Relationship Between Foreign Aid and Night Lights Data

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Using night lights data as a proxy for economic activity

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Abstract

This paper investigates the relationship between committed foreign aid and night light data from 1992 to 2008. Two aid data classifications were used: (i) humanitarian, early impact, late impact, and other aid and (ii) humanitarian and non humanitarian aid. The results show that the elasticity of our measure of night lights to humanitarian aid is negative and statistically significant at the 5% level for year 0 and 1 and statistically insignificant for year 2 onwards. The elasticities for early impact, late impact and non humanitarian aid are positive and statistically significant for year 1 and onwards. Foreign aid positively impacts night light data and suggestively imply that foreign aid positively impact, albeit weakly, economic activity.The heterogeneity of the results was investigated. The results were not sensitive to a change from non calibrated to calibrated satellite images but did differ depending on the percentage electrification of a country, percentage of the total population that live in urban environments, and the initial level of prosperity of a country.

Introduction

The link between foreign aid and indicators of growth in the developing world has been the subject of intense scrutiny and debate over the last two decades. A large body of literature on the aggregate aid effectiveness for economic development exists. However, conclusions are still unclear. For example, a meta study of the aid effectiveness literature produced a list of 106 papers showing that foreign aid can be effective, ineffective, or even harmful (Doucouliagos and Paldam, 2008).

There are three main challenges in the estimation of the impact of foreign aid on economic activity. First, they require a strategy to disentangle correlation from causation. However, empirically observed covariation is only a necessary and not sufficient condition for causality

Second, there is also the question of the timing of causal relationships between aid and growth. According to Clemens et al. (2012), most cited research has focused on measuring the effect of aggregate aid on contemporaneous growth, while many aid-funded projects can take a long time to influence growth (such as a vaccination campaign or school feeding project). Clemens et al. (2012) further argue that foreign aid includes flows that are not intended or used to promote expansion in generalised productive capacity (such as humanitarian assistance or disaster relief).

Finally, despite continuous revisions of knowledge, methodologies, and techniques for measuring income and economic activity using conventional ground survey-based data, reliable yearly statistics at the national level are often a luxury. Many poor countries lack both the resources and the capacity to acquire reliable data, despite decades of international statistical support. This sad state of affairs has been deplored by a number of studies that showed potentially serious measurement errors in growth figures in developing and emerging economies (Henderson et al., 2012; Johnson et al., 2013; Ravallion and Chen, 1999).[1]

In response to the problems of measuring GDP, there is a long tradition in economics of considering various proxies that cover periods or regions for which GDP data are not available at all or not available in a timely fashion. Most recently, Chen and Nordhaus (2011) compare the relationship of night light data with growth of different countries

[1] This problem is further compounded by the fact that relative to developed countries, in many developing countries a much smaller fraction of economic activity is conducted within the formal sector.

according to the quality of their statistical systems and conclude that "luminosity has informational value for countries with low-quality statistical systems, particularly for those countries with no recent population or economic censuses".

I will exploit this result in this paper and explore the relationship of foreign aid on economic activity using an area weighted sum of the night light intensity that can be observed from outer space. Even though changes in lights observable from space are subject to measurement error, the latter are arguably not related to aid or not as important as measurement error in GDP. I will also take the critiques offered by Clemens et al. (2012) seriously and, using their classification, divide our aid data into four groups: humanitarian aid, early impact aid, late impact aid and other aid.

The elasticity of our measure of night light to both early impact aid and late impact aid is positive and occurs after a small period of latency. Total non humanitarian aid, defined as total aid less humanitarian aid, is also positive and significantly associated with gowth from year 0 onwards. Assuming that night light is a good proxy for human economic activity, this is suggestive that aid is effective at promoting growth. The results obtained were, however, sensitive to heterogeneity: elasticities between aid and night light were positive only for countries that were more rural, poorer or have a lower access to electricity and statistically insignificant for their counterparts.

The results show that humanitarian aid is negatively correlated with GDP for the year in which aid is received and the following year. This fits the idea that the purpose of humanitarian aid is not to promote growth.

This paper contributes to the aid and growth literature by using a new proxy to measure the impact of foreign aid on developing countries at the cross country level (Boone, 1995; Burnside and Dollar, 2000; Clemens et al., 2012; Doucouliagos and Paldam, 2008, 2011; Findley et al., 2011; Hansen and Tarp, 2001; Rajan and Subramanian, 2005a; Collier and Dollar, 2002, 2001; Collier and Hoeffler, 2004; Easterly and Levine, 2004; Dalgaard and Hansen, 2001; Dalgaard et al., 2004; Rajan and Subramanian, 2005b; Berthélemy, 2006; Rajan and Subramanian, 2008). This paper also shows that the definitions used by Clemens et al. (2012) can be further relaxed: foreign aid data can be divided into humanitarian and non humanitarian aid rather than humanitarian, early impact and late impact aid since the demarcation between the last two can be ambiguous.

Background and Literature Review

Night lights

Croft (1978) was the first to recognise that night lights could be used as a means for detecting human presence and hence as a proxy for economic activity. However, the first 20 years of images were recorded on film strips, which greatly impeded the accessibility and application of these datasets (Welch, 1980). Since the establishment of a digital archive in 1992 by the National Oceanic and Atmospheric Administration/National Geophysical Data Center (NOAA/NGDC), these night lights data have been widely exploited by the scientific community. Popular applications of the DMSP/OLS nighttime images include monitoring human settlement; estimating urban population and population density, socio-economic activity, energy and electricity consumption, and gas emissions; measuring impacts of urban growth on the environment; detecting nocturnal fishing vessels; mapping night time sky brightness and forest fires; assessing effects of emissions on ecosystem and human health; and evaluating damage from natural disasters and military action during wars (see Huang et al., 2014).

The relationship between night lights and Gross Domestic Product or Gross Regional Product is well established. At the regional level, Bhandari and Roychowdhury (2011) used DMSP-OLS stable night lights throughout India in 2008 at a sub-national level to show that district level stable light correlates to district level GDP for India. Likewise, Doll et al. (2006) find a strong relationship between night light and Gross Regional Product (GRP) for 11 European Union (EU) countries and the US. These papers suggest that relationship between stable night lights and GDP is stronger for larger cities, yet slightly weaker when analysing the relationship at a regional level. At the national level, an earlier study by Elvidge et al. (1997) focused on the correlation between luminosity and gross domestic product (GDP) at the country level and found a strong correlation ($R^2 = 0.97$) between illuminated area and GDP (both expressed in logarithms) for 21 countries. Sutton and Costanza (2002) find a high correlation between luminosity and GDP per square kilometre at the national level. Chen and Nordhaus (2011) compare the relationship of light data with growth of different countries according to the quality of their statistical systems and conclude that "luminosity has informational value for countries with low-quality statistical systems, particularly for those countries with no recent population or economic censuses". Another study of interest that examines the correlation of cross country night lights with economic activity is Henderson et al. (2012) who use DMSP-OLS stable night lights to create a statistical framework to augment official income growth measures. Data from Henderson et al. (2012) as well as data from NOAA will be used in the study.

The use of night lights data to proxy economic activity is, however, not without its limitations. Small (2004) estimated that 2 percent of the human population clusters in densities of less than ten people per square kilometre on 50 percent of the potentially habitable land area on Earth and argues that large rural areas of intermediate population densities contain only small, isolated illumination and "...many small settlements are not detected or even illuminated at night". Small et al. (2011) further argue that although night lights and population density are correlated at high valued DNs, this relationship is weaker with lower DN values leading to either one of two conclusions: (i) lower DNs may relate to lower built area density with dimmer outdoor lighting; or (ii) that a small number of discrete lighted areas exist. This idea is reiterated by Elvidge et al. (1997) who suggest that DSMP-OLS stable night lights do not provide a direct observation of rural populations across a large land mass. Therefore, the use of night lights as a proxy for rural population estimates appears to be inaccurate.

Another limitation of DSMP-OLS stable night lights is its high reliance on access to electricity (Small et al., 2011). Elvidge et al. (2012) explain that night lights are primarily related to outdoor lighting, as opposed to the leakage of indoor light. This suggest that lights observed would be from light post or illuminated front store signs both of which rely on access to electricity rather biomass burning.

Aid Effectiveness

Hansen and Tarp (2001) divide the studies in the aid and growth literature into three generations. The first generation, using the Harrod-Domar model as its theoretical workhorse, mainly focused on the aid-savings link: saving leads to investment and growth so that a rapid increase in external capital investment was expected to increase growth. The failure of many developing countries to emulate the success of Post World War II Europe suggested that the relation of aid and growth was more complex. The second generation investigated the aid-investment-growth link more directly without focusing on saving. While a majority of the aid-growth studies of this generation suggested a positive impact, the result that captured attention was Paul Mosley's "micro-macro" paradox. This puzzle raised doubts concerning the appropriateness of the underlying growth model and the empirical techniques used.The third generation studies of more sophisticated econometric studies were ushered by Boone (1995) and the Millennium Development Goals (MDGs) in 2000. Interest in the topic of aid effectiveness was renewed and has since then has gathered some significant momentum.

A key study of the third generation is Burnside and Dollar (2000). The study shows that an increase in aid flows strengthens economic growth in poor countries when the policy environment is conducive to this. In the presence of poor policies, aid was not found to have any positive effect on growth.

The Burnside and Dollar result was supported by a number of follow-up studies (Collier and Dollar, 2002, 2001; Collier and Hoeffler, 2004). Subsequent studies have, however, suggested that the Burnside and Dollar results were not robust. Dalgaard and Hansen (2001) argue that the Burnside and Dollar results are sensitive to the treatment of outliers and when removing outliers they found that aid had no effect on growth. Easterly and Levine (2004) discovered that the results were sensitive to an expansion of the dataset to cover more countries and years. Dalgaard et al. (2004) introduce a geographical variable into the aid-growth perspective to find that, on average, aid seems to work for areas outside the tropics.

Hansen and Tarp (2001) analyse the impact of aid on real GDP per capita across countries and conclude that "aid in all likelihood increases the growth rate, and this result is not conditional on 'good' policy. There are, however, decreasing returns to aid, and the estimated effectiveness of aid is highly sensitive to the choice of estimator and the set of control variables. When investment and human capital are controlled for, no positive effect of aid is found." This clearly contradicts the Burnside and Dollar result.

Roodman (2004) studied the robustness of the findings in Burnside and Dollar (2000), Hansen and Tarp (2001), Collier and Dollar (2002),Collier and Dollar (2001), Collier and Hoeffler (2004), and Dalgaard et al. (2004) and demonstate that non-robustness is a common feature of the cross-country aid effectiveness literature. Most sensitive were the results of Burnside and Dollar (2000), Collier and Dollar (2002) and Collier and Dollar (2001), while Dalgaard et al. (2004) and Hansen and Tarp (2001) proved more stable.

Rajan and Subramanian (2005b) argue that aid flows reduce partner country competitiveness through exchange rate appreciations. Their study finds no evidence that aid works better in better policy or geographical environments, or that certain forms of aid work better than others.

More recently, Moyo (2009) adds a more controversial perspective on the aid effectiveness debate and argues that aid results in corrupt political regimes, as political leaders have incentives to maintain relationships with donor countries as opposed to focusing on policy within their own countries. She, therefore, suggests that foreign aid has a negative impact on economic growth and that political factor should be taken into consideration when determining the effectiveness of aid.

From the above, it is clear that the literature on aid effectiveness has been considerable but no clear conclusions on the effect of aid have been drawn. This situation is succinctly summed up by Clemens et al. (2012) as "literature that has been alternately described as marred by aid proponents' "confirmation bias"or described as marred by aid opponents' selective reading of the empirical evidence." In fact, Doucouliagos and Paldam (2010), using a meta-analysis covering 106 papers containing a total of 1217 estimates, found that the estimates of the effect of aid are widely scattered.

Heterogeneity in the type of aid provided is a pervasive problem for the aid-growth relationship. Moreover, growth and poverty reduction may not always be the main motives for providing aid. Berthélemy (2006) shows that strategic motives and self-interest by donors to a large extent explain aid allocation. Clemens et al. (2012) divide aid into three categories to discover that the effects on growth differ considerably. Using models from Boone (1995), Burnside and Dollar (2000), and Rajan and Subramanian (2005a), Clemens et al. show aid aimed at short term goals have a small positive effect on short-run growth, although the magnitude of this relationship is modest, varies greatly across recipients and diminishes at high levels of aid. The authors also show that this positive relationship disappears with aid aimed at long term goals since they measure the effect of aggregate aid on contemporaneous growth while many of these aid-funded projects can take a long time to influence growth. The effect of timing on aid is thus important.

Finally the micro-macro paradox of aid effectiveness as suggested by Mosley (1986) is relevant for this study. Specifically, Mosley suggests that microeconomic data at the project level shows evidence of aid producing positive economic returns, yet when macroeconomic data is used to regress the effect of aid on growth at a national level it appears ineffective.

Data

Night Light Data

There are different versions of the night light data; three of particular importance are the "raw", the "stable lights", and the "raw-calibrated" versions. The stable lights version removes ephemeral events such as fires and background noise. The raw-calibrated version is currently available only for 2006 and has the advantage of not being saturated (top-coded) at the highest intensities. This paper, therefore, reports primarily the results based on the stable lights data and use the latter to create *empirically* calibrated data, as will be discussed below.

The main source of satellite data on the intensity of night time lights comes from Defense-Meteorological Satellite Program-Optical Line Scanner (DMSP-OLS) that is managed by the National Oceanic and Atmospheric Administration (NOAA) of the Unites States. The weather satellites are in asynchronous orbit and circle the earth 14 times a day and measure light intensity. NOAA uses observations from every night between 8:30 pm and 10:00 pm during the dark half of the lunar cycle in seasons when the sun sets early, but removes observations affected by cloud coverage or northern or southern lights. It further processes the data by setting readings to zero when these are likely to reflect forest fires, other ephemeral lights such as auroral activity, or background noise. These restrictions remove intense sources of natural light, leaving mostly man-made light. Observations where cloud cover obscures the earth's surface are also excluded. Finally, data from all orbits of a given satellite in a given year are averaged over all valid nights to produce a satellite-year dataset. NOAA provides annual data for the time period from 1992 to 2013 for output pixels that correspond to 30 arc-seconds (approximately 0.86 square kilometers at the equator) between 65 degrees south and 75 degrees north latitude.

The data come on a scale from 0 to 63, with higher values implying more intense night time lights. Night time lights intensity is a proxy for economic activity, as most forms of consumption and production in the evening require light. The largest exception are lights generated by the flaring of natural gas, as a byproduct of oil production. As reported by Elvidge et al. (2012), gas flares in 2000 covered 0.9 percent of the world's land area, with 0.34 percent of world population. Since gas flares represents stable light that is not affected by foreign aid, we exclude them from our analysis (Henderson et al., 2012). This represents 3.1 percent of land based lights.

Using the same methodology as Henderson et al. (2012) and Michalopoulos and Papaioannou (2014), we apply a log transformation to the average night time light intensity. Also, in order not to lose observations with no reported night time light, we follow Michalopoulos and Papaioannou (2014) in using the logarithm of average night time light intensity plus 0.01 as the dependent variable. Adding just a small constant before taking the logarithm ensures that the coefficients remain close to (semi-) elasticities (Hodler and Raschky, 2014). This can be justified on the basis that absence of reported night time light typically does not imply absence of night time light, and certainly not absence of economic activity. It is rather an artifact of the way the data is collected and processed: man-made night time light in these regions may have been below the detection limit of the satellites' sensors or incorrectly identified as ephemeral light or background noise (Henderson et al., 2012).

A small fraction of pixels (0.1 percent), generally in rich and dense areas, are censored at 63. However, none of the saturated pixels are in recipient countries of foreign aid and hence does not affect our data. Finally, sensor settings vary over time due to possible degradation of the sensor as well as between satellites due to a lack of inter calibration since the primary purpose of the satellites is not to observe night light data. This makes the comparisons of digital numbers over years problematic. We will control for such issues using year fixed effects. Methods for the inter calibration of satellite images have been developed over the years. The most popular approach by Elvidge et al. (1997) for inter-calibration consists of using a region characterized by stable night-time lights as a reference between satellite-year images. The area of Sicily from the satellite F121999 is used and a polynomial function is applied to each pixel. This was applied to our satellite-year data for a sample of countries to create calibrated data. However, the process of calibration is computationally onerous and results obtained are similar to the uncalibrated data (see table 6). Therefore uncalibrated data was used in most of the analysis that follows.[2]

Aid Data

The Organisation for Economic Co-operation and Development (OECD) Creditor Reporting System (CRS) publishes donor-reported aid data at the project level. The twenty-three members of the Development Assistance Committee (DAC) submit their data on individual aid activities to the CRS where they are verified by OECD staff. The CRS data reflect DAC members' official statistics on aid flows to developing countries. Multilateral agencies report to the DAC on a voluntary basis. Definitions used in the CRS are discussed and agreed unanimously by DAC members, and are regularly adapted to respond to the needs of DAC members and to political changes in the provision of Official Development Assistance. CRS data are thus comparable between countries, and they are recognized internationally as the most reliable and complete source of information on aid flows (Petras, 2009). Validated CRS data are made public by the OECD DAC Secretariat and are freely available on the OECD website.

Aid data was downloaded for the period of 1992 to 2008. Using the same 'purpose' code used by Clemens et al. (2012), the disaggregated data was classified as *Humanitarian Aid*, *Early Impact Aid*, *Late Impact Aid*, and *Other Aid*. Humanitarian aid is that which finances activities without any plausible growth-related goal, such as emergency food aid and disaster relief. Early impact aid is defined as aid which might plausibly affect growth

[2] Another method of calibration consists of shifting the satellite images by a few pixels and finding the coefficient of correlation between the new shifted image and a reference year image. This shift-based method of Zhao et al. (2011) to correct images assumes that light sources are temporally highly correlated i.e. on a average area of high DNs is more likely to have high DNs from the reference year to the year being calibrated. Though this approach is theoretically sound, the level of correction is usually of the order of 1 pixel. Since we are working at the country level, this level of precision is not necessary.

within a few years afterwards. Late-impact aid is aid which finances activities that are likely to take many years or even decades to affect growth, such as vaccination campaigns or basic education. All other aid that was not included in the above 3 categories was labelled as Other Aid.

The data was aggregated at the year-country-purpose level. Commitment amounts were converted to constant 2014 dollars using the GDP deflator provided by the CRS.

Other data

The World Development Indicators database was used to test the heterogeneity of the results. Series used were Access to electricity (% of population), Urban population (% of total), and GDP at market prices (constant 2010 US$). All series, except for Access to electricity, are for the year 1992. The Access to electricity series is for the year 1990.

Summary Statistics

From table 1, a total of 6873 observations are used in our samples ranging from a year 1992 to 2008. The log(DN), uncalibrated and log(DN), calibrated are very similar in range with a minimum of -6.47 and -6.26 and a maximum reprectively and the same maximum of 6.07. The mean and stadard deviation between the calibrated and uncalibrated are also very similar. The mean committed dollars per project for early-impact, late-impact, humanitarian, and other aid is $3,203, $13,589, $2,686 and $2,686 while the standard deviation of the commited dollars per project is $4,159, $18,936, $4,814, and $653 respectively. The number of observation amongst the different types of aid, except for other aid, was similar .

Model

In order to carry out a cross country panel data analysis of the impact aid on night light intensity, the following linear regression model was specified with the logarithm of the area weighted sum of the digital number (DN) as the dependent variable and log of the committed amount as the independent variable.

$$\log(DN_{i,t+l}) = \alpha + \beta \cdot \log(Commitment_{i,t}) + \gamma_t + \delta_i + \epsilon_{i,t} \tag{1}$$

where the subscript i refers to the country and t to the time period. l is a number between 0 and 4 and represents the lead operator applied to the dependent variable. γ_t and δ_t represent country and time fixed effect respectively. $\epsilon_{i,t}$ is the random disturbance. I cluster the standard errors at the country level to relax the homoskedasticity assumption and allow the error terms to be heteroskedastic and correlated within groups.

To explore the heterogeneity in our main result, subgroup analyses were conducted. The categories used were the Access to electricity (% of population), urban population (% of total), Agriculture, value added (% of GDP), and GDP at market prices (constant 2010 US$). Countries were categorized as high or low for a specific category if the value for the country being classified is above or below the mean for all countries in our sample.

In both econometric models, a log-log regression is performed and the coefficient of interest is interpreted as an elasticity, that is, a change of 1% in foreign aid causes a β% change in the amount of night light intensity.

Results

Table 2 shows the main results of this paper.

The early impact section of Panel A for table 2 shows the elasticity of early impact aid on light intensity. The estimates are not statistically significant at conventional level for year 0 and 1 but is positive for year 2 onwards. In year 2, a 1% increases in early impact foreign aid is associated, on average, with an increase of 0.06% in light intensity. This result is statistically significant at the 1% level. A back of the envelope calculation using the results of Henderson et al. (2012) show that a 0.06% increase in light is associated with 0.02% increase in GDP. Though we cannot impute causation but only correlation from the regression, the result is suggestive that after a short period of latency, early impact aid is effective, at least at increasing the amount of light and possibly economic activity. As mentioned in the literature review, the relationship between light intensity and growth is complex and our results can only provide support to the claim that aid is effective.

The results for late impact aid are insignificant in year 0 but positive from year 1 onwards. The results are statistically significant at the 5% level and the 10% level for years 1 to 3 and year 4 respectively. A 1% increase in long term foreign aid is associated with approximately a 0.1% increase in light intensity per area. The results seem at first surprising given the definition of late impact aid used by Clemens et al. (2012) and the fact that the coefficients are statistically larger than in the case of early impact aid. Further investigation would be required to better understand this phenomenon. However, possible explanations for these results are:

- Though most of the effect is expected after a relatively longer period of time, investment must occur today. Consider an investment in human capital, more specifically an investment in education that consists in increasing the number of schools in a given district. Though the benefits of a better education will be reaped many years in the future, investment in supporting infrastructure is done today. In our example, schools are built now and money is spent on wages. The latter, through various macroeconomic channels (such as a multiplier effect, consumption smoothing, etc), boost economic activities. That being said, it is uncertain whether present investment increases translate to increase in future economic activities.[3]

- Countries that receive mostly late impact aid are different from countries that receive mostly early impact aid as they are able to meet their short-term goals and are already well on their way to prosperity. Our results would, in this case, be spurious in nature.

In the Total Aid section of Panel A, the coefficients for years 2 and 3 are positive and statistically significant at the 10% level while for years 0, 1,and 4 they are statistically insignificant. This suggests a weak positive relationship between total aid and night lights. However, since total aid encompasses all of the different types of aid such weak and unclear results were to be expected. To test this, on the basis that humanitarian aid is not meant to promote growth, we subtract it from total aid and run the regressions again. The results are reported in table 3. The coefficient for year 1 changed from being statistically insignificant to being significant at the 5% level while coefficient for year 2 and 3 increased and are now statistically significant at the 5% level. From this point onwards, we will exclude humanitarian aid from total aid.

The coefficient of the regression of logarithm of committed humanitarian aid on log of weighted sum of digital number is negative and significant at the 5% level for year 0 and year 1. This suggests that humanitarian aid increases as light intensity decreases. Assuming that changes in night light intensity is a good proxy for changes in economics activity, the results, by extension, suggest that humanitarian aid increases as economic activity decreases. This result is consistent with the definition that was used to classified aid as humanitarian, that is, aid whose primary purpose is to provide crisis relief and not to promote growth. This is further supported by the fact that the coefficient for year 2 onwards is statistically not different from zero, that is, humanitarian aid has no noticeable relationship on future night lights and hence growth.

[3] As described by Clemens et al. (2012), long term growth cannot be measured in the relative short time frame of the study. The model used measures only contemporaneous growth.

Tables 4 and 5 investigate the heterogeneity of our main results. From the analysis of the percentage of the population that live in an urban environment, the coefficients for the high group are almost all statistically insignificant while the effect of both total aid and early impact aid is positive and generally statistically significant for the low group. Similar findings are obtained when analyzing the percentage electrification or the level of GDP of a country.

This suggests three possible scenarios: (1) foreign aid does not work for relatively richer, more urbanized countries; (2) night light data is not a very good proxy for economic activity in richer, more urbanized countries; or (3) the relative percentage change in intensity is smaller at high level of DNs compared to lower level of DNs for the same unit change in light intensity. Scenario 1 provides support for papers like Rajan and Subramanian (2008) and Chatterjee et al. (2007) where aid substitutes for, instead of supplementing, public spending and does not promote growth. It is also easy to see why scenario 2 is possible. For highly urbanized cities with access to electricity, external lighting already exists such that people do not invest in more external lights or at least to a lesser extent than in rural areas as they get richer.

The main results are also heterogeneous across continents. Table 5 shows the heterogeneity for early impact aid. The coefficient for Asia and the Americas are statistically insignificant. The coefficient of the regression is positive for all years for Africa and statistically significant at the 10% and 5% levels for years 0 to 1 and years 2 to 4 respectively. Finally, the coefficients for Europe are very large and positive. However, the sample size for Europe was very small and make the results for that continent unreliable.

Table 6 investigates the use of calibrated and uncalibrated satellite images. Results for humanitarian aid, late impact aid, and non humanitarian aid were robust to the change. Early impact aid results were less robust: coefficients from both group are close in magnitude but the level of significance decreased for the calibrated data. The main reason for using the calibrated data was to decrease measurement error. Panel B, C, and

D supports the hypothesis that classical measurement error leads to attenuation bias here. However, the process of calibrating the data is computationally expensive and the results are almost the same. This suggests that non calibrated data can be used interchangeably where necessary.

Conclusion

This study examines the relationship between foreign aid and the area weighted sum of night lights at the country level and finds that there is a small, positive and statistically significant relationship between aid - early impact, late impact, and non-humanitarian aid - and night light. Humanitarian aid has a small negative and statistically significant relationship with night lights for years 0 and 1 and a statistically insignificant relationship with lights for year 2 onwards. The results for early impact and non-humanitarian aid are heterogeneous: elasticities of night lights to aid is positive when considering countries that were more rural, poorer or have a lower access to electricity at the beginning of the sample, and statistically insignificant for the others.

The results were also heterogeneous to being classified according to the continents of the recipient. Given the work of Henderson et al. (2012) that show a positive relationship between night light and economic activity, our results suggest that the foreign aid is positively associated with economic activity. However, back of the envelope calculations show that the elasticity between night light data and economic activity is of the order of 0.02 to 0.04, that is, a 1% increase in foreign aid only raises economic activity by 0.02% to 0.04%. The results were not sensitive to a switch from non calibrated to calibrated satellite images.

Future work to understand the impact of foreign aid on night light could include (i) using disbursed aid amounts instead of committed aid amounts, (ii) exploring the relationship at the sub-national level, and (iii) exploring the heterogeneity of the relationship with different forms of governance and with different level of corruptions.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	6873	2000.09	4.87	1992	2008
Log(DN), uncalibrated	6869	-0.81	1.94	-6.47	6.07
Log(DN), calibrated	6334	-0.56	1.98	-6.26	6.07
Committed Dollars					
Total	2473	19034	26029	42	288377
Early Impact	2345	3203	4159	38	34961
Late Impact	2460	13589	18936	43	230142
Humanitarian	2068	2686	4804	39	49248
Other	1172	491	653	41	4862

Committed dollars is reported in millions of constant 2014 dollars.

Table 2: Main Results

Panel A

	Log(Commitment)									
	Total Aid					Early Impact Aid				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Lights/Area)										
Year 0	-0.0115					0.0318				
	(0.0338)					(0.0200)				
Year 1		0.0589					0.0323			
		(0.0417)					(0.0200)			
Year 2			0.108*					0.0606***		
			(0.0615)					(0.0223)		
Year 3				0.135*					0.0691**	
				(0.0746)					(0.0326)	
Year 4					0.093					0.0718**
					(0.0868)					(0.0328)
N	2471	2470	2469	2468	2467	2343	2343	2343	2342	2342
adj. R-sq	0.988	0.844	0.729	0.625	0.545	0.988	0.988	0.975	0.852	0.851

Panel B

	Log(Commitment)									
	Late Impact Aid					Humanitarian Aid				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Lights/Area)										
Year 0	0.0277					-0.0251**				
	(0.0355)					(0.0116)				
Year 1		0.0982**					-0.0244**			
		(0.0409)					(0.0116)			
Year 2			0.0981**					0.0386		
			(0.0452)					(0.0346)		
Year 3				0.0993**					0.0392	
				(0.0492)					(0.0346)	
Year 4					0.105*					0.0487
					(0.0536)					(0.0350)
N	2458	2457	2457	2457	2457	2068	2068	2067	2067	2067
adj. R-sq	0.988	0.843	0.843	0.828	0.815	0.988	0.988	0.988	0.988	0.988

OLS estimates of the regression of log(Lights/Area) at different lead values against log(Commitment) with time and country fixed effects. Aid is received in year 0.
Humanitarian aid is aid that finances activities without any plausible growth-related goal, such as emergency food aid and disaster relief. Early impact aid is defined as aid which might plausibly affect growth within a few years after being received. Late-impact aid is aid which finances activities that are likely to take many years or even decades to affect growth, such as vaccination campaigns or basic education. All other aid that do not fix the above 3 categories was labeled as Other (not shown).
The definitions for the different type of aids was adopted from Clemens et al. (2012).
Standard errors were clustered at the country level and are displayed in parantheses.
Significant at the *10%, **5%, and ***1% levels.

Table 3: Non Humanitarian aid

	Log(Commitment)				
	(1)	(2)	(3)	(4)	(5)
Log(Lights/Area)					
Year 0	0.0226				
	(0.0379)				
Year 1		0.0869**			
		(0.0406)			
Year 2			0.129**		
			(0.0589)		
Year 3				0.156**	
				(0.0746)	
Year 4					0.123
					(0.0907)
N	2463	2462	2461	2460	2459
adj. R-sq	0.988	0.844	0.728	0.625	0.545

OLS estimates of the regression of log(Lights/Area) at different lead values against log(Commitment) with time fixed and country fixed effects.
Non humanitarian aid is total aid less humanitarian aid.
Standard errors were clustered at the country level and are displayed in parantheses.
Significant at the *10%, **5%, and ***1% levels.

Table 4: Heterogeneity

Panel A

	Total Aid		Early Impact Aid		Total Aid		Early Impact Aid	
	% Access to electricity				% Population Urban			
Log(Lights/Area)	Low	High	Low	High	Low	High	Low	High
Year 0	0.0934	-0.0335	0.0640**	-0.0046	0.0551	0.0169	0.0649*	0.0053
	(0.0695)	(0.0341)	(0.0308)	(0.0223)	(0.0606)	(0.0513)	(0.0337)	(0.0232)
Year1	0.1410***	0.0796	0.0640**	-0.0034	0.1490**	0.0587	0.0665*	0.0051
	(0.05)	(0.0656)	(0.0308)	(0.0224)	(0.0665)	(0.0508)	(0.0336)	(0.0232)
Year 2	0.1434**	0.1778	0.0933***	0.0285	0.1977***	0.1168	0.0949***	0.0333
	(0.064)	(0.1088)	(0.0311)	(0.0308)	(0.0746)	(0.0842)	(0.0338)	(0.0283)
Year 3	0.1397	0.2521*	0.1111***	0.0404	0.2122**	0.1537	0.1395***	0.0145
	(0.0915)	(0.1358)	(0.0388)	(0.0548)	(0.0938)	(0.1095)	(0.0466)	(0.0382)
Year 4	0.1211	0.2397	0.1137***	0.0433	0.1997*	0.1408	0.1412***	0.0161
	(0.1171)	(0.1577)	(0.0393)	(0.0556)	(0.1129)	(0.1314)	(0.0474)	(0.0377)

Panel B

	Total Aid		Early Impact Aid	
	GDP			
Log(Lights/Area)	Low	High	Low	High
Year 0	0.0396	-0.0432	0.0316	-0.0048
	(0.0474)	(0.0339)	(0.0313)	(0.0181)
Year1	0.1381*	0.0203	0.0317	-0.0048
	(0.0693)	(0.0538)	(0.0313)	(0.0181)
Year 2	0.1853*	0.1059	0.0731**	0.0043
	(0.1011)	(0.1042)	(0.035)	(0.0208)
Year 3	0.2151	0.1814	0.1166**	0.0131
	(0.1293)	(0.1294)	(0.0476)	(0.0458)
Year 4	0.1954	0.2359	0.1134**	0.0123
	(0.1391)	(0.1609)	(0.0481)	(0.0456)

Each entry is from a separate OLS regression of log(Lights/Area) at different lead values against log(Commitment) with time and country fixed effects for different categories. Countries were classified into each category based off data for the year 1992 from the OECD. Aid is received in year 0. The time period is 1992-2008.
For % Population, % Electrification, and GDP category, countries were grouped as *High* if their value was higher than the mean of all countries. The reverse applies to the *Low* category.
Standard errors are in parentheses, adjusted for clustering by country.
Significant at the *10%, **5%, and ***1% levels.

Table 5: Heterogeneity for early aid impact across different continents

	Log(Commitment)			
Log(Lights/Area)	(1)	(2)	(3)	(4)
Year 0	0.0740*	0.1937***	0.0740*	-0.0134
	(0.0397)	(0.0471)	(0.0397)	(0.0189)
Year 1	0.0740*	0.1937***	-0.0227	-0.0138
	(0.0397)	(0.0471)	(0.0453)	(0.0189)
Year 2	0.0970**	0.2013***	0.0058	0.0073
	(0.0427)	(0.0450)	(0.0482)	(0.0303)
Year 3	0.1440**	0.4544	0.0932	-0.0299
	(0.0584)	(0.3337)	(0.0670)	(0.0392)
Year 4	0.1464**	0.4508	0.0923	-0.0180
	(0.0583)	(0.3338)	(0.0672)	(0.0401)
Continent	Africa	Europe	Asia	America

Each entry is from a separate OLS regression of log(Lights/Area) at different lead values against log(Commitment) with time fixed and country fixed effects for different categories. Aid is received in year 0.
Standard errors are in parentheses, adjusted for clustering by country.
Significant at the *10%, **5%, and ***1% levels.

Table 6: Comparison of data from calibrated vs. uncalibrated satelite images

Panel A: Early Impact Aid	Log(Commitment)									
	Uncalibrated					Calibrated				
Log(Lights/Area)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year 0	0.0275					0.0283				
	(0.0192)					(0.0191)				
Year 1		0.0288					0.0298			
		(0.0192)					(0.0191)			
Year 2			0.0551**					0.0511**		
			(0.0228)					(0.0226)		
Year 3				0.0628*					0.0504	
				(0.0338)					(0.0344)	
Year 4					0.0733**					0.0586
					(0.0358)					(0.0372)
N	2156	2158	2156	2161	2161	2156	2158	2156	2161	2161
adj. R-sq	0.989	0.989	0.975	0.847	0.849	0.989	0.989	0.977	0.852	0.852

Panel B: Humanitarian Aid	Log(Commitment)									
	Uncalibrated					Calibrated				
Log(Lights/Area)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Year 0	-0.0237**					-0.0244*				
	(0.0118)					(0.0132)				
Year 1		-0.0221*					-0.0230*			
		(0.0118)					(0.0132)			
Year 2			0.0516					0.0442		
			(0.0367)					(0.0375)		
Year 3				0.0449					0.0376	
				(0.0366)					(0.0376)	
Year 4					0.0508					0.0400
					(0.0365)					(0.0372)
N	1924	1921	1915	1912	1915	1924	1921	1915	1912	1915
adj. R-sq	0.988	0.988	0.837	0.836	0.829	0.988	0.988	0.839	0.837	0.830

Panel C: Late Impact Aid	Log(Commitment)									
	Uncalibrated					Calibrated				
Log(Lights/Area)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Year 0	0.0269					0.0337				
	(0.0358)					(0.0353)				
Year 1		0.1049**					0.1133**			
		(0.0494)					(0.0477)			
Year 2			0.1241**					0.1348***		
			(0.0505)					(0.0488)		
Year 3				0.1164*					0.1211**	
				(0.0597)					(0.0564)	
Year 4					0.1467**					0.1508**
					(0.0664)					(0.0626)
N	2254	2254	2261	2259	2256	2254	2254	2261	2259	2256
adj. R-sq	0.989	0.838	0.842	0.829	0.820	0.988	0.843	0.845	0.833	0.829

Panel D: Non Humanitarian	Log(Commitment)									
	Uncalibrated					Calibrated				
Log(DNLights/Area)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
Year 0	0.0224					0.0279				
	(0.0383)					(0.0378)				
Year 1		0.0978*					0.1024**			
		(0.0517)					(0.0495)			
Year 2			0.1673**					0.1689***		
			(0.0678)					(0.0639)		
Year 3				0.1271**					0.1238**	
				(0.0598)					(0.0566)	
Year 4					0.0970					0.1029
					(0.0791)					(0.0763)
N	2257	2256	2255	2255	2254	2257	2256	2255	2255	2254
adj. R-sq	0.989	0.839	0.725	0.699	0.603	0.988	0.843	0.734	0.709	0.613

Each entry is from a separate OLS regression of log(Lights/Area) against log(Commitment) at different lag values with time and country fixed effects for different categories. Aid is received in year 0. The time period is 1992-2008.
Standard errors are in parentheses, adjusted for clustering by country.
Significant at the *10%, **5%, and ***1% levels.

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