects FE	Growth 2SLS	Growth 2SLS (FE)
Pr(Aid) * Above IDA threshold					-0.9545*** (0.1519)	-1.4332*** (0.1455)			0.1930** (0.0984)	-0.3291*** (0.0832)		
(Log) Total aid, t-1	0.0009** (0.0004)	-0.0017** (0.0007)					0.0011 (0.00097)	0.0050 (0.0074)			0.0132 (0.0474)	0.0103 (0.0321)
(Log) No. of projects, t-1			0.0029*** (0.0009)	-0.0032** (0.0015)								
(Log) Nighttime light in 2000	0.0124*** (0.0014)		0.0122*** (0.0014)		0.0426*** (0.0080)		0.0123*** (0.0014)		0.0388*** (0.0062)		0.0117*** (0.0024)	
(Log) Size of population, t-1	-0.0039** (0.0015)	-0.1039*** (0.0259)	-0.0039** (0.0015)	-0.1036*** (0.0259)	0.0092 (0.0116)	-1.0583*** (0.2752)	-0.0043*** (0.0016)	-0.0965*** (0.0273)	-0.0314*** (0.0083)	-0.4128*** (0.1437)	-0.0038* (0.0022)	-0.0979*** (0.0296)
Population Growth	-0.1985*** (0.0711)	-0.8501*** (0.2846)	-0.2045*** (0.0714)	-0.8698*** (0.2873)	-1.3260** (0.6058)	-0.2711 (2.0456)	-0.1948*** (0.0721)	-0.8455*** (0.2856)	0.5237 (0.3998)	0.5518 (0.9348)	-0.2075*** (0.0761)	-0.8759*** (0.2892)
(Log) Area	0.0105*** (0.0018)		0.0103*** (0.0018)		0.0369*** (0.0117)		0.0102*** (0.0018)		0.0470*** (0.0088)		0.0096*** (0.0029)	
(Log) Distance to capital	0.0054*** (0.0012)		0.0054*** (0.0012)		0.0739*** (0.0119)		0.0054*** (0.0014)		0.0475*** (0.0088)		0.0049* (0.0026)	
Pr(Aid) in region before IDA crossing					6.1926*** (0.0352)		0.0086 (0.0585)		3.0706*** (0.0366)		-0.0254 (0.1472)	
Region-FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country-Period-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	21	21	21	21	21	21	21	21	21	21	21	21
Number of regions	8375	8375	8366	8366	8375	8375	8375	8375	8366	8366	8366	8366
R2	0.11	0.10	0.11	0.10	0.63	0.24	0.11	0.10	0.60	0.28	0.11	0.10
First stage F-stat.					39.48	97.07			3.84	15.65		
Observations	31977	31977	31942	31942	31977	31977	31977	31977	31942	31942	31942	31942

Notes: OLS, 2SLS and corresponding region-fixed-effects regressions (FE). Dependent variables indicated in column head: Growth in nighttime light (*Growth*), Log of per-capita aid disbursements plus 0.01 (*Aid*), Log of per-capita project count plus 0.01 (*Projects*). Pr(Aid) calculated as mean incidence of aid disbursements to a region before six years past the crossing of the IDA income threshold. All other variables are averaged over 3-year-periods. Standard errors, clustered at the region-level, in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

as the negative correlation including them. The results are very similar when we focus on the number of World Bank projects rather than aid amounts, as shown in columns 9-12.⁴⁸

In summary, our results differ tremendously across specifications. Controlling for region-fixed effects, we do not find any significant effect of aid on growth at the ADM1 level. This holds for the specification following Clemens et al. (2012) and according to our preferred identification strategy. Rainfall growth and its square turned out to be weak instruments at this level so that we did not run an aid-growth regression here. At the smaller ADM2 level, we find that growth decreases with aid according to the fixed-effects specifications following Clemens et al. (2012) and Brückner (2013). Readers that are convinced of the identification strategies suggested there, and the way we adopt them to suit our purpose of analyzing the effectiveness of aid at the regional level, might thus conclude that aid reduces growth. However, we remain insufficiently convinced that these strategies allow deriving causal effects of aid. Instead, we prefer to conclude in line with the results from the regressions using our preferred identification strategy, the interaction of the probability of receiving aid with having passed the IDA's income threshold, that there is no evidence that aid affects growth.

Putting these results in perspective of our expectation of a stronger link between aid and growth at the regional level compared to the country level, our estimates are suggestive. Where we were able to directly compare results for the regional level with results at the country level – the analysis following Clemens et al. (2012) – we indeed find the coefficients to be significant in the regional analysis but not at the country level. While our results for the instrumental variables estimates are not directly comparable to results from the cross-country literature, comparing the larger ADM1 regions to the smaller ADM2 regions indeed shows stronger correlations between aid and growth at the ADM2 level. This suggests that analyses at smaller regional levels might indeed lead to stronger correlations between aid from a larger number of donors than we could consider here and (nighttime light) growth.

In what follows, we disaggregate our results according to continents and income-status, following the United Nations' classification as of 2014.⁴⁹ Table 6 shows the results for the amount of aid disbursed and the number of projects, following the specification of Tables 1-3. We show the

⁴⁸Note however that the instrument is weak at the ADM2 level when we exclude region-fixed effects, and the correlation of our instrument with the number of projects is positive rather than negative (see column 9 in Table 5).

⁴⁹We also tested whether aid is more effective in certain policy environments than others. We do not find this to be the case. Specifically, we interacted aid disbursements with the Polity IV indicator of democracy, the share of people with secondary education in the population, the Fraser Index of Economic Freedom, as well as three different indicators for the intensity of civil conflict, measured by the number of fatalities within a region and period. None of the interactions is robustly significant at conventional levels. Detailed results are available on request.

Table 6: Analysis by continents, 2000-2012

	SSA		ECA		EAP		LAC		MENA		SAS		LDCs	
	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2
Total aid	0.0031	0.0054***	0.0018	-0.0012**	-0.0034	-0.0012	0.0009	0.0007**	0.0017	-0.0012	0.0060	0.0003	-0.0000	0.0038***
FE	0.0006	0.0027*	-0.0007	-0.0031***	-0.0021	-0.0037***	0.0005	-0.0002	0.0029	0.0031	0.0017	-0.0020**	-0.0006	0.0012
2SLS	0.0390***	-0.0034***	0.0312***	0.0149***	-0.0302***	-0.1036***	0.0220***	0.0793***	-0.0055***	0.0026**	-0.0281***	0.0501***	0.6077***	0.0500***
<i>F-stat.</i>	(0.31)	(1.94)	(6.27)	(14.36)	(0.30)	(3.03)	(0.74)	(0.17)	(1.38)	(0.99)	(1.38)	(2.57)	(0.00)	(3.49)
2SLS (FE)	0.0184***	0.0239***	0.0208***	0.0015*	0.3851***	-0.0867***	0.0501***	0.1474***	0.0367***	-0.2895***	0.0225***	-0.0372***	0.0379***	0.2879***
<i>F-stat.</i>	(0.52)	(1.25)	(9.77)	(25.36)	(0.07)	(3.77)	(0.25)	(0.63)	(1.17)	(0.58)	(3.20)	(5.42)	(1.41)	(0.71)
Number of countries	42	42	28	28	15	15	29	29	10	10	8	8	41	41
Number of regions	534	6191	594	8184	277	13696	471	17865	205	3823	142	4408	540	6167
Observations	1998	19578	2319	31132	1031	46910	1845	67404	817	14746	531	16116	1955	18612

	SSA		ECA		EAP		LAC		MENA		SAS		LDCs	
	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2	ADM1	ADM2
Projects	-0.0047	0.0083***	0.0033*	-0.0009	-0.0084*	-0.0019	0.0021	0.0015***	0.0022	-0.0020	0.0056	0.0019	-0.0001	0.0075***
FE	0.0051	0.0045*	-0.0017	-0.0029**	-0.0025	-0.0061***	0.0017	-0.0003	0.0049	0.0049**	-0.0050	-0.0028	0.0022	0.0063***
2SLS	0.1033***	-0.0824***	0.0437***	0.0112***	-0.1302***	0.0700***	0.0346***	-0.4370***	-0.0338***	0.1034***	-0.0221***	0.1157***	1.8913***	0.0460***
<i>F-stat.</i>	(0.31)	(1.88)	(6.15)	(14.93)	(0.30)	(2.73)	(0.74)	(0.28)	(1.29)	(0.92)	(1.38)	(2.37)	(0.00)	(3.31)
2SLS (FE)	-0.1090***	0.1570***	0.0184***	0.0147***	0.0762***	0.1119***	-0.1653***	-0.0342***	0.0773***	-0.1141***	0.0008	-0.0750***	-0.0170**	0.3892***
<i>F-stat.</i>	(0.52)	(1.11)	(9.98)	(24.83)	(0.07)	(3.91)	(0.25)	(0.62)	(1.19)	(0.41)	(3.20)	(4.90)	(1.41)	(0.83)
Number of countries	42	42	28	27	15	15	29	29	10	10	8	8	41	41
Number of regions	534	6185	594	8165	276	13687	465	17846	205	3817	142	4405	540	6146
Observations	1996	19639	2338	30947	1018	46925	1816	67507	820	14651	531	16134	1951	18532

Notes: Shows the coefficients of the respective aid variable. OLS, 2SLS and corresponding region-fixed-effects regressions (FE). Dependent variable: Growth in nighttime light. The regressions include country-period fixed-effects and, if FE is specified, also region-fixed effects. Logged nighttime light in 2000, logged population size, population growth, logged area, and logged distance to capital are included as control variables in the OLS and 2SLS regressions. All variables are averaged over 3-year-periods. F-statistics refer to the corresponding first stage. Standard errors, clustered at the region-level, in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SSA: Sub-Saharan Africa; ECA: Europe and Central Asia; EAP: East Asia and Pacific; LAC: Latin America and Caribbean; MENA: Middle East and Northern Africa; SAS: South Asia; LDCs: Least-developed countries.

resulting coefficient of aid disbursements or project numbers and indicate whether the coefficient is statistically significant. For the 2SLS regressions we include the first-stage F-statistics in parentheses. We do not separate the sample using our preferred instrument – the interaction of crossing the IDA-threshold with the probability to receive aid – given that the resulting number of countries and regions would be too low for meaningful regressions.

The results show some differences across continents. Focusing on the region-fixed effects specifications without using instruments, there is no significant correlation between aid and growth at the ADM1 level. At the ADM2 level, growth increases with aid in Sub-Saharan Africa, but decreases with aid in Europe and Central Asia, East Asia and Pacific, and South Asia. If we focus on the least developed countries only, there is no significant correlation between aid and growth. Turning to the 2SLS regressions employing rainfall growth and its square as instruments, the first-stage F-statistic exceeds 10 only in the regressions restricted to Europe and Central Asia. Contrary to the results with OLS, these regressions show that growth increases with aid.

The lower panel of Table 6 shows results corresponding to the number of projects. Overall, these results are very similar, with the exception of an insignificant coefficient for South Asia in the fixed effects regression at the ADM2 level and a significant and positive correlation between projects and growth in this specification in least developed countries. Overall, while not showing strong evidence of a positive causal effect of aid and growth, these results imply that the effects of aid on growth are likely to be heterogeneous across groups of countries. Unfortunately, rainfall growth and its square turned out to be weak in most specifications, so that these coefficients hardly show more than interesting correlations however. We thus leave a deeper analysis of heterogeneous effects of aid for future research.

4 Conclusion

The aim of this paper was to bring the aid effectiveness debate to the regional level. We hypothesized that the effects of aid might be discernible regionally, even if aid amounts are too low to be measurable at the country level. The lack of sub-regional analyses might thus contribute to the lack of robust evidence in the aid effectiveness literature.

Our regressions used geo-coded data for World Bank aid to a maximum of 2,283 regions in 130 countries over the 2000-2011 period, testing whether and to what extent aid affects development, measured as nighttime light growth. We presented results using three different identification strategies. First, we followed Clemens et al. (2012), relying on aid that can

reasonably be expected to affect growth in the short run, controlling for country- and region-fixed effects, and lagging aid appropriately to allow time for it to become effective. Second, we purge aid of those parts that are endogenous to growth, using data on rainfall growth and its square in the spirit of Brückner (2013). However, our instruments are too weak to allow us to draw any strong conclusions.

Our preferred identification strategy exploited variation arising from interacting a variable that indicates whether or not a country crossed the IDA’s income threshold for concessional aid with a recipient region’s probability of receiving aid. This comes with the disadvantage that the analysis only includes those countries that crossed the IDA threshold during the time our sample covers. Controlling for the levels of the interacted variables, the interaction provides a powerful and excludable instrument for a sample of 478 regions from 21 countries.

Overall, our results show significant correlations between aid and (nighttime light) growth. Our results highlight the importance of measuring aid flows at the regional level, showing correlations that are markedly stronger at the smaller ADM2 regional level, compared to the larger ADM1 and the country level. However, once we take account of the endogeneity of aid – and potential attenuation bias, e.g., through measurement error in the geo-coding process – we find no significant effect of World Bank aid on growth, neither at the ADM1 nor the ADM2 level.

While the World Bank is one of the world’s largest donors, the amounts of aid we could track here only represent a share of all World Bank project aid, and are of course comparably small when put in perspective to aid amounts included in most aid effectiveness studies at the country level (usually using aid from all major Western donors). One reason for the insignificant result might thus be that the amounts of (region-specific) World Bank aid alone are too low to measurably affect growth, even at the regional level. Our failure to detect a significant effect of aid on growth is likely to be aggravated by the potential fungibility of aid.⁵⁰ To the extent that aid is fungible, the aid might have positive growth effects in other regions that we fail to measure with our analysis. The same might hold if regional spillovers are important. Of course, this would not threaten our conclusion regarding the effect of aid on growth *in the regions that receive the aid*.

It is important to emphasize that these results not necessarily hold for aid more broadly. First, our analysis is limited to countries that passed the IDA-income threshold at some time

⁵⁰Fungibility is likely to be partial rather than full (van de Sijpe, 2013). Van de Walle and Mu (2007) find evidence of a “flypaper effect” rather than full fungibility in their study of a road rehabilitation project co-financed by the World Bank in Vietnam.

during our sample period, giving rise to the question of external validity. As Galiani et al. (2014) show, countries crossing the IDA income threshold do not display systematically different growth patterns than countries below the income threshold, controlled for initial income. They consequently expect their estimated effect of aid on growth to hold in a broader set of countries rather than being limited to countries that passed the threshold. The same will arguably be true for the results of our study. Second, the focus of our study was on project aid that could be attributed to specific regions with sufficient precision. Other forms of aid – like budget support to the central government, for example – are not covered here, and might differ in their impact. And third, the results for the World Bank do not necessarily translate to other donors also.⁵¹

Analyzing the effect of aid on growth at the regional level for a broader set of donors is currently prevented by the unavailability of aid data on the regional level. Other than for the World Bank, current data availability would allow a similar analysis for Chinese aid in Africa, where geo-coded data for a similar period of time as we have used here has recently been made available (Dreher et al., 2014). More broadly, another promising extension includes the analysis of the effects of aid on broader indicators of social development than growth at the subnational level, which is equally missing from the current literature. Geo-coding aid flows for a larger number of donors across the world remains a challenge for future research on the effectiveness of aid.

⁵¹Note however that Rajan and Subramanian (2008) do not find differential effects of budget compared to project aid on growth at the country level. The same holds for bilateral compared to multilateral aid.

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Appendix

Table A.1: Description of key variables

Variable	Source	Description
Nighttime light intensity	NOAA	Sum of nighttime light intensity values falling within the borders of an administrative region
Total aid (p.c.)	AidData (2015) / World Bank	Average annual disbursement through World Bank projects within a region divided by regional population, 2011 US\$
Early-impact aid (p.c.)	AidData (2015) / Clemens et al. (2012)	Subcomponent of "Total aid" from projects in early-impact sectors, classified on the basis of Clemens et al. (2012)
Late-impact aid (p.c.)	AidData (2015) / Clemens et al. (2012)	Subcomponent of "Total aid" from projects in late-impact sectors, classified on the basis of Clemens et al. (2012)
No. of projects (p.c.)	AidData (2015)	Average annual number of project with non-zero disbursements within a region divided by regional population
Size of population	CIESIN (2005)	Estimated headcount of population based on satellite image gauges of population density
Area	Global Administrative Areas (GADM)	Size of the administrative region, square metres
Distance to capital	Global Administrative Areas (GADM)	Shortest distance between the centre of an administrative region and the country capital, kilometres
Annual rainfall	Schneider et al. (2011)	Average annual rainfall estimated from the sum of rainfall intensity values falling within the borders of a region
Above IDA threshold	based on Knack et al. (2014)	Binary indicator taking value 1 if a country is six years past the crossing of the IDA income threshold
Pr(Aid)	own calculations	Mean incidence of aid disbursements to a region before six years past the crossing of the IDA income threshold

NOAA: National Oceanic and Atmospheric Administration.

CIESIN: Center for International Earth Science Information Network.

Table A.2: Descriptive Statistics, ADM1, Estimation sample (2000-2012)

	Mean	Median	SD	Min.	Max.
Nighttime light intensity	2.45	0.60	5.89	0.00	63.00
Growth in nighttime light	0.06	0.04	0.12	-0.33	0.62
Size of population, t-1 (in 1,000)	2361.73	498.43	9115.85	0.79	189844.11
Area (in million square km)	41037.08	7396.56	122254.88	17.38	3066310.00
Distance to capital (in km)	403.97	227.15	643.78	0.61	11212.19
Total aid, t-1 (per capita)	2.39	0.60	4.43	0.00	37.65
Early-impact aid, t-1 (per capita)	1.20	0.00	2.75	0.00	22.56
Late-impact aid, t-1 (per capita)	0.99	0.07	1.95	0.00	18.02
No. of projects, t-1 (per 1,000 capita)	0.00	0.00	0.00	0.00	0.01
No. of early-impact projects, t-1 (per 1,000 capita)	0.00	0.00	0.00	0.00	0.00
No. of late-impact projects, t-1 (per 1,000 capita)	0.00	0.00	0.00	0.00	0.01
Rainfall Growth	0.01	0.01	0.06	-0.15	0.21
Pr(Aid) in region before IDA crossing	0.62	0.70	0.31	0.00	1.00
Observations	9124				
Number of countries	130				
Number of regions	2281				

Table A.3: Specification at country-level, 2000-2012

	(1)	(2)	(3)	(4)
(Log) Total aid, t-1	-0.0006 (0.0022)			
(Log) No. of projects, t-1		-0.0010 (0.0024)		
(Log) Early-impact aid, t-1			0.0020 (0.0020)	
(Log) Late-impact aid, t-1			-0.0003 (0.0020)	
(Log) No. of early-impact projects, t-1				0.0010 (0.0019)
(Log) No. of late-impact projects, t-1				0.0003 (0.0027)
(Log) Size of population, t-1	-0.0079 (0.0967)	-0.0079 (0.0970)	-0.0179 (0.0975)	-0.0123 (0.0970)
Country-FE	Yes	Yes	Yes	Yes
Period-FE	Yes	Yes	Yes	Yes
Number of countries	130	130	130	130
R2	0.22	0.22	0.22	0.22
Observations	1529	1529	1529	1529

Notes: Within-country regressions (FE). Dependent variable: Growth in nighttime light. All variables are averaged over 3-year-periods. Standard errors, clustered at the country-level, in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.