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THE IMPACT OF FOREIGN AID ON LOCAL DEFORESTATION

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The Impact of Foreign Aid on Local Deforestation

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Abstract

The aim of this thesis is to answer the question: does foreign aid have an impact on local environmental degradation, specifically deforestation, in recipient countries? I link geocoded data on aid projects in Uganda to high resolution satellite data on deforestation over the time periods 2000 to 2014, creating a unique panel data set over deforestation in 677,142 forest pixels. I estimate the effect of aid on deforestation using a fixed effects regression approach, controlling for temporal and spatial trends in deforestation. I find that foreign aid has a negative effect on deforestation and decreases deforestation rates by approximately 14% on average, suggesting that proximity to aid projects hinders local deforestation, although the effect does seem to be concentrated to the southern part of Uganda.

Keywords: Deforestation, foreign aid, environmental degradation, Uganda.

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1 Introduction

Forests are an integral part of life for people around the world, and forests also play a crucial role in the overall ecosystem. Forests provide biodiversity, carbon storage, water supplies and contributes to climate regulation (Hansen et al., 2013). Naturally, forests have a wider impact, and ecosystems have been shown to be of substantial economic value (Costanza et al., 1998). In developing countries, including Uganda, local forests can provide essential resources, including food, fuel and building materials (Kayanja and Byarugaba, 2001), which people depend on (Waiswa et al., 2015), implying that changes in forest cover can have far-reaching effects on a local level. Changes in forest cover can also have global consequences; around one fifth of greenhouse gas emissions are attributed to forest loss (Burgess et al., 2012), thus making it an important part of the puzzle in studying and preventing global climate change. Understanding the determinants and drivers of deforestation could have important policy implications for climate change mitigation and ecological preservation.

Environmental and biodiversity protection are often considered incompatible with the fight against poverty (Adams et al., 2004; Kareiva et al., 2008). Research has suggested a link between development projects and environmental degradation - while development and aid projects can lead to increases in welfare, they might also impact the surrounding environment negatively (Adams et al., 2004; Shandra et al., 2011). Although resolving the conflict between poverty reduction and ecological preservation has been claimed to be difficult (McShane et al., 2011; Buchanan et al., 2016), it is not unrealistic (Kareiva et al., 2008). Development projects can be planned in such a way that they minimize impact on the environment, and in the case of infrastructure projects, this can include careful project siting (Ledec and Posas, 2003).

Theoretically, the link between environmental degradation and development projects could be explained through both direct effects, including contributing to forest clearance when e.g. building infrastructure (Buchanan et al., 2016), and through intermediary channels, where foreign aid could induce changes in behaviour that affect the environment. Research has shown that externalities to foreign aid include income and economic growth (Alix-Garcia et al., 2013;

Foster and Rosenzweig, 2003) conflict (Nunn and Qian, 2014; Crost et al., 2014; De Ree and Nillesen, 2009; Wood and Sullivan, 2015), and changes in institutions (Djankov et al., 2008; Jones and Tarp, 2016). These activities can affect forests through driving up demand for resource intensive goods (Alix-Garcia et al., 2013), altering the cost of forest extraction (Burgess et al., 2015), changing individual discount rates (Burgess et al., 2015) or weakening political institutions (Djankov et al., 2008).

While there are clear indications pointing towards foreign aid having an impact on the environment, there is little rigorous empirical evidence. Arvin et al. (2006); Mak Arvin and Lew (2009), analysing cross-country data have pointed towards some effects, although causal inference is implausible due to data and methodological limitations. More recent studies include Buchanan et al. (2016), who make use of geocoded World Bank aid project data to study the effects on forest cover in Important Bird and Biodiversity Areas (IBA), and BenYishay et al. (2016) who study geocoded Chinese development aid projects and its effect on deforestation in ecological hotspots. While Buchanan et al. (2016) find no difference in forest cover with respect to aid, BenYishay et al. (2016) find significant, heterogeneous effects within their sample.

This thesis will add to the previous literature in three important aspects. Firstly, I construct a unique panel data set of deforestation in Uganda over from 2001 to 2013 by linking georeferenced aid project data for Uganda from AidData, with high resolution satellite data on forest cover changes, provided by Hansen et al. (2013). I have data on deforestation in 677,142 forest pixels, with a resolution of 600 by 600 metres, linked with 13 years of aid project data, creating a unique, and high resolution, data set. Secondly, I do not restrict my sample in the same way that previous studies have. Instead, I take a more holistic approach in studying the overall effect of aid projects on deforestation across the whole of Uganda, allowing for more general inference of the impact of aid. Finally, this thesis provides methodological improvements: my identification strategy relies on estimating the within-pixel variation in deforestation with respect to foreign aid, by including polynomials by year, up to the third degree, in latitude and longitude, I control for and I also control for time varying general spatial patterns as well as other spatial and temporal trends. Additionally, I explicitly estimate the deforestation response function, instead of relying on cut offs effect distance that can be rather arbitrary or difficult to motivate. Although endogeneity of aid project allocation cannot be entirely ruled out, in many aspects I provide a more robust claim for causal inference than the previous literature.

The results show that the estimated effect of being in the proximity of a foreign aid project is -0.0237%, which can seem small but could be economically significant when compared to baseline deforestation rates. The implication of this result is that foreign aid has a protective effect on forest cover, and can help in slowing down local deforestation. The mechanisms behind this effect is however unclear – a potential avenue for future research could be to try and disentangle theses mechanisms. Another avenue is to examine whether these estimates hold for other countries and when taking aid project type and sector into account.

Nonetheless, this is one of the few studies which has studied and tried to answer this question. This thesis builds on both the literature studying the externalities of foreign aid and the literature studying the determinants of deforestation in developing countries. Knowing the impact of foreign aid on the environment in recipient countries is highly relevant for policy design – if foreign aid provides more benefits than previously known, it could influence the welfare analysis of aid, affecting e.g. the cost-benefit analysis of aid projects.

The outline for this thesis will be as follows: in Section 2, I present the background and theoretical foundation for the effects of aid on deforestation. Section 3 provides a description of the data used in this thesis, and in Section 4 I explain the empirical strategy. In Section 5 I present the regression results. Section 6 will cover the robustness checks, and Section 7 the conclusion and discussion.

2 Aid, Deforestation, and Mechanisms

In this section, I will first provide a review of the potential mechanisms through which aid and development projects can have an impact on local environments, and on local forest cover. Secondly, I will review the current empirical evidence that exists on the link between foreign aid projects and environmental impact, and how my thesis differs from previous research.

2.1 Mechanisms and Channels

Aid and development projects could affect the local environment and ecological systems through different mechanisms. One mechanism is destruction due to infrastructure projects, such as clearing forestry to build roads or dams (Buchanan et al., 2016). Other potential mechanisms are indirect, where aid projects could have an impact on the environment in recipient countries through intermediary channels. A burgeoning literature studying the externalities of aid provide a number of such channels, where aid projects can influence behaviour in such a way that it affects deforestation. Potential channels include conflict (Nunn and Qian, 2014; Wood and Sullivan, 2015; Crost et al., 2014; De Ree and Nillesen, 2009), income and economic growth (Alix-Garcia et al., 2013; Galiani et al., 2014; Dreher and Lohmann, 2015; Civelli et al., 2017) and governance and institutions (Moss et al., 2006; Jones and Tarp, 2016; Djankov et al., 2008).

Although there is a long-standing debate on whether aid has an impact on economic growth (Burnside and Dollar, 2000; Easterly et al., 2003), recent studies have pointed towards foreign aid having a positive effect, e.g. using credible instrumental variable strategies (Galiani et al., 2014), geocoded sub-national aid project data (Civelli et al., 2017) or a combination (Dreher and Lohmann, 2015). Why economic growth can lead to an increase in environmental impact can be explained by the environmental Kuznets curve (EKC), which postulates an inverted U-shaped relationship between income and environmental degradation, where environmental quality initially decreases with income, until a certain point where increases in income improve environmental quality (Bhattarai and Hammig, 2001; Dinda, 2004). A potential explanation for this relationship is that an increase in income can induce a higher demand for resource intensive goods (Alix-Garcia et al., 2013). However, an increase in income could also benefit the environment by raising demand for environmental resources, inducing higher investment in them or raising the opportunity cost for extracting them (Alix-Garcia et al., 2013).

Most empirical research points towards the fact that foreign aid can increase conflict and war in recipient countries; through capture and looting of aid to fund fighting (Nunn and Qian, 2014; Wood and Sullivan, 2015) or incentivizing sabotage as a political strategy (Crost et al., 2014) since aid projects can pose a challenge to fighters' authority, triggering further violence (Wood and Sullivan, 2015). Empirical evidence points to the fact that civil conflict and war does have an impact on deforestation – Burgess et al. (2015) find that the civil war in Sierra Leone decreased the rate of deforestation during the period of active warfare. Nackoney et al. (2014) find that fighting in the Democratic Republic of Congo also slowed deforestation, but that deforestation increased after fighting subsided. Burgess et al. (2015) argue that conflict could affect deforestation through weakened property rights enforcement, shortening individual's time horizons and contributing to higher individual discount rates, all which can lead to an increased extraction of natural resources such as forests, or through physical destruction of surrounding environments due to e.g. bombings (Burgess et al., 2015). However, Burgess et al. (2015) and Nackoney et al. (2014) note that civil conflict can delay or slow down forest change by raising the opportunity cost of extraction, seeing as fighting increases the relative risk of such activities.

Another factor in environmental degradation is institutions and governance, which influence laws and regulations on forest management and whether these are followed (Hargrave and Kis-Katos, 2013). There are a number of theoretical arguments in favour of the hypothesis that aid is a detriment to institutions (Moss et al., 2006; Jones and Tarp, 2016). Djankov et al. (2008) suggest that there exists an "aid curse" similar to the natural resources curse, since both types of resources can be appropriated by politicians or elites. The evidence is mixed: while Djankov et al. (2008); Busse and Gröning (2009) find negative effects on institutions, Jones and Tarp (2016) find a small but significant positive effect. A more thorough review can be found in (Ravallion, 2014). Poor governance and institutions can lead a "race to the bottom", where local administrations engage in rent seeking behaviour, inducing higher rates of (illegal) forest extraction Burgess et al. (2012). Hargrave and Kis-Katos (2013) argue that policies such as control and sanctioning play an important role in the effort against illegal damaging of forests.

2.2 Aid and Deforestation

Despite an extensive discussion on the impact of aid and development projects on the environment (Adams et al., 2004; Kareiva et al., 2008), the empirical evidence on this topic remains sparse. Mak Arvin and Lew (2009) analyze the impact of foreign aid flows on national carbon dioxide damage, water pollution and net deforestation in recipient countries. The authors find that there does exist a correlation between the inflow of aid and measures of environmental damage. Similarly, Arvin et al. (2006) find that there does exist a relationship between aid flow and some measures of environmental impact, e.g. deforestation. However, the two studies mentioned both use nationally aggregated data in a cross-country analysis, making the identification of a causal estimate difficult. Therefore, they should most likely be interpreted as finding evidence in favour of a correlational relationship rather than a causal impact.

Newer research includes (Buchanan et al., 2016), who study the effect of World Bank aid projects on forest cover in Important Bird and Biodiversity Areas (IBA) across the world. Making use of satellite image data on forest cover and geocoded aid project data, they compare areas within a 10 kilometre distance to an aid project to areas between 10 and 100 kilometres away, and find that areas close to aid projects experience less deforestation than comparison areas. However, their estimation strategy of using e.g. propensity matching and Wilcox rank tests, suggests that the estimated effects cannot be interpreted as proving a causal relationship.

One of the most convincing studies is BenYishay et al. (2016), who study the impact of Chinese aid projects on forest cover in two ecologically sensitive areas in Tanzania and Cambodia. The estimation strategy relies on a differences-in-differences approach, where the treatment is exposure to aid, calculated as the inverse of the distance to an aid project comparing forest pixels that have either experienced aid projects. The forest pixels are of the size 5,000 meter by 5,000 meters. They find different effects across their sample, where proximity to active aid projects had a slowing effect on deforestation in Cambodia, while in Tanzania the effect was the opposite. Additionally, BenYishay et al. (2016) argue that local environmental regimes, e.g. designated protected areas, has a significant impact on deforestation rates. Alix-Garcia et al. (2013) exploits a discontinuity in the assignment of the Mexican conditional cash transfer *Oportunidades* (which represents a substantial increase in income for recipients) programme to study its effects on the ecological footprint. They find that deforestation increases close to recipient communities, and argue that the effect is due to an increased demand for dairy and beef, two goods requiring land intensive production. While this is a study on the effects of a conditional cash transfer program intended to raise household income, it does provide evidence in favour of the hypothesis that increases in household income, and plausibly local economic growth as well, contributes to deforestation. Local aid project can affect local economic growth either through a direct increase in income, through providing work or resources or through local economic multipliers.

The present thesis differs from previous studies in some important aspects. In order to answer the question of whether development or aid projects can have an impact on local deforestation, I take a more holistic approach than Buchanan et al. (2016) and BenYishay et al. (2016). I choose to study the average effect of an aid project, and include all available geocoded projects to estimate their impact, seeing as aid can have an impact through various channels, as I argued earlier. I also do not limit my study to any particular sensitive area, instead I include all land in Uganda, since I am interested in the more general effect of aid on deforestation.

This thesis also offers a methodological improvement compared to previous studies. While BenYishay et al. (2016) explicitly control for factors such as economic growth (proxied by night-time lights), precipitation and temperature, I instead allow the trends in deforestation to vary across time and space, to control for varying spatial patterns in deforestation. This allows me to control for more unobservable factors which can potentially influence the results. Additionally, I estimate the effect of aid within each pixel using pixel fixed-effects, to try and control for unobservable characteristics across pixels.

Despite the fact that many of the possible mechanisms speaks towards foreign aid projects having no effect or increasing deforestation, it should be mentioned that the evidence at this point in time is sparse. Additionally, the effect of e.g. an increase in income is, as mentioned, dependent on the level of income. Both conflict and changes in institutional quality can also affect deforestation in either direction, as explained in (Burgess et al., 2012, 2015), for example. Although there is little previous research, the study closest to this question is BenYishay et al. (2016), where they find mixed results; aid seemed to have a protective effect in Cambodia and the opposite effect in Tanzania, suggesting that there are no obvious priors with regards to the result.

3 Data

3.1 Forest Data

Data on sub-national forest cover is provided by Hansen et al. (2013)[1]. The data are provided in a raster[2] format and covers the whole globe from between the years 2000 to 2014. Forest cover is calculated using algorithms that process high resolution Landsat satellite images, where the baseline forest cover in 2000 is calculated for each 30 by 30 metre (0.00025 by 0.00025 degree resolution) pixel. For each subsequent year until 2014, each pixel is coded as either being deforested (assigned a value of 1) or not (assigned a value of 0) for each year. Vegetation that reached a height of 5 metres or taller is defined as trees. Since this data covers the whole globe, I use administrative border information from GADM[3] to extract only the cells that are a part of Uganda, and exclude water surface and missing data.

I aggregate the original data to a coarser resolution, resulting in forest pixels of the resolution 600 by 600 meters (0.005 by 0.005 degree resolution), in order to facilitate faster and easier computation. For Uganda, this results in 677,142 unique pixels. After the aggregation, each forest pixel now contains 400 original forest pixels. Deforestation is then effectively a measure of the share of original pixels that are deforested from one year to another.

Forest cover as a measure of environmental degradation has been used in a number of studies, including Alix-Garcia et al. (2013) in Mexico, Alvarado and

[1] https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html
[2] An image data type.
[3] http://www.gadm.org/download.

Figure 1: The forest cover of Uganda in year 2000 (in %).

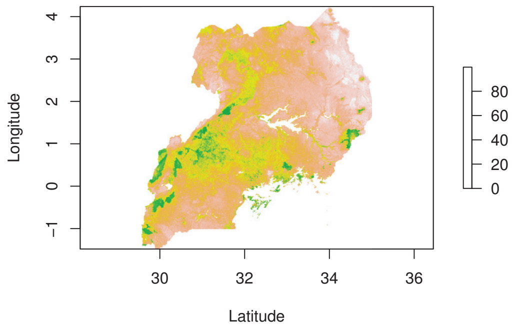
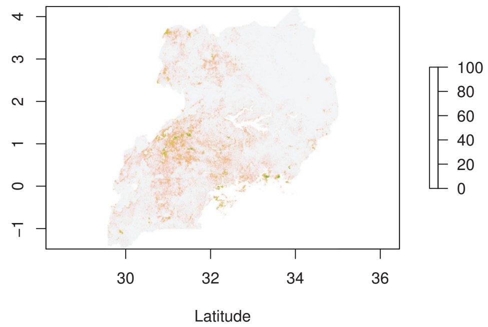


Figure 2: The cumulative deforestation of Uganda between 2001 and 2014 (in %).



Toledo (2016) in Ecuador, and Bare et al. (2015); Arvin et al. (2006); Mak Arvin and Lew (2009) for cross-country analyses. Advantages to using forest cover as a measure of environmental impact is its binary nature where forests are either there or not, making forest cover relatively easy to record and verify objectively using satellite images. Additionally, publicly available forest data is both spatially refined and publicly available, unlike many other types of environmental data such as pollution or emissions.

Figure 1 and 2 shows plots of the spatial distribution of the cumulative deforestation between the years 2001 and 2014, and a plot of the spatial distribution of baseline forest cover for the year 2000. The average baseline pixel forest cover in 2000 is 30%.

3.2 Foreign Aid Data

I use georeferenced aid project data for Uganda provided by the organization AidData[4]. The process and methodology of georeferencing projects is explained in depth by Strandow et al. (2011), and roughly consists of reviewing documents related to aid projects in order to determine the most precise location possible

[4]Available at aiddata.org/subnational-geospatial-research-datasets.

for each project. It should be noted that this data set is not exhaustive in the sense that it contains all aid projects in Uganda. The original data set covers the time period of 1978 to 2014 and contains projects from a total of 56 different donors, resulting in a total of 2,426 projects. Of these, 229 have no specified time period, and 412 are outside of the study time period, 2000 to 2013. Information on projects include coordinates, planned disbursement value and type of aid. Projects included in the data are of various types, e.g. health interventions and infrastructure projects.

It is important for the analysis that there is a high level of spatial accuracy, and I therefore follow Isaksson and Kotsadam (2016) in excluding all projects that have a precision code above 3, i.e. where the projects can only be determined at the most aggregated district level in Uganda. This also effectively excludes budget support that has been georeferenced to the capital, Kampala. I restrict my sample further and exclude 210 observations that have an imprecise geocoding precision. After these restrictions have been made, 1,804 projects. I will also show that my main results hold for including projects of all precision as well. Table 1 shows descriptive statistics of the aid event variable used in the analysis, disaggregated by each year included in the final panel data set. Figure 3 shows the spatial distribution of all aid projects, over the time period 2000 to 2013, on a map of Uganda.

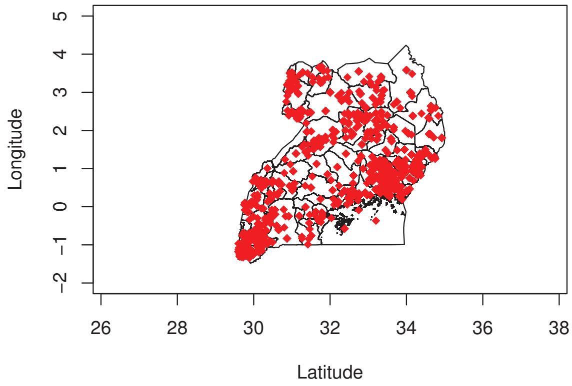
After joining foreign aid projects to forest pixels, each forest pixel can have several several projects within a certain distance from its centroid. The distribution of the projects is however heavily skewed (as can be seen in 6), and I therefore construct an aid event variable which takes on the value of 1 if the number of projects is larger than one, and zero if the number of joined projects is 0. In the table below, the aid event consequently describes the share of forest pixels that have an aid event within 10 kilometres of its centroid, by each year.

A notable feature of Table 1 is that both the deforestation rate and the share of pixels affected by aid events is concentrated between 2005 and 2014. In order to verify the results, I also perform regressions where I only make use of data between 2005 and 2013, which can be seen in Table 9. The results are not substantially different compared to the main results, where the whole time period was included, as shown in Table 3.

Table 1: Descriptive statistics of the aid event variable and pixel deforestation rates, from the panel data set.

	Deforestation		Aid event	
	Mean	Standard deviation	Mean	Standard deviation
2000	-	-	0.0053	0.0725
2001	0.1545	1.2109	0.0653	0.2470
2002	0.0599	0.5671	0.0093	0.0960
2003	0.0671	0.6891	0.0140	0.1174
2004	0.0989	0.9110	0.0146	0.1200
2005	0.1551	1.2157	0.0322	0.1766
2006	0.1558	1.1749	0.2325	0.4224
2007	0.1918	1.3522	0.1289	0.3351
2008	0.1956	1.2503	0.1185	0.3232
2009	0.1279	0.9363	0.2438	0.4294
2010	0.1757	1.2428	0.2166	0.4119
2011	0.3359	1.8928	0.1989	0.3992
2012	0.1598	1.1507	0.0052	0.0722
2013	0.2942	1.5935	0.0964	0.2951
Total	0.1734	1.2287	0.0987	0.2982

Figure 3: Map of Uganda showing the spatial distribution of foreign aid projects.



3.3 Administrative and Elevation Data

I link each forest pixel to administrative districts of Uganda. I use the Uganda administrative boundaries provided by the Global Administrative Areas database[5], constructed by Hijmans et al. (2010). The data provide boundaries for the four levels of administrative districts in Uganda, of which I use the first administrative level, which contains 56 districts and two lakes. The second administrative level are called sub-district. I use elevation data from the Shuttle Radar Topography Mission (SRTM)[6], that is of the same high spatial resolution as for forest cover, provided and made public by the U.S. Geological Survey.

3.4 Constructing the Panel Data

I combine all of the data sources above to create a panel data set, where I have the deforestation rates and a measure of aid for each unique forest pixel for each available year. I link all aid projects that are within a 100 kilometre radius from a forest pixel centroid, to that specific pixel. This results in a panel where there are

[5] Available at gadm.org/download.

[6] Available at lta.cr.usgs.gov/SRTM1Arc.

677,142 unique forest pixels over the years 2000 to 2014, where the year 2000 only has data on forest cover. A more thorough description of the panel data creation process can be found in A.1.

4 Estimation Framework

A difficulty in identifying the causal impact of aid projects on deforestation is that aid allocation is not randomly assigned. This can lead to selection bias if aid projects are systematically allocated to areas with unobservable characteristics across Uganda. This implies that a forest pixel's proximity to an aid project could be predetermined either by its level of deforestation or unobservable characteristics that contribute to deforestation. Although I try to account for these concerns, I cannot entirely rule out the case where the results are in fact affected by unobservable characteristics, and not aid in itself.

The empirical strategy of this thesis is comprised of two steps. The first step is estimating the distance over which the response function of deforestation to foreign aid projects operates. The response function of deforestation to aid projects is a function that describes how an aid projects affects deforestation with respect to the distance between the forest pixel centroid and the aid project location. I approach this question empirically, by including sequential "rings" of aid (where a ring signifies whether there is an aid project in the ring from a 10 to 20 kilometre radius from a pixel). In the second step, I use the results from estimating the response function to choose an appropriate distance in where to estimate the impact of aid. While the analysis in this thesis builds on the assumption that the impact of aid will affect deforestation over a certain distance, an additional assumption must be that the effect will decay the farther away an aid project is in relation to a forest pixel. Thus, choosing an appropriate distance over which the response function operates requires thoughtful consideration.

Finding the appropriate distance is both a empirical and theoretical question – in much of previous research, authors choose a cut off in distance, and do not try to explicitly estimate or model the response function. Knutsen et al. (2016) chooses to include projects that are of a 50 kilometre distance to mines, an approach followed by Isaksson and Kotsadam (2016), while Kotsadam and Tolonen (2016) use a 20 kilometre cut off citing e.g. estimated commuting distances in Sub-Saharan Africa. Studies concerned particularly with the impact of aid projects have used the inverse distance weighted by a spatial weights matrix as treatment (BenYishay et al., 2016) and (Buchanan et al., 2016) compare projects within 10 kilometres to projects within a 10 to 100 kilometre distance.

To the best of my knowledge, there is little theoretical evidence pointing toward a specific cut off in distance when analysing the local effects of aid projects. An arbitrary choice of distance can result in finding null effects where there should be an effect, or vice versa. It also allows for a certain degree of cherry picking, where it is easy to simple choose an effect distance that yield significant results. I therefore treat this as an empirical problem, which I show and explain in more detail in Section 5.1.

The aid project data includes information on the number of aid projects and the committed monetary value of projects. However, the distributions of these two variables are heavily skewed – Kernel density plots of these can be found in the A.2. Measures on the value of aid projects can also be fraught with measurement error, leading researchers have chosen to use an event variable instead (Tolonen, 2016). Consequently, I have constructed a binary aid event variable, aid_{it}, which takes on the value 1 if forest pixel i is within the specified distance to an aid project in time t, and 0 if that is not the case.

For estimating the effects of aid on deforestation, I use the following baseline specification:

$$deforestation_{it} = \beta_1 aid_{it} + pixel_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where $deforestation_{it}$ is the rate of deforestation for forest pixel i in year t. Deforestation is defined as the percentage of the forest ithat disappears from one year to another. $pixel_i$ is the pixel fixed-effects, and γ_t the year fixed-effects. ε_{it} is the regression error. Pixel fixed-effects are included as to remove the time invariant characteristics of pixels, meaning that I compare changes in forest cover within pixel. Including year fixed effects control for the time trend in deforestation for the whole sample, i.e. Uganda.

While this does account for some potential threats to identification, there are still remaining concerns. Since I have included the whole of Uganda's land area in the analysis, there will be a considerable degree of variation within the sample. These variations can be climatic, topological, or related to vegetation and weather. These potential confounders are both observable and unobservable. By including a polynomial function of latitude and longitude by year, $f(X, Y)$ with X being the longitude and Y the latitude, I can control for some of these time varying spatial patterns and thereby avoiding them influencing the results. Interacting the function with time also controls for different trends in spatial patterns over time. In the final specification, the function includes the third order polynomial in latitude and longitude, which controls for potential time varying spatial patterns that are unrelated to aid projects. To control for time and elevation specific trends in deforestation, Z_i, the level of elevation in pixel i by year is also included in the specification;

$$deforestation_{it} = \beta_1 aid_{it} + pixel_i + \gamma_t + f(X, Y) \times \gamma_{xyt} + Z_i \times \gamma_{zt} + \varepsilon_{it} \tag{2}$$

Data which have either a temporal or spatial dimension, or both, also come with practical concerns. Owing to the construction of the forest data, where natural occurring phenomena such as forests are disaggregated into pixels, a degree of spatial autocorrelation between observations is assumed – disaggregating natural occurring phenomena such as forests into pixels can be considered as being spatially autocorrelated by default. If the standard errors are not modelled to allow for the presence of spatial autocorrelation, estimation can yield standard errors that are too small, causing erroneous inference (Cameron and Miller, 2015). I allow for the presence of spatial autocorrelation by clustering the standard errors at the (first) district level, where there are a total of 56 districts. Although this does not explicitly account for all possible variations of spatial autocorrelation it does allow for serial correlation in the standard errors, and provides a conservative choice of modelling the standard errors since the districts cover large areas, and therefore allows for spatial autocorrelation.

5 Results

In this section, I present the estimation results. In 5.1, I present the approach to finding an appropriate distance cut off. In section 5.2, I present the main results, and in Section 5.3 I present results from sub-sample regression estimations. Aid, the variable of interest, is measured as a binary variable, where $aid_{it} = 1$ if there is one or more aid projects within a distance of a forest pixel i, and $aid_{it} = 0$ if no projects are matched.

5.1 Estimating the Response Function

In order to estimate over which distances the response function operates, I fit the following specification:

$$deforestation_{it} = \beta_1 aid_{it,0-10km} + \beta_2 aid_{it,10-20km} + ... + \beta_{10} aid_{it,90-100km} + pixel_i + \gamma_t + \varepsilon_{it} \tag{3}$$

where β_k is the coefficient for the effect of each "ring". The ring can be though of as intervals around the forest pixel, where each ring represents there being an aid project within a distance between e.g. 10 and 20 kilometres from a forest pixel's centre. Each ring is estimated within 10 kilometre intervals. The rest of the specification is identical to the baseline specification, where $pixel_i$ and γ_t, pixel and year fixed-effects, are included.

As discussed earlier, there should be a distance cut off over which the response function operates. After this cut off, the effect of aid on deforestation should decay towards zero as the distance between aid project and forest pixel increases, provided we are not simply picking up noise. The advantage of estimating the distance with a separate variable for each ring, per the equation above, is that the response function is estimated more precisely, avoiding picking up the average effect of a longer distance from the origin.

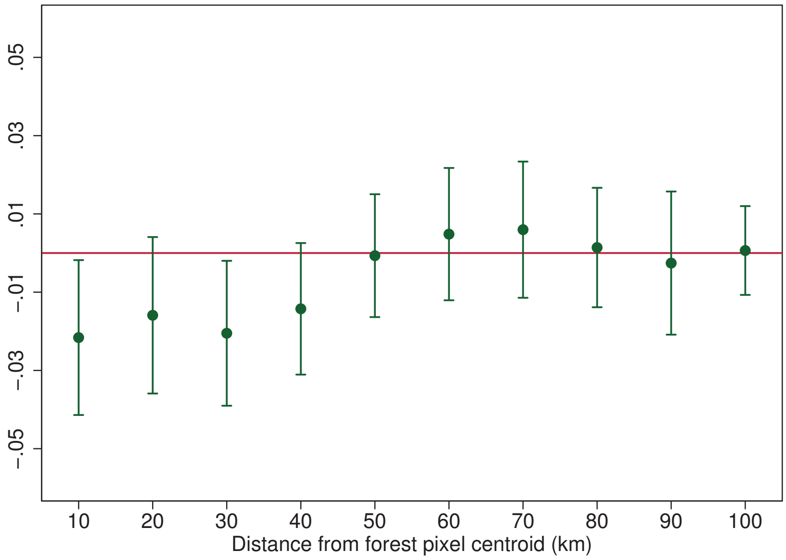
The results of the estimations are presented in Table 2 and in 4. A 10 km distance ring is added for each specification, starting with only estimating the effect between 0 and 10 kilometres, up until 90 to 100 kilometres. Table 2 shows that the point estimates for the rings are significant until the 20-30 kilometre ring, after

Table 2: Regression table with event distance rings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
0 - 10 km	-0.0272**	-0.0250**	-0.0226**	-0.0211*	-0.0211*	-0.0215*	-0.0216*	-0.0216*	-0.0216*	-0.0216*
	(0.0118)	(0.0111)	(0.0109)	(0.0110)	(0.0113)	(0.0115)	(0.0116)	(0.0116)	(0.0117)	(0.0116)
10 - 20 km		-0.0194*	-0.0168	-0.0152	-0.0152	-0.0156	-0.0159	-0.0160	-0.0159	-0.0159
		(0.0111)	(0.0104)	(0.0105)	(0.0107)	(0.0110)	(0.0115)	(0.0117)	(0.0119)	(0.0119)
20 - 30 km			-0.0214**	-0.0195**	-0.0196**	-0.0200**	-0.0205*	-0.0206*	-0.0205*	-0.0205*
			(0.00974)	(0.00928)	(0.00944)	(0.00984)	(0.0104)	(0.0108)	(0.0110)	(0.0110)
30 - 40 km				-0.0133	-0.0133	-0.0138	-0.0143	-0.0144	-0.0142	-0.0143
				(0.0100)	(0.00985)	(0.00984)	(0.00969)	(0.00982)	(0.00996)	(0.00997)
40 - 50 km					0.000273	-0.000271	-0.000719	-0.000797	-0.000649	-0.000668
					(0.0106)	(0.00988)	(0.00959)	(0.00936)	(0.00929)	(0.00932)
50 - 60 km						0.00528	0.00479	0.00470	0.00486	0.00483
						(0.0113)	(0.0106)	(0.0104)	(0.0101)	(0.0101)
60 - 70 km							0.00593	0.00583	0.00601	0.00597
							(0.0111)	(0.0107)	(0.0103)	(0.0104)
70 - 80 km								0.00125	0.00144	0.00141
								(0.00950)	(0.00897)	(0.00894)
80 - 90 km									-0.00253	-0.00257
									(0.0110)	(0.0109)
90 - 100 km										0.000645
										(0.00675)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170
F-statistic	5.342	2.810	2.621	2.009	1.634	1.367	1.176	1.358	1.228	1.170
No. of observations	8802846	8802846	8802846	8802846	8802846	8802846	8802846	8802846	8802846	8802846

Standard errors within parantheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Figure 4: The response function of deforestation to aid projects.



which each subsequent ring that is added yields statistically insignificant results. The regression results indicate that aid does have an effect of deforestation, until the 30 kilometre mark. We can see that the effect of the 10-20 kilometre ring is rather weak, and disappears once the 20-30 ring is added. This indicates that the effect within the 10-20 kilometre ring could be weak, which is an argument in favour of choosing the 0-10 kilometre ring instead. Additionally, the F-statistic for the joint significance hypothesis test in the coefficients decreases with each ring that is added, indicating that the effect on deforestation operates within 0 and 10 kilometres from an aid project.

To corroborate these results, I estimate a similar regression using circles instead, and the results are presented in Table 7. All specifications in Table 2 and Table 7 contain pixel and year fixed-effects, and the standard errors are clustered at the first district level (56 districts in total). This is consistent with the assumption that if an effect does exist within a certain distance, the effect should decay the farther away from the forest pixel an aid event takes place. It is also reassuring that the coefficients are consistent when adding more and more rings, since this indicates that the response function eventually decays to zero.

5.2 Main Effects

From estimating the response function using the data, I chose a 10 kilometre cut off in distance. All specification include standard errors that are clustered on the Uganda first district level, forest pixel-fixed effects and year fixed-effects. This means that the coefficient of the aid variable should be interpreted as the effect on deforestation of there being one or more aid projects within a 10 kilometre radius of a forest pixel centroid. An underlying assumption is also that all aid events have the same weight in the regression as long as it is within the cut off, i.e. that the effect is not adjusted explicitly with respect to distance.

Table 3: Regression results for the main specification.

	(1)	(2)	(3)	(4)	(5)
Aid event	-0.0272**	-0.0264**	-0.0289**	-0.0337**	-0.0237*
	(0.0120)	(0.0121)	(0.0131)	(0.0142)	(0.0134)
Pixel FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Elevation	No	Yes	Yes	Yes	Yes
Linear polynomial	No	No	Yes	Yes	Yes
Quadratic polynomial	No	No	No	Yes	Yes
Cubic polynomial	No	No	No	No	Yes
Mean	0.1734	0.1734	0.1734	0.1734	0.1734
R-squared	0.170	0.170	0.172	0.174	0.177
No. of observations	8802846	8802846	8802846	8802846	8802846

Standard errors within parantheses.

* p<0.10, ** p<0.05, *** p<0.01

The regression results are shown in Table 3. The first specification is the baseline specification, where pixel fixed effects and year fixed effects are included. The second model also includes elevation by year controls. Specifications (3)-(5) include polynomials in latitude and longitude by year, and all specifications have standard errors clustered on the first district level. All point estimates of the main specification are statistically significant at conventional significance levels. The estimates remain significant when controlling for time specific trends in elevation, time specific spatial trends and varying general spatial patterns. The most restrictive specification (5), yields a significant point estimate of -0.0237. Although this coefficient is rather small in absolute value, it should be compared to the baseline deforestation rate over the whole time period, 0.1734%. This indicates that the presence of one or more aid projects within a 10 kilometre radius of a forest pixel decreases deforestation by approximately 14%. This indicates that this effect could also be economically significant, apart from the statistical significance.

Interestingly, the point estimates remain significant across all specifications. This means that even when controlling for pixel fixed-effects, differential time trends in elevation and a third order polynomial in latitude in longitude by year, which means we control for general spatial patterns of deforestation across Uganda, e.g. picking up unobservable characteristics that are difficult to account for in other structural models. This means that it is possible to exclude a number of unobservable characteristics of forest pixels that could influence the results instead of aid, increasing the credibility of the results, as well as strengthening the case that foreign aid does have an impact on deforestation.

5.3 Heterogeneous Effects

As previously discussed, deforestation rates are likely to vary over time and space. There is good reason to believe that geographic differences across areas, as well as climatic and weather related unobservables, can influence deforestation. In the main specification, I control for differences in deforestation across space and time using more flexible specifications, but these controls do not indicate whether there are differences across the sample, and in that case, where the differences arise.

Uganda is divided into four larger administrative regions, the Central, Western, Eastern and Northern regions, which roughly reflect different climatic and geographic differences, evidenced by e.g. forest cover patterns which are concentrated to the south. A map of the geographic division of regions can be seen in **??**. Therefore, I provide sub-sample estimations for each four of the administrative regions, in order to coarsely uncover if there are differences across Uganda. The standard errors are clustered at the second district level, where there are a total of 162 districts, since the higher district level do not have enough clusters to be on the safe side (Cameron and Miller, 2015).

Table 4: Sub-sample estimations by administrative region.

	(1) Central	(2) Western	(3) Northern	(4) Eastern
Aid event	-0.0721**	-0.0624*	0.0141	0.00779
	(0.0273)	(0.0313)	(0.0122)	(0.0257)
Pixel FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Elevation	Yes	Yes	Yes	Yes
Coordinates × Year	Yes	Yes	Yes	Yes
Quadratic polynomial	Yes	Yes	Yes	Yes
Cubic polynomial	Yes	Yes	Yes	Yes
Mean	0.2670	0.0901	0.0761	0.3197
R-squared	0.191	0.164	0.192	0.166
No. of observations	2176772	1308203	3584191	1733680

Standard errors within parantheses.

* p<0.10, ** p<0.05, *** p<0.01

As evidenced by the regression table, there are differences across regions. The point estimates for the Central and Western regions are negative, which is in line the point estimates for the whole sample. The point estimates are however substantially larger than the average effect for all regions, with -0.0721 for the Central region and -0.0624 for the Western, compared to -0.0237 for the whole sample. Comparing these estimates to those of the Eastern and Northern regions are revealing, where these estimates are insignificant and also have a different sign. The difference between the Central and Western regions to the Northern and Eastern regions is statistically significant. This suggests that the Central and Western regions are driving the bulk of the results in the main specification, while the evidence is inconclusive with regards to Eastern and Northern regions. These results also suggest that there are heterogeneous effects that could be further explored.

6 Robustness

A crucial assumption in the identification strategy of this thesis is that aid is not allocated in the proximity of certain forest pixels in a systematic manner. Although this assumption cannot be entirely verified as holding up, there are tests that I can do. One such test is to verify whether the allocation of aid projects is predetermined by the rate of deforestation. If this was the case, it would suggest that forest pixels either have unobservable characteristics that influences the allocation of aid which in turn could affect the results, or that aid projects are allocated towards areas in where forest pixels have high rates of deforestation. This would also violate the previously mentioned assumption. In order to test this, I estimate two specifications, one where I include the contemporaneous effect and the lead of the aid event variable, and one where I include only the lead. Additionally, I also include specifications where aid events two years into the future is included.

As can be seen in 5, the point estimates for the lead is highly insignificant in all specifications, shows a very small effect and the opposite sign compared to the main results. This suggests that forest aid is not determined by deforestation rates, and strengthens the validity of my results. In addition to the lead test, I also make two alterations to the sample that I have used. First, I estimate an equation where I exclude all forest cells that have a forest cover that is 0%. These forest cells might bias the estimates, as they will not be deforested at any point in time, and therefore can be considered incomparable to the other cells. Second, I follow BenYishay et al. (2016) in excluding forest pixels with a forest cover of less than 10%, for similar reasons as the other exclusion. The results from these regressions can be seen in Table 7. As we can see, the alterations to the sample change the point estimates very little, indicating that low-forest cells do not drive the results.

I also include all projects that I drop due to the imprecise geocoding, and provide the regression tables in A.3. They show largely similar and significant

Table 5: Regression table with the lead of aid.

	(1)	(2)	(3)	(4)
Aid event in t	-0.0203		-0.0206	
	(0.0131)		(0.0142)	
Aid event in $t+1$	0.00866	0.00733	0.0124	0.0110
	(0.00851)	(0.00858)	(0.00846)	(0.00858)
Aid event in $t+2$			0.00415	0.00485
			(0.00884)	(0.00909)
Pixel FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Elevation	Yes	Yes	Yes	Yes
Linear polynomial	Yes	Yes	Yes	Yes
Quadratic polynomial	Yes	Yes	Yes	Yes
Cubic polynomial	Yes	Yes	Yes	Yes
Mean	0.1734	0.1734	0.1734	0.1734
R-squared	0.193	0.193	0.203	0.203
No. of observations	8125704	8125704	7448562	7448562

Standard errors within parantheses.

* p<0.10, ** p<0.05, *** p<0.01

estimations, although with larger standard errors, thus yielding less statistically significant results.

Table 6: Regression table with alternative samples.

	0%		10%	
	(1)	(2)	(3)	(4)
Aid event	-0.0338**	-0.0237*	-0.0346**	-0.0268*
	(0.0142)	(0.0134)	(0.0152)	(0.0144)
Pixel FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Elevation	Yes	Yes	Yes	Yes
Linear polynomial	Yes	Yes	Yes	Yes
Quadratic polynomial	Yes	Yes	Yes	Yes
Cubic polynomial	No	Yes	No	Yes
Mean	0.1735	0.1735	0.1906	0.1906
R-squared	0.174	0.177	0.173	0.175
No. of observations	8796476	8796476	7979127	7979127

Standard errors within parantheses.

* p<0.10, ** p<0.05, *** p<0.01

7 Conclusion and Discussion

In this thesis, I find that aid projects do have an impact on local deforestation in recipient countries. The results from the main regressions show that the estimated impact of experiencing at least one aid project is negative with respect to deforestation, meaning that foreign aid decreases the rate of local deforestation. The point estimate for the effect is -0.0237. On its own, the effect can seem economically insignificant. However, comparing this estimate with the average level of deforestation over the time period, 0.1734%, which is a reduction of about 14%. This is an effect implying that the effect could be substantial. Sub-sample estimations by the four larger administrative regions reveal an interesting pattern, where the Central and Western regions, roughly corresponding to the southern half of Uganda, appear to be driving the results. The point estimates for the Central and Western regions are almost four times larger than the point estimate for the whole sample. While statistically insignificant, estimates for the Northern and Eastern regions show a positive impact. While I cannot draw any far-reaching conclusions regarding this pattern, a potential explanation behind the heterogeneity in the effect of aid is that the administrative regions reflect the allocation of forests quite well, where the majority of forest is allocated in the Central and Western parts, although there is substantial deforestation in the Northern region. In comparison with previous studies, mainly (BenYishay et al., 2016), I provide more general with respect to the types of aid projects included as well as the studied sample.

The results in this thesis adds to the literature and debate on the relationship between foreign aid and environmental impact. While many have considered poverty alleviation to be incompatible with environmental and ecological preservation, there have been little rigorous empirical evidence on the subject. These results are also policy relevant, seeing as they suggest that foreign aid can have positive externalities that were previously unknown, which could change assumptions about both welfare benefits and deciding on how to allocate and design foreign aid projects.

A drawback of this thesis is that by including only one country in the analysis, the external validity of the results can be questioned. Although it is difficult to conclude whether these results can be generalized to other settings or time periods, they hold up against a variety of different controls and specifications, as well as robustness checks. A drawback of the design of my empirical strategy is that I cannot interpret the point estimate of my variable of interest as an exact behavioural response to aid projects. A problem in trying to replicate these results for e.g. the whole world is the lack of georeferenced aid project data. However, extending the analysis towards more countries can be an avenue for future research.

Another important aspect absent in this thesis is a further analysis of the mechanisms that could be behind these results. Potential mechanism from previous studies include protected area status that some forest in Uganda have, which was argued to have a protective effect by BenYishay et al. (2016). Another possible mechanism could be the World Bank's efforts in "greening" aid projects, and perhaps attracted followers. It should however be said that it is difficult to draw any robust conclusions with this thesis. The continued efforts to georeference aid projects will probably provide an improvement in analysing the effects of aid projects, e.g. if there is a more complete coverage and a larger number of countries covered.

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A Appendix

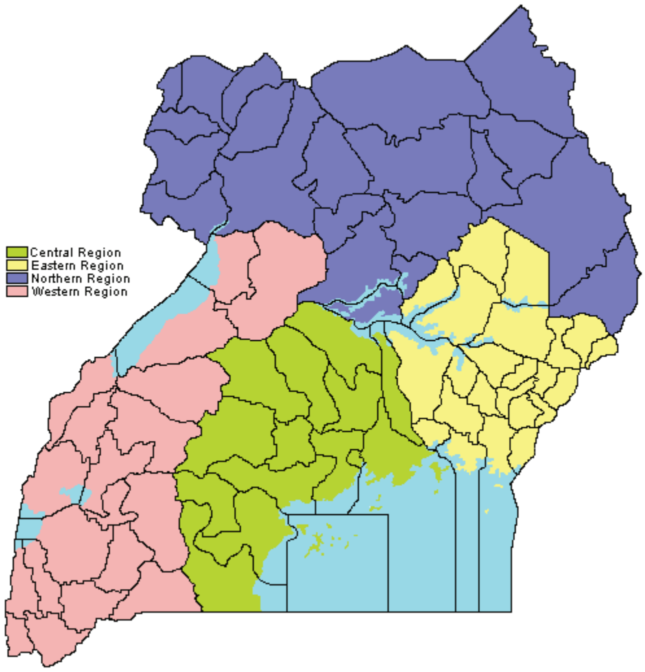
A.1 Data Processing

I process the data in the following way: I first download the relevant raster tiles which encompass Uganda, including the rasters containing information on yearloss, datamask and forestcover2000. I combine these rasters into a larger one, and use the datamask to exclude those cells that either contain no data or are permanent water bodies, for both the forestcover2000 and yearloss. I then disaggregate the yearloss raster into separate raster files for each year, which I aggregate by a factor of 20 using the function mean, resulting in 600 by 600 metre pixels with the mean number of deforested "original" 30 by 30 metre pixels. All these calculations were done in ArcGIS. I then read these raster data files into R as a raster stack, which I then convert into a data frame format and export is as a CSV-file and read it into ArcGIS to perform a spatial join, where the aid projects are linked to the forest pixels in a JOIN ONE TO MANY spatial join within a 100 kilometre radius. The resulting tables for each year are appended and collapsed and summed in Stata, resulting in a panel with forest cover changes by each of the 677,142 unique pixels for each year during the time period.

Since I found no available shapefiles for the four larger, administrative regions of Uganda, I used the map in Figure 5, found in Section A.2, to find the names of the districts and then manually assign them to a region.

A.2 Graphs and Maps

Figure 5: Geographic division of administrative regions, Uganda.



Source: CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=769386

Figure 6: Distribution of the number of aid projects.

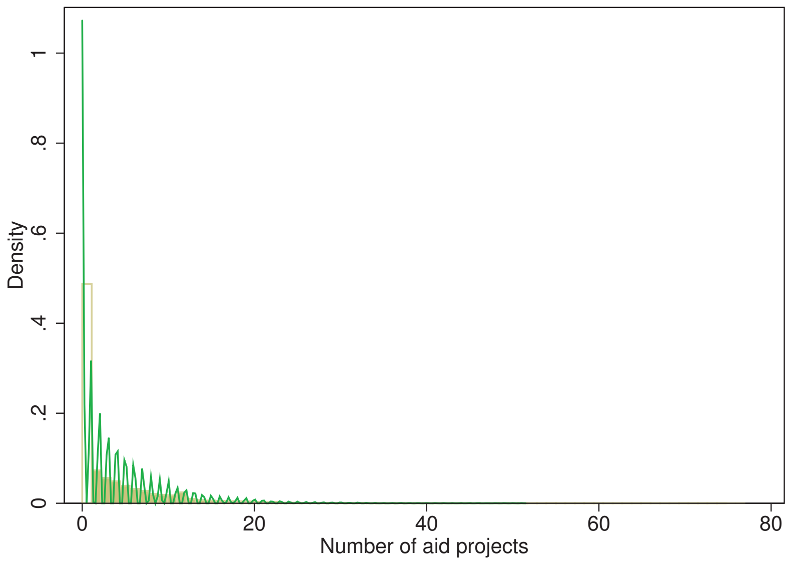
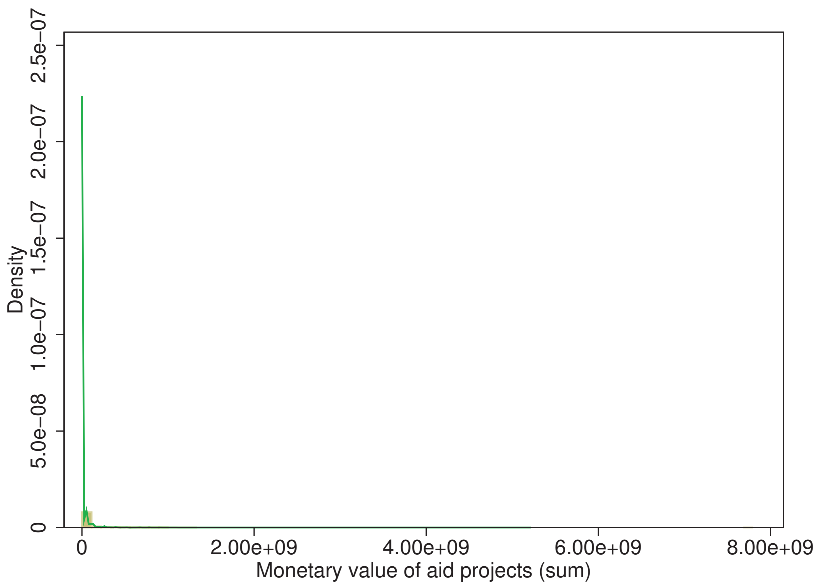


Figure 7: Distribution of the value of aid projects.



A.3 Tables

Table 7: Regression table with event distance circles.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
0 - 10 km	-0.0272**									
	(0.0118)									
0 - 20 km		-0.0242*								
		(0.0126)								
0 - 30 km			-0.0255*							
			(0.0132)							
0 - 40 km				-0.0163						
				(0.0113)						
0 - 50 km					0.000416					
					(0.0127)					
0 - 60 km						0.00577				
						(0.0147)				
0 - 70 km							0.0139			
							(0.0169)			
0 - 80 km								0.00431		
								(0.0158)		
0 - 90 km									-0.000126	
									(0.0141)	
0 - 100 km										-0.00469
										(0.0138)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170
No. of observations	8802846	8802846	8802846	8802846	8802846	8802846	8802846	8802846	8802846	8802846

Standard errors within parantheses. Standard errors are clustered at the Ugandan district level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8: Regression table using all available foreign aid projects.

	(1)	(2)	(3)	(4)	(5)
Aid event	-0.0200*	-0.0193*	-0.0217*	-0.0259**	-0.0175
	(0.0104)	(0.0105)	(0.0114)	(0.0128)	(0.0118)
Pixel FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Elevation	No	Yes	Yes	Yes	Yes
Coordinates × Year	No	No	Yes	Yes	Yes
Quadratic polynomial	No	No	No	Yes	Yes
Cubic polynomial	No	No	No	No	Yes
Mean	0.1734	0.1734	0.1734	0.1734	0.1734
R-squared	0.170	0.170	0.172	0.174	0.177
No. of observations	8802846	8802846	8802846	8802846	8802846

Standard errors within parantheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 9: Regression table using only the time period 2005 to 2013.

	(1)	(2)	(3)	(4)	(5)
Aid event	-0.0280*	-0.0265*	-0.0299*	-0.0380**	-0.0291*
	(0.0150)	(0.0149)	(0.0159)	(0.0173)	(0.0168)
Pixel FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Elevation	No	Yes	Yes	Yes	Yes
Linear polynomial	No	No	Yes	Yes	Yes
Quadratic polynomial	No	No	No	Yes	Yes
Cubic polynomial	No	No	No	No	Yes
Mean	0.2047	0.2047	0.2047	0.2047	0.2047
R-squared	0.217	0.218	0.219	0.221	0.223
No. of observations	6094278	6094278	6094278	6094278	6094278

Standard errors within parentheses.

* p<0.10, ** p<0.05, *** p<0.01