Master Essay

Protected Areas in the Democratic Republic of Congo: An Effective and Equitable Tool for Forest Conservation?

Malte Ladewig*

supervised by Gunes Gokmen

June 27, 2021

Abstract

Tropical rainforests cover large parts of the Democratic Republic of Congo. In light of recent surges in deforestation in the country, protected areas are a decisive component of the national conservation strategy. Intended to preserve ecosystems, the way in which these areas are organized can have vital implications for people who reside within them through the changes they cause to environmental and socio-economic conditions. This thesis uses protected area boundaries in a geographic regression discontinuity design to investigate how protected areas affect both deforestation rates and the livelihoods of local communities. The findings suggest that protected areas in the Democratic Republic of Congo are not efficiently avoiding forest loss, but nevertheless have positive effects on education and health. In the current state, the protected areas of the country therefore seem unable to reconcile conservation and poverty alleviation ambitions.

Keywords: Deforestation, poverty alleviation, geographic regression discontinuity

*MSc Economics | Department of Economics | malte.ladewig@posteo.de

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List of Abbreviations

DHS	Demographic & Health Survey
DRC	Democratic Republic of Congo
ICDP	Integrated conservation and development programs
IV	Instrument variable
MPI	Multidimensional Poverty Index
PA	Protected Area
RD	Regression Discontiunity
WDPA	World Database on Protected Areas

1 Introduction

Tropical rain forests have important functions for the stability of the global ecosystem. They are home to large numbers of plant and animal species, and play a vital role in regulating the global carbon cycle (Lewis, 2006). An estimated 15% of current anthropogenic greenhouse gas emissions can be attributed to deforestation and forest degradation (van der Werf, G. R. et al., 2009). With climate change continuing to pose one of the greatest contemporary challenges, forest protection is a fundamental building block in climate mitigation (Pachauri and Mayer, 2015).

The main rainforest regions stretch along the equator and include parts of South-East Asia, the Amazon and the Congo Basin. The latter is the second largest tropical rainforest in the world (van Butsic et al., 2015) and covers large parts of the Democratic Republic of Congo (DRC). To protect the primary forest areas from resource extraction, hunting and deforestation, protected areas (PAs) have been introduced in many parts of the country. As a result, about 13.8% of the DRC has the status of being protected (UNEP-WCMC, 2021). Given that a high share of the country's population relies on the forest to make a living (Debroux et al., 2007), PAs can have implications for the socio-economic conditions of local communities if they restrict access to the natural environment. In a country that is ranked 175th out of 189 in the Human Development Index and where 73% of the population lives on less than 1.90$ per day (The World Bank, 2021), it is of great importance that forest protection does not further diminish well-being of the most vulnerable people. Whether these negative effects of PAs on livelihoods exist or not is disputed in the literature, indicating that it depends on the context as well as the aspect of life that is studied (Roe, 2008; Oldekop et al., 2016). It is thus crucial to find out under what circumstances conservation and poverty reduction policies can be integrated, such that one is not implemented at the cost of the other.

The thesis aims to enhance the understanding of how PAs contribute to the deforestation-poverty nexus in the DRC by answering two questions: (1) *Are PAs an effective tool to prevent forest loss?*; and (2) *what are the socio-economic impacts of PAs on communities who live inside them?*.

The method that is used to do so follows a Regression Discontinuity (RD) design and is not the first to use PAs in this setting. Baragwanath and Bayi (2020) studied the effect of transferring full forest property rights ("homologation") to indigenous communities on deforestation outcomes in Brazil, and Bonilla-Mejía and Higuera-Mendieta (2019) investigated the role that institutional quality plays into the efficiency of PAs in protecting forests in Colombia. Anderson et al. (2016) complemented RD with a difference-in-differences model to find out whether PAs in the Brazilian Amazon can explain the observed decrease in deforestation rates.

While the above mentioned studies rely on RD to estimate deforestation outcomes related to PAs, none of them consider socio-economic outcomes in their analysis. There have been attempts of using matching estimators to do so. Clements et al. (2014), for instance, analysed the effect of PAs on livelihoods of people in Cambodia. They found that households outside of PAs are more likely to be better off, but argued that this finding can be explained by better infrastructure and is independent of the creation of PAs. Ferraro et al. (2011) used a matching procedure to estimate how PAs impact poverty in Costa Rica and Thailand with heterogeneous effects as results, indicating significant poverty reduction for households above median poverty level, but insignificant results for those living in more severe poverty. However, contrary to RD, matching estimation in essence still relies on the choice of observables for the creation of treatment and control groups and therefore remains susceptible to potential endogeneity problems (Smith and Todd, 2005).

This thesis aims to fill this gap in the literature by using PAs in a geographic RD to estimate the effect they have not only on deforestation, but also on livelihoods. To the best of my knowledge, it is the first to use a RD design to investigate if PAs can lead to desirable win-win situations where socio-economic outcomes and forest protection are harmonized, and also the first to attempt a quantitative impact study in this matter for the DRC. The analysis produces two main findings. Firstly, results suggest that PAs in the DRC are not able to protect tropical rainforests. Even though average forest loss inside the areas is below the national average, the RD shows no discontinuities in deforestation rates at PA borders and only gradual decreases as one moves further inside. Secondly, inspite of the first finding, the RD estimates imply that PAs still lead to significantly higher education and health outcomes for households who reside in them. The results therefore indicate that PAs in the DRC are not able to produce desirable win-win outcomes between forest conservation and poverty reduction.

The thesis is structured as follows. Section 2 outlines the state of deforestation, livelihoods and conservation in the DRC. In section 3, the data is presented that is used for the RD model. The latter is introduced in section 4. Section 5 presents the estimation results and presents a number of specification checks. Finally, section 6 discusses potential mechanisms behind the findings.

2 Forests and livelihoods in the Democratic Republic of Congo

2.1 Recent trends in deforestation rates

The Congo Basin rainforest is an important carbon storage (Mayaux et al., 2013) and habitat to a large variety of endemic species (Duveiller et al., 2008). Besides playing a crucial role for the regional and global climate, it also provides a living for millions of people depending on it for nutrition, income, medicine and more (Sunderland, 2011; Debroux et al., 2007). At the same time, deforestation and forest degradation have become a serious concern in the previous decades, with DRC having witnessed the seventh largest net forest loss of all countries between 2000 and 2010 (FAO, 2010). However, when viewed in relation to the country's large forest cover, actual deforestation rates have long been considered low when compared to other tropical rainforest regions (FAO, 2010). Several studies have attempted to quantify the rate of forest loss in the country, all finding net annual deforestation rates around 0.2% during differently sized intervals between 1990 and 2010 (Duveiller et al., 2008; Ernst et al., 2013; Potapov et al., 2012; Hansen et al., 2013). However, Hansen et al. (2013) also identified that forest cover loss increased by 13.8% when comparing the periods 2000-2005 and 2005-2010. This is in line with the most recent estimates from the FAO, who calculated that forest loss quadrupled to 0.83% for the period 2010-2020 when compared to their estimates for 2000-2010 (FAO, 2010, 2020). To gain a better understanding of the recent surge in deforestation rates, it is important to look at the underlying drivers.

2.2 Drivers behind deforestation

The most pressing driver of worldwide deforestation is agricultural expansion, accounting for roughly 80% of it (Hosonuma et al., 2012). While Brazil and Indonesia experience high forest loss due to large-scale industrial agriculture and plantations, agriculture in the Congo Basin is traditionally driven by subsistence and small-scale farming (Seymour and Harris, 2019). Debroux et al. (2007) claimed this to be an important explanation for why deforestation rates in the latter have for a long time been comparably low, as political instability and lack of infrastructure made large-scale agricultural investments unattractive. The dominant farming system in the DRC is slash-and-burn cultivation, a farming practice where small patches of land have the vegetation cut down and burned. The so exposed land is then used for agriculture. When the soil fertility declines after some time, the field is abandoned and the process repeats on a different patch. The forest impact of shifting cultivation is disputed. While some argued that it constituted the main factor for land conversion in the DRC (Potapov et al., 2012; Ickowitz et al., 2015, e.g.), others held that abandoned patches are quickly taken back by the forest and downplay their environmental impact (Ernst et al., 2013; Mpoyi et al., 2013).

Even though small-scale farming still prevails, the witnessed surge in deforestation over the past years is related to changes in land use away from small-scale towards more industrialized farming techniques. Fueled by foreign investment (Galford et al., 2015), agricultural intensification has led to higher land rents induced by increased productivity, making agriculture profitable even in remote areas with substantial transportation costs and poor infrastructure (Phelps et al., 2013). This in turn imposes pressure on ecosystems and drives up forest loss. Besides agriculture, mining, logging and infrastructure expansion increased the pressure on rainforests in the Congo Basin (Pyhälä et al., 2016), as well as the widespread use of wood for cooking and heating (Hosonuma et al., 2012; Galford et al., 2015).

2.3 Forest dependencies

Conservation policy can have sensitive implications for small-scale farmers who rely on land access to practice shifting cultivation (Sunderlin et al., 2005), but it is not the only way through which people are affected by it. A high share of the population relies in one way or another on forests and its resources (Debroux et al., 2007). Bushmeat is an important dietary component and source of income (Wilkie and Carpenter, 1999; de Merode et al., 2004), as are fruits and vegetables from forests (Debroux et al., 2007). Furthermore, rural as well as urban populations rely heavily on forest plants for medical treatments (Ndoye et al., 2006). Especially DRCs indigenous groups of hunter-gatherers who are mostly self-sustained, sometimes consolidated under the derogatory term Pygmies, are dependent on functioning ecosystems around them (Debroux et al., 2007; Mpoyi et al., 2013). Other forest based poverty alleviation paths consist of timber extraction and non-timber forest products (e.g. fuel or medicine). Furthermore, environmental services are to be mentioned, such as payment schemes that compensate avoided forest extraction through external direct payments or internal benefits from functioning ecosystems in terms of water supply or on-farm agricultural productivity (Sunderlin et al., 2005).

2.4 Protected areas in the Democratic Republic of Congo

The increasing deforestation rates that the DRC has witnessed in the previous decade put conservation policies on the agenda more than ever. An important part of these is the establishment of PAs. According to the International Union for Conservation of Nature (IUCN), PAs are "a clearly defined geographical space, recognised, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values" (Borrini et al., 2013, p.5). With the first PAs having been established in the beginning of the 19th century in the USA, the concept of designating land as protected has become a popular tool for land conservation all over the world throughout the second half of the century (Adams and Hutton, 2007). Today, the IUCN classifies PAs into six different categories depending on their degree of forest use restriction, and into four governance types, namely governance by government, shared governance, governance by private entities and governance by indigenous peoples and local communities (Borrini et al., 2013).

Following upon the end of colonial rule in DRC, all land that was formerly claimed from local communities by the Belgium colonizers was transferred to the newly installed central government, who continues to retain control over it and grants land use concessions (Kipalu et al., 2016; Nasi et al., 2012). The traditional view of PAs in DRC underlies a notion of a dichotomous relation between nature and humans, in which ecosystems have to be protected from destructive forces of human interference (Adams and Hutton, 2007). In combination with a generally fragmented and autocratic state, this dualism arguably led to the continuation of a system in which the government imposed protection status in absence of cooperation or consent with local communities (Inogwabini, 2014; Pyhälä et al., 2016) and used it to exert power over land and populations (Marijnen, 2018). A consequence is the legitimization of military authority in the PA enforcement (Adams and Hutton, 2007; McNeely, 2003), despite the fact that many local and indigenous communities have sustainably lived in the respective ecosystems long before "green militarization" started to emerge (Kipalu et al., 2016).

In the light of wide-spread poverty and increasing pressure on tropical rainforests, it is imperative to find means to protect forests without compromising local lifestyles. A viable approach could be the involvement of forest residents into forest management (Tole, 2010). However, community forests which allow local and indigenous people's participation in setting the terms of management are still uncommon in the DRC (Mpoyi et al., 2013; Pyhälä et al., 2016). An attempt to change this towards more inclusive forest protection policies was made with a new land decree in 2014 that allowed communities to request concessions (Kipalu et al., 2016). Such concessions are conditional on three requirements: (1) the land must have been held customarily by communities before, (2) it must have PA status and (3) the form of forest use must be aligned with sustainability criteria (Kipalu et al., 2016).

While quantitative studies that investigate the effect of PAs on livelihoods in the DRC are lacking, a few scholary articles have attempted to estimate their impact on deforestation with mostly positive results. Bowker et al. (2017) found PAs to have significantly lower deforestation rates across countries in Africa. In an instrumented random effects estimation for the DRC, van Butsic et al. (2015) also found that PAs significantly reduce deforestation. In accordance with this, Potapov et al. (2012) used satellite-based Landsat images to find that forest cover loss in PAs was more than twice as low as the national average (0.4% and 1.1%, respectively), while the forest loss within a 10km buffer zone around PAs was close to the national average, indicating that forest protection inside PAs does not lead to higher logging rates outside. Similarly, Zhuravleva et al. (2013) found a forest loss in PAs that is 3.4 times lower than the national average (0.3% and 1.02% respectively) and a five times lower rate within PAs than in a five kilometres buffer zone outside. Of the different types of PAs, national parks have the lowest deforestation rate (0.06%), while hunting reserves display the highest (0.6%) (Zhuravleva et al., 2013).

3 Data

The main data that is used in the RD covers livelihood indicators, protected area locations and deforestation rates, all of which come from different sources. While the regression models are run in STATA, the spatial dimension of the analysis also required the use of QGIS.

3.1 Livelihood indicators

To investigate how conservation policies affect the livelihoods of people in the DRC, data from the 2013/2014 wave of the Demographic and Health Survey (DHS) is used. It entails extensive information on living and health conditions for 18827 women and 8656 men from 18171 households. Upon request, the DHS also provided access to the stored GPS information for the data. For reasons of confidentiality, the survey households do not have unique coordinates each but instead have been aggregated into one coordinate per sampling cluster. The average cluster size in the here used survey wave consists of 155 households. Additionally to the aggregation, all clusters have been geo-masked in a procedure that randomly reallocated urban clusters between zero and two kilometres, as well as rural clusters between zero and five kilometres from their original location (Burgert et al., 2013).

The geographic aggregation procedure adds some peculiarities to the RD analysis, as the conventional RD requires continuous running variables while cluster aggregated coordinates introduce mass points. The issue will be further discussed in section 4. The geo-masking can also impact the estimates of the model. Given that the reallocation follows randomly, it introduces measurement error in the location variable, which can result in attenuation bias and decreases efficiency (Wooldridge, 2009). Therefore, the results from the model are potentially understated.

Table 1: Multidimensional Poverty Index, adapted from Alkire and Santos (2010)

Poverty dimension	Deprivation criteria	Deprived if...
1. Health	i) Child mortality	...any child has died in a household.
	ii) Nutrition	...a household member has a low BMI and if children count as stunted or underweight.
2. Education	iii) Years of schooling	...a household has no member with at least six years of schooling.
	iv) School attendance	...at least one child in school age does not attend school.
3. Standards of living	v) Electricity	...a household has no electricity.
	vi) Drinking Water	...a household does not have access to safe drinking water within 30 minutes walking distance.
	vii) Sanitation	...the sanitation is not improved, or shared with other households.
	viii) Housing	...walls, floor or roof use low quality materials.
	ix) Cooking fuel	...a household cooks with wood, charcoal, crop residues or dung.
	ix) Assets	...a household does not own more than one among radio, TV, telephone, bike, motorbike or refrigerator and does not own a car or truck.

To obtain indicators of livelihood from the survey data, the DHS variables are used for the construction of different deprivation indicators. The procedure used in this endeavour relies on the Alkire & Foster Multidimensional Poverty Index (MPI), whose different elements are displayed in table 1. Following Alkire and Santos (2010), the MPI consists of the three dimensions: health, education and standards of living, of which each is generated from different deprivation criteria. The advantage of the MPI over conventional income-based poverty measures is that it reflects non-monetary indicators that are decisive for well-being (Alkire and Santos, 2010). The deprivation criteria are indicators, taking the value one if a household is deprived in the category. The poverty score is then constructed from a weighted average, where each poverty dimension weighs one-third and each criterion is weighted equally within its dimension. While most deprivation criteria

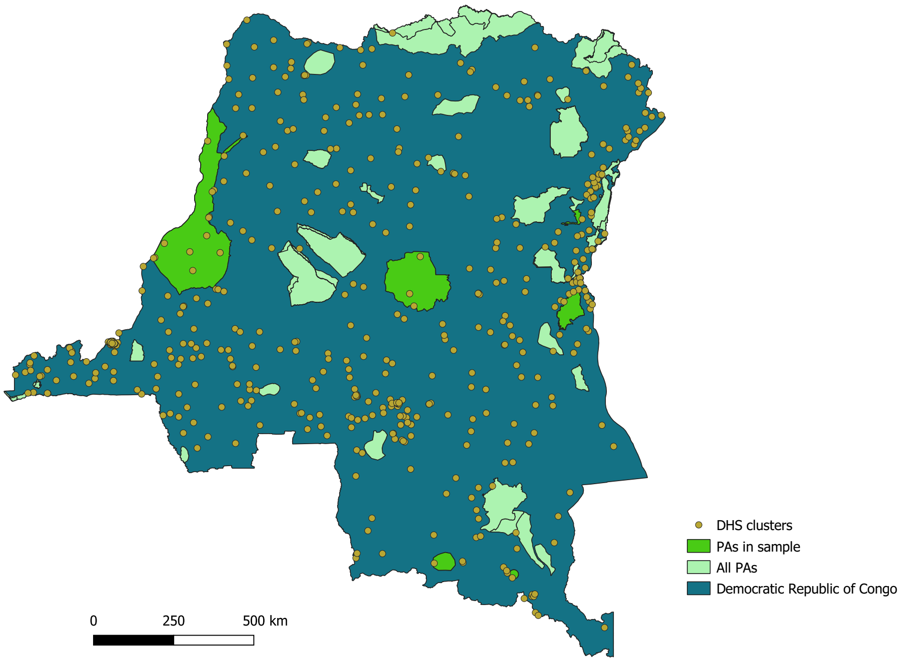

Figure 1: Protected Areas and DHS clusters in the DRC

are straight-forward to calculate from the DHS data, identifying deprivation in nutrition requires the usage of age-specific WHO distributions. A household member or child is then considered health deprived if they are located at least two standard deviations below the official WHO median.

After each deprivation criteria is calculated, a deprivation score for each of the three poverty dimension can be constructed as their average. In a last step, the poverty dimensions then generate the multidimensional poverty score, each weighting one third in the aggregate. The RD model in section 4 uses the overall multidimensional poverty, but also the disaggregated poverty dimensions as outcomes in order to allow for a deeper understanding of how PAs affect deprivations in different aspects of life.

3.2 Protected areas

The geocoded livelihood indicators constructed from the DHS are then connected to PA locations. The World Database on Protected Areas (WDPA) gathered shapefiles with 49 polygons for different PAs in the DRC. The WDPA was created in a cooperation between the United Nations Environment Programme and the International Union for Conservation of Nature. It only lists PAs that conform with the IUCN definition of the term, as cited in section 2, and relies on countries to provide exact coordinates of the areas (UNEP-WCMC, 2019). A limitation of the data is that it is not possible to assess how precise the available shapefiles are, as the RD requires the information whether a cluster lies inside a PA or not.

The location of the PA polygons in the DRC is shown in figure 1, as well as the location of clusters from the DHS. To link the two, each DHS cluster is assigned to the PA within the closest euclidean distance, thereby forming an environment of DHS clusters around each PA. As the map reveals, not all PAs have DHS observations located inside. Since a local treatment effect of living inside a PA cannot be estimated without any observations that are actually treated, these PAs are removed from the sample. Likewise, all PAs that have been established within the 5 years before the DHS sample wave are not included in the analysis, as the effect of PAs on livelihoods is unlikely to show immediately. The restrictions reduce the sample to seven PAs: *Itombwe*, *Kisimba Ikobo*, *Lac Tshangalele*, *Lufira*, *N'Sele*, *Ngiri* and *Sankuru*. They are displayed in bright green in figure 1. Now, a total of 19 clusters with 3,291 observations are still located inside PAs, as opposed to 126 clusters with 22,884 observations outside.

3.3 Deforestation

Besides livelihood indicators, the aim is also to identify how deforestation rates are affected by PAs and thus if they are an effective policy to protect forests. For this part of the analysis, data from the Global Forest Change (GFC) by Hansen et al. (2013) is used. The GFC originates from Landsat images and provides deforestation values on a 30 meter resolution for the whole DRC. The authors define a forest as an area with at least 25% tree cover and a minimum height of five meters (Hansen et al., 2010). Deforestation accordingly occurred when the tree cover has declined below the critical value of 25%. Each tile in the raster is assigned a value in the range from 0 to 19, where 0 translates as no deforestation and values from 1 to 19 refer to the year in which the respective tile has been deforested. For example, if a pixel lost its forest in the year 2001, it is coded with the value 1. If it did so in 2002, it will be assigned the value 2, and so on. Using QGIS, the GFC data is then used to construct an indicator variable, taking the value 1 if a given tile has been deforested over the years and 0 otherwise.

Since the PAs have been established in different years, it is important to ensure that deforestation in areas that received protection status later in time does not bias the results.

Otherwise, forest loss from the years before a PA was created would count as deforestation inside. As mentioned in the previous subsection, the polygons selected for the sample are not established later than 2008. Therefore, all deforestation that occurred earlier is not counted, and the indicator only switches on if a tile is coded with a value of eight or higher.

3.4 Covariates

Lastly, there are a number of covariates that are used in the regression model. *Growing season length*, *precipitation* and *temperature* data come from the Climate Research Unit of the University of East Anglia. The latter two are calculated as mean value for the years 2000, 2005, 2010 and 2015 to average out annual variations. *Slope* as a measure of ruggedness is used from the United States Geological Survey, and proximity to water as the geodesic distance to the nearest lake from the Global Self-consistent Hierarchical High-resolution Geography Database. All covariates are computed as mean values for a 10km radius around each cluster coordinate.

4 Regression discontinuity design

The model that is motivated in this study follows a RD design. Even though it deviates in some important aspects from a classical RD, it nevertheless has to obey to the basic assumptions behind RD to make it valid, which will be explained in the following.

4.1 Regression discontinuity assumptions

Say a researcher is interested in determining the causal effect that a certain event has on an observable outcome. In an ideal world, the way to go would be to study the outcome for the exact same population twice - once under the condition that the individuals were affected by the event and once under the condition that they were not (Angrist and Pischke, 2009). The problem with showing causality in social sciences is that one of the two is typically a counterfactual and unobservable. An individual is either affected by the event and considered as "treated" or not. The closest a researcher can get is to randomly assign treatment to one group of the population under study, while leaving the rest untreated. If all characteristics but the treatment status are balanced across the groups, the difference in the expected outcomes between the two,

$$E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0], \tag{1}$$

will give the causal effect of the treatment on the treated (Angrist and Pischke, 2009). However, unbalanced characteristics across groups can introduce bias, and it is no longer possible to distinguish how much of the observed difference in the outcome is due to treatment and how much due to other confounding variables.

In absence of the opportunity to assign treatment randomly, which is often the case when for instance the effect of a policy is examined, it is common to identify quasi-experimental frameworks, designed by nature, which imitate the randomized control study as good as possible so that causality can still be estimated. One of the most commonly used methods for this is the RD. In a sharp RD setting, it is assumed that a treatment follows deterministically from an observable characteristic, in the following called forcing variable. When an observation surpasses a certain threshold value of the forcing variable, the treatment indicator switches on (Lemieux and Milligan, 2008), such that

$$D_i = \begin{cases} 1 \text{ if } x_i \geq x_0 \\ 0 \text{ if } x_i < x_0 \end{cases} \tag{2}$$

for threshold x_0 and treatment indicator D_i. If the threshold value is arbitrary in the sense that it does not depend on other observables than the forcing variable whether or not an observation lies just above or just below, it can be assumed that the only difference between individuals for a small window on either side of it is the treatment status (Calonico et al., 2019). In that case, treatment is assigned as good as random around the threshold, and given a treatment effect exists, it will show in a discontinuous jump of the dependent variable at the threshold (Imbens and Lemieux, 2008).

4.2 Geographic regression discontinuity model

This analysis uses the identification strategy as above for a geographic RD under the assumption that the exact location of PA border is to some extent arbitrary. As shown in section 2, the central government is in control of land in the DRC and makes land concessions that declare areas as protected. Hence, demarcation lines have not evolved

Table 2: Differences in covariates

	Outside	Inside	Difference
		Panel A - <35km	
Growing season length	12.48	13.18	0.70
	(1.68)	(1.99)	(0.56)
Proximity to water	52652.49	126192.41	73539.91
	(33422.34)	(160458.66)	(83375.35)
Slope	1.71	1.16	-0.55
	(1.78)	(1.57)	(0.37)
Precipitation	120.05	129.56	9.50
	(16.38)	(21.83)	(8.85)
Temperature	22.88	22.55	-0.33
	(2.38)	(2.64)	(0.49)
Observations	2,730	2,284	5,014
		Panel B - <25km	
Growing season length	12.48	12.78	0.31
	(1.87)	(2.16)	(0.88)
Proximity to water	50835.71	114813.74	63978.04
	(35545.62)	(147795.66)	(70087.87)
Slope	2.13	1.53	-0.60
	(1.91)	(1.68)	(0.41)
Precipitation	117.85	125.42	7.58
	(17.13)	(22.80)	(8.17)
Temperature	22.50	21.92	-0.58
	(2.58)	(2.80)	(0.66)
Observations	1,952	1,687	3,639
		Panel C - <15km	
Growing season length	13.16	12.57	-0.59
	(1.09)	(2.15)	(0.93)
proximity_to_water	44767.53	98467.69	53700.16
	(34717.61)	(144435.53)	(59849.69)
Slope	2.07	1.65	-0.42
	(2.03)	(1.72)	(0.36)
Precipitation	126.63	122.76	-3.87
	(8.14)	(22.09)	(8.81)
Temperature	21.96	21.73	-0.23
	(3.14)	(2.86)	(0.54)
Observations	1,173	1,540	2,713

The table shows differences in means of covariates for 35km, 25km and 15km bandwidth. Clustered standard errors at PA level are depicted in parantheses and significance stars indicate p-values smaller than 0.1, 0.05 and 0.01 for *, ** and *** respectively.

naturally, and the areas chosen for PAs are usually in remote regions of the country (Joppa et al., 2008). It can then be assumed that areas on either side of the boundaries did not show any characteristic differences at the time the PAs were established. Given this assumption holds, any differences that can be observed today would be outcome of the imposition of protection. Table 2 provides evidence that geographic covariates across boundaries are balanced and observations do not show systematic differences that could bias a treatment effect. Across all three chosen bandwidths of 35, 25 and 15 kilometres, differences in means are not statistically significant for any of the control variables. This strengthens the assumption that the exact boundaries of PAs have not been chosen based on certain geographic criteria.

Given that PA boundaries are placed exogenously, the RD model then follows as

$$y_{icp} = \alpha + \gamma PA_c + f(location_c) + \delta Z_c + \phi_p + \epsilon_{icp} \tag{3}$$

where y_{icp} are deforestation or livelihood outcomes for household i in cluster c and proximity of PA p, $f(location_c)$ is a function of a cluster's location that changes with different specifications and is further explained below, PA_c a treatment dummy, taking the value 1 if an observation lies inside a PA and 0 otherwise, and Z_i are potential covariates. The latter serve to improve efficiency of the estimator, correct small sample bias and control for characteristic differences of observations further away from the threshold, even though it must be noted that the added covariates should not be themselves affected by the assignment of treatment since this would lead to bias in the estimation of the treatment effect (Imbens and Lemieux, 2008). Therefore, the chosen covariates in the model are *growing season length*, *proximity to water*, *slope*, *precipitation* and *temperature*, which are all time-invariant geographic controls. At the same time, these variable also determine agriculture suitability of land and are henceforth expected to be good predictors of deforestation pressure, as argued in section 2. Similar to Dell (2010), the inclusion of fixed effects ϕ_p for each PA and its surrounding environment p controls for heterogeneity across different PAs.

The main specification of the here proposed model differs from the conventional RD design in two important points. Firstly, the usual RD model typically assumes that there is only one forcing variable to determine treatment status. Location, however, is two-dimensional, typically captured in longitude and latitude. As Keele and Titiunik (2015)

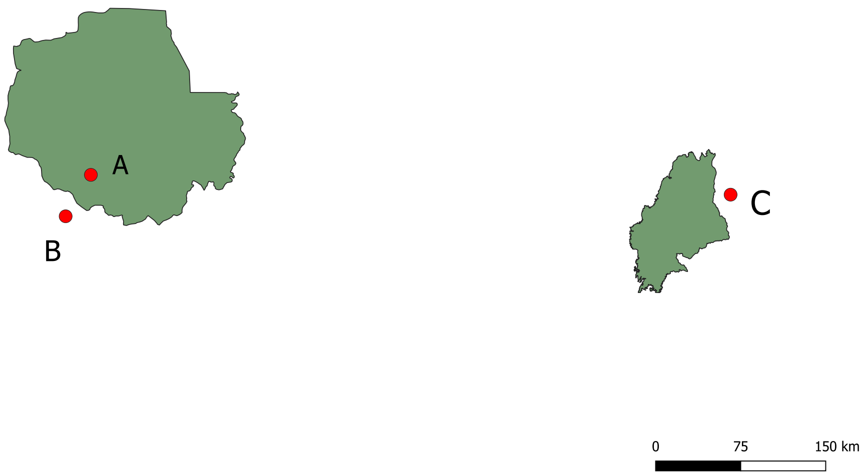

Figure 2: Problem with conventional RD in a geographic RD setting

note, using distance in a one-dimensional forcing variable can lead to severe problems with identifying the treatment effect, as shown in figure 2. The two green polygons are the nature reserves *Itombwe* and *Sankuru* in the DRC, points A, B and C are fictional observations. Assume B and C both have the same distance to a PA boundary. The conventional RD would use this distance as the forcing variable, thereby implicitly treating B and C as if they were equally distant to A. Not only is C much further away from A and therefore more likely to differ in important characteristics. Its distance is also measured to an entirely different PA that could deviate in the estimated treatment effect.

Instead of using a one-dimensional forcing variable, Keele and Titiunik (2015) suggest a two-dimensional RD of longitude and latitude as remedy, as for instance done in Dell (2010) or Lowes (2017). The term $f(location_c)$ in equation 3 then takes the form $longitude + latitude + longitude \times latitude$. As Dell (2010) notes, the two-dimensional RD has stronger data requirements than the one-dimensional, given that it has more degrees of freedom. For this reason, and in line with Gelman and Imbens (2019), the here chosen specification is linear in longitude and latitude and not a higher-order polynomial.

The second difference to conventional RD stems from the fact that the DHS data only keeps track of the coordinates on the cluster level. All individuals of one cluster therefore share the same location information (see section 3). According to Keele et al. (2017), this leads to mass points in the forcing variable and poses a problem to the conventional RD estimation that assumes continuity. A solution to this problem is to narrow the sample to a small enough window around the threshold in order to allow for the assumption that conditional expectation functions on either side of it are the same (Cattaneo et al., 2015). While the conventional RD assumes continuity and extrapolates across the threshold, a non-parametric approach as suggested above considers observations around the threshold as locally randomized (Sekhon and Titiunik, 2017). Instead of needing to identify the full functional form that applies to the entire sample, this non-parametric estimation only compares individuals close to the threshold (Angrist and Pischke, 2009). Different bandwidths can be compared to increase robustness of the results. A problem with the non-parametric approach is that it has high data requirements around the threshold. As a compromise, this analysis will use a semi-parametric approach as applied for instance in Dell (2010) that narrows the sample to a smaller window while still controlling for distance in the model specifications. With the assumption that treatment depends in a discontinuous way on longitude and latitude while other characteristics do so continuously, the treatment effect can be identified.

Despite the concerns expressed above, additional robustness is lent to the results by specifying $f(location_c)$ as the euclidean distance to the closest PA border, with negative values outside of PAs and positive values inside. The deterministic treatment threshold then coincides with the PA boundary at the distance of 0. These one-dimensional RD specifications should have lower data requirements than the two-dimensionals in longitude and latitude. The simplest form is to use a linear term of this distance measure. Further flexibility can be added by including an interaction term $x_i \times D_i$, since it allows different slope parameters on either side of the threshold. As Imbens and Lemieux (2008) noted, this ensures that outcome observations to the left of the threshold do not influence the expected conditional outcomes to the right and vice versa, even though in practise this typically does not change the estimates much (Angrist and Pischke, 2009).

If the model mistakenly assumes that the relationship is linear where it really is not, non-linearity in parameters can be misinterpreted as a discontinuous jump at the threshold. In the worst case, this leads to the identification of a treatment effect where there would be none if the model was correctly specified (Angrist and Pischke, 2009). The inclusion of polynomial terms in the model can abate the problem, such that model 3 turns into

$$y_icp = \alpha + \gamma PA_c + \beta_1 x_c + \beta_2 x_c^2 + ... + \beta_s x_c^s + \delta Z_c + \phi_p + \epsilon_i cp \tag{4}$$

with x representing euclidean distance to the nearest PA and s indicating the degree of the polynomial function. For reasons stated above, the here chosen number of polynomial degrees does not exceed two.

It should be noted that the outcome variables y_{icp} in model 3 characterise as limited dependent variables. Deforestation is the share of deforested area within two kilometer radius around the cluster, and the livelihood indicators are either averages of binary deprivation dummy variables or deprivation dummies themselves. By construction, all outcomes therefore only take values from zero to one. Some scholars argue that models with limited dependent variables will likely lead to violation of normality and homoskedasticity assumptions, and thereby introduce bias in the OLS estimates (Paolina, 2001, e.g.). Contrarily, Angrist and Pischke (2009) hold that in estimating treatment effects, it should not make a difference whether one uses OLS, Probit or Tobit type of models, as what truly matters is the conditional expectation function. As long as treatment and control group are not expected to differ in any characteristic but the treatment status, the type of model should not matter much. They prove their point by comparing estimates of the three models and find no big differences in the estimates. Therefore, the regressions in this thesis are run with OLS, as their coefficients are easier to interpret compared to logistic regression types. This is in line with other RD studies that use binary outcome variables, such as Dell (2010).

5 Results

The results that are presented in this section are subdivided into deforestation and multidimensional poverty outcomes. The main model is specified as a two-dimensional RD of latitude and longitude, but alternative specifications follow at the end of the section as robustness checks.

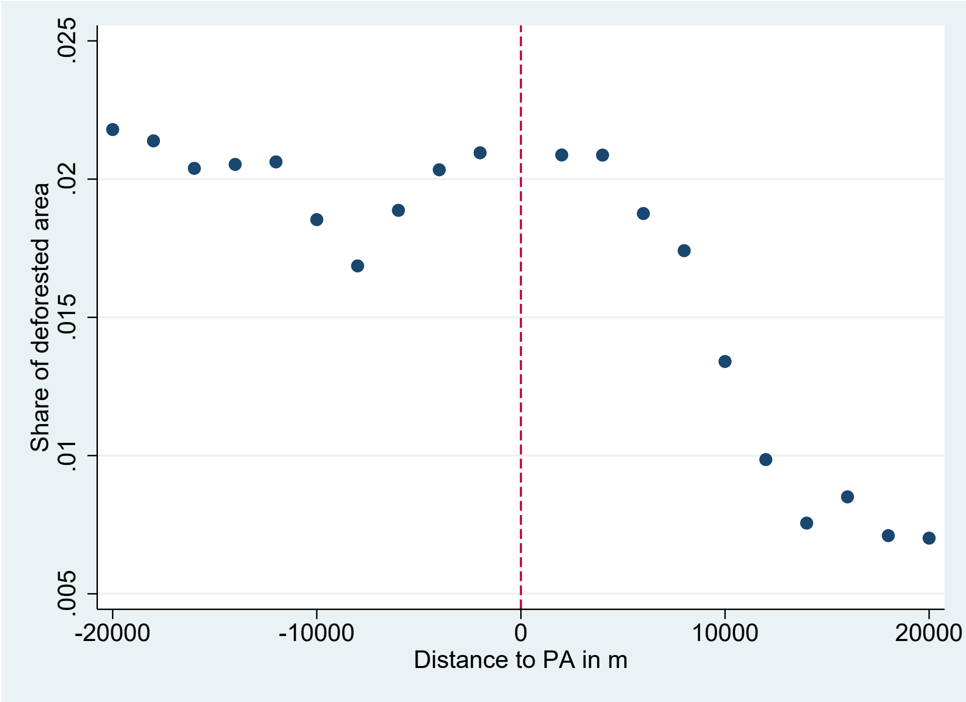

Figure 3: Mean deforestation inside and outside of Protected Areas

5.1 Deforestation outcomes

The first result of interest is whether or not PAs fulfil their main purpose in conserving forests. Figure 3 provides preliminary evidence from the GFC data. The ordinate shows the average deforestation rate from 2008 to 2020, the abscissa indicates the distance to a PA, calculated as two kilometre buffer rings. The values shown are averages for all 45 PAs established no later than 2008. If PAs indeed work to reduce deforestation, it should show in a discontinuity of forest loss as soon as a PA border is crossed. This is clearly not the case. Instead, the figure depicts a gradual decrease that sets in six kilometres behind the boundary and increases in slope as one moves further into PAs.

Deforestation pressure increases in areas that are closer to human settlements. To lend more robustness to the findings from figure 3, GFC data is linked with the DHS clusters in a RD model. This way, it can be estimated whether or not areas around human settlements experience a lower forest loss inside PAs or not. Panel A in table 3 depicts estimation results of model 3, with y_{cp} being average deforestation for a five kilometre radius around each cluster coordinate and $f(location)$ a linear polynomial in latitude and longitude. In columns (2), (4) and (6), geographic controls *growing season length*, *precipitation*, *slope*, *proximity to water* and *temperature* are added. Only one estimate across the three different bandwidths of 35, 25 and 15 kilometres in Panel A is negative

Table 3: Two-dimensional RD with longitude and latitude

	<35km		<25km		<15km	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A - Deforestation (5km)			
PA	-0.007	0.039	0.002	0.031	0.052	0.065
	(0.016)	(0.037)	(0.040)	(0.070)	(0.064)	(0.383)
Observations	29	29	22	22	16	16
R^2	0.38	0.67	0.50	0.83	0.93	0.97
			Panel B - Multidimensional Poverty			
PA	-0.070***	-0.114*	-0.034	-0.163**	-0.086	-0.382
	(0.010)	(0.035)	(0.038)	(0.039)	(0.088)	(0.149)
Observations	4933	4933	3610	3610	2703	2703
R^2	0.08	0.14	0.05	0.12	0.09	0.16
			Panel C - Education			
PA	-0.132*	-0.184**	-0.089	-0.208*	-0.154	-0.586*
	(0.039)	(0.033)	(0.067)	(0.054)	(0.105)	(0.172)
Observations	5007	5007	3639	3639	2713	2713
R^2	0.10	0.12	0.07	0.09	0.08	0.12
			Panel D - Health			
PA	-0.013	-0.045*	0.004	-0.067**	0.001	-0.128**
	(0.015)	(0.017)	(0.003)	(0.014)	(0.014)	(0.029)
Observations	4933	4933	3610	3610	2703	2703
R^2	0.02	0.03	0.03	0.04	0.04	0.04
			Panel E - Standards of Living			
PA	-0.053***	-0.107	-0.018	-0.215*	-0.106	-0.430
	(0.004)	(0.062)	(0.053)	(0.074)	(0.143)	(0.299)
Observations	5014	5014	3639	3639	2713	2713
R^2	0.09	0.30	0.18	0.38	0.30	0.44
Controls	No	Yes	No	Yes	No	Yes
Fixed effects	PA	PA	PA	PA	PA	PA

Each estimation includes a linear polynomial in latitude and longitude as location function. The respective outcomes are indicated in the panel heading. The column group names refer to the estimation bandwidth that is used. Columns (2), (4) and (6) include growing season length, precipitation, slope, proximity to water and temperature as geographic controls. Distance is specified as $latitude + longitude + (latitude \times longitude)$. Standard errors are clustered at the PA level, where each observations is assigned to the cluster of the PA with the closest euclidean distance. Significance at 0.05, 0.01 and 0.001 level are indicated through *, ** and *** respectively.

(column (1), -0.007), while the rest is positive, indicating increases in deforestation rates between 0.002 and 0.056 percentage points around clusters inside PAs. As for all other regression outputs presented in this section, standard errors are clustered for each PA environment in order to account for spatial correlation of households living around and inside the same PA.

The results make an interpretation of coefficients as a treatment effect impossible, as all are statistically insignificant and low, implying that PAs do not have the deforestation reducing effect in the DRC as they are supposed to. However, the credibility of the results is reduced by the fact that the number of observations is small as a result of averaging deforestation at the cluster level, also showing in the inflated R^2 from overspecifying the model as the bandwidth becomes smaller.

A further concern is the choice of the radius within which forest loss is calculated around each cluster. To test the sensitivity of the results to different lengths, the same models are run with alternative radius specifications. The findings do not change even when deforestation is averaged over two kilometres and ten kilometres radius instead of five kilometres around DHS clusters, as shown in tables 5 and 6 in the appendix.

5.2 Multidimensional poverty outcomes

Panel B presents results for multidimensional poverty. The sign of the coefficients flipped compared to Panel A. Now, all estimated coefficients are negative, implying reductions in multidimensional poverty as one moves into PAs. Estimates for the 35 kilometre bandwidth with and without controls are significant at the 0.001% and 0.05% confidence level respectively (p-values of 0 and 0.018) and indicate decreases in the rate of multidimensional poverty of about 0.1 percentage points inside PAs. The 25 kilometre bandwidth only shows significant results when geographic controls are added with a p-value of 0.08, implying a multidimensional poverty reduction of about 0.2 percentage points inside PAs. Coefficients for the 15 kilometre bandwidth are not significant, even though the one in column (6) lies just outside the 5% significance level with an associated p-value of 0.05. It also is much stronger than the other coefficients, indicating decreases in the multidimensional poverty rate of around 0.4 percentage points inside PAs.

As explained in section 3, the multidimensional poverty score is a weighted average of the three dimensions education, health and standard of living. Instead of looking at the effect on the aggregate poverty score, a more nuanced understanding of the effect of PAs on livelihoods of people can be obtained from analyzing the impact on deprivations for the different dimensions. Results for such regressions are shown in Panels C-E. All outcomes are indicating deprivations, meaning that negative values are associated with lower poverty and vice versa. Education in Panel C shows the strongest results. Households inside PAs tend to be less deprived of education as compared to households outside. This holds across all of the bandwidths. Three of the six specifications show significance at the 5%, one of them even at the 1% significance level. Coefficients imply decreases in education deprivation between roughly 0.1 and 0.2 percentage points, with the exception of about 0.6 percentage points in column (6).

Panel D contains estimates with health deprivation as the outcome variable. Even though three specifications show significant negative effects, this panel is the only of the five with ambiguous signs across bandwidths, as two of the six estimates are positive, even if very small and insignificant (columns (3) and (5)). However, both turn negative when controls are added to the regression. Decreases in health deprivation as indicated by the other coefficients range from of 0.013 (column (1)) to 0.128 percentage points (column (6)).

Finally, and in line with the other poverty outcomes, estimates for standards of living in panel E are all negative. Two specifications reveal significance at the 0.001% (column (1)) and 0.05% significance level (column (4)). Estimates indicate decreasing deprivation in standards of living between roughly 0.1 and 0.2 percentage points, again with the exception of a much higher coefficient in column (6).

Summing up table 3 for the two-dimensional RD in longitude and latitude, results imply that there is no sign of a treatment effect of PAs on deforestation rates, while they hint at poverty reducing impacts on households who reside inside. This effect seems to be carried by all three poverty dimensions, even if strongest by education.

5.3 Specification checks

5.3.1 Threshold manipulation

A potential concern for the validity of the RD estimates is threshold manipulation (Lemieux and Milligan, 2008). This would set in if migration occurred across PA boundaries, such that the randomization assumption no longer holds. For instance, it could be the case

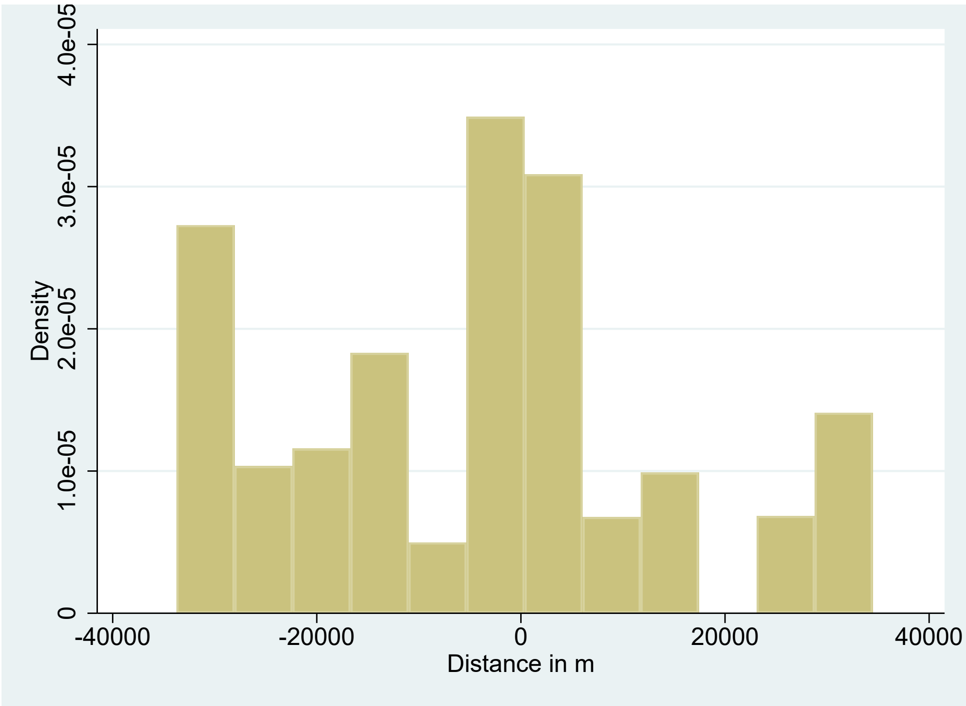

Figure 4: Observation density around the border to Protected Areas

that people who migrate away from PAs are in general systematically worse off than those who stay. The migration would then make it seem as if it increased livelihoods of people inside PAs, while in reality, it only induced the poorer people to out-migrate (Frandsen, 2017).

To test for threshold manipulation through migration, figure 4 plots the density of observations in a 35 kilometre window around PA boundaries. If people migrate into or from PAs, a drop in density should become visible where the distance measure is 0. The histogram reveals an irregular accumulation of observations for a small bandwidth on either side. As the densities across the threshold are similar, this does not hint at systematic migration in a certain direction, but can still lead to biased estimates (Barreca et al., 2016).

Accounting for these potential irregularities, and following Barreca et al. (2011), a *Donut RD* is estimated where all observations within five kilometre distance from the border are removed and thus a "hole" around the threshold created. If the hole is small enough, the randomization assumption in equation 1 should still hold, but the bigger the hole gets the less balanced are characteristics across the PA boundaries (Barreca et al., 2011). Assuming that five kilometres on each side of the border do not lead to imbalances, the Donut estimation can exclude observations located within the distance that shows irregularities in density accumulations in figure 4. The regression results of the Donut RD for the different poverty outcomes can be seen in table 8 in the appendix C. All estimates are in line with those in table 3 in sign and magnitude, which confirms the earlier findings.

5.3.2 One-dimensional specifications with euclidean distance

Further robustness to the results from table 3 is added by testing different specifications with one-dimensional RDs, displayed in table 4 and table 7. Here, distance is no longer specified as a polynomial of longitude and latitude, but instead as the euclidean distance from one cluster coordinate to the closest PA border, with negative values outside PAs and positive values inside. Panel A shows results for a linear function of distance, Panel B quadratic, Panel C linear with different slope parameters on each side of the cutoff and Panel D also includes quadratic terms that are interacted with the PA dummy. The functional form therefore increases in flexibility from Panel A to Panel D, but with it also the data requirements.

Table 4 contains coefficients for 5km deforestation rates (columns (1)-(3)) and multidimensional poverty (columns (4)-(6)). The different specifications with deforestation as outcome variable are mostly positive but slightly higher than those from the two-dimensional RD. Panel B and C estimates for the 15 kilometre bandwidth are even significant, indicating increases between 0.2 and 0.25 percentage points inside PAs, while all other specifications do not reach significance at the 0.1% level.

Results for multidimensional poverty resemble the ones in table 3. With one exception for the quadratic specification in column (6), estimated coefficients are negative and mostly of similar magnitude as before, indicating poverty decreases between roughly 0.1 and 0.16 percentage points inside PAs. Of the twelve specifications, nine show statistical at the 0.1% level.

As before, the same specifications of euclidean distance to PA boundaries are also tested for the estimates of the different poverty dimensions. Table 7 in appendix B depicts the results. Estimated coefficients for education in columns (1)-(3) are mostly in accordance with those from the two-dimensional RD, but with lower significance levels. Furthermore, 15 kilometre bandwidth estimates in Panel B and D are positive in sign, casting some doubt on the existence of a potential treatment effect. The findings

Table 4: RD estimates for deforestation rate and multidimensional poverty as outcomes

	Deforestation rate (5km)			Multidimensional poverty		
	<35km	<25km	<15km	<35km	<25km	<15km
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A - Linear					
PA	0.080	0.030	0.107	-0.099^{+}	-0.121	-0.163^{+}
	(0.055)	(0.061)	(0.078)	(0.051)	(0.060)	(0.071)
R^2	0.64	0.77	0.88	0.12	0.10	0.12
	Panel B - Quadratic					
PA	0.066	0.039	0.253***	-0.107^{+}	-0.140^{+}	0.072
	(0.062)	(0.097)	(0.033)	(0.053)	(0.058)	(0.065)
R^2	0.68	0.78	0.91	0.12	0.10	0.15
	Panel C - Linear with spline					
PA	0.066	0.033	0.201**	-0.104^{+}	-0.140*	-0.019
	(0.063)	(0.084)	(0.033)	(0.053)	(0.053)	(0.021)
R^2	0.68	0.78	0.91	0.12	0.10	0.14
	Panel D - Quadratic interaction					
PA	0.065	-0.007	-10.190	-0.148*	-0.158**	-6.812***
	(0.090)	(0.024)	(.)	(0.041)	(0.027)	(0.000)
R^2	0.68	0.82	1.00	0.13	0.11	0.19
Observations	29	22	16	4933	3610	2703
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	PA	PA	PA	PA	PA	PA

The table shows estimates for deforestation rates and multidimensional poverty as dependent variables, with different bandwiths in each column. Standard errors are clustered at the PA level, where each observations is assigned to the cluster of the PA with the closest euclidean distance. Significance at 0.1, 0.05, 0.01 and 0.001 level are indicated through $^{+}$, *, ** and *** respectively. The control variables included are Growing season length, proximity to water, precipitation, slope and temperature.

for reductions in health deprivation in columns (4)-(6), however, gain more robustness, as point estimates are negative throughout and significant at the 0.1% level in ten of the twelve specifications. Magnitudes are slightly stronger than in table 3, indicating mostly decreases in health deprivation between 0.07 and 0.09 percentage points. Lastly, estimates for standards of living in columns (7)-(9) also seem sligthly stronger than the two-dimensional RD coefficients, implying mostly decreases in deprivation between 0.15 and 0.19 percentage points. Here, seven of the twelve estimates are significant at the 0.1% level.

All in all, the results in table 4 and 7 are mostly in accordance with those from the two-dimensional RD in longitude and latitude, thus giving them more credibility and robustness. There is still no evidence of PAs having effects on deforestation rates, while poverty outcomes again indicate significant reductions in deprivations. Even though slight doubt is casted upon earlier identified effects on education, those on health and standard of living gain robustness and are even slightly stronger than in the two-dimensional RD.

6 Discussion

Section 5 provides two interesting insights into PAs in the DRC. Firstly, the results imply that PAs do not work efficiently in conserving forests, and secondly, PAs seem to decrease poverty of the households living inside them. Both findings are discussed in the following.

6.1 De jure and de facto protection

The result that PAs appear to not work in protecting forests at first seems to contradict the literature, which predicts lower deforestation rates inside PAs (Bowker et al., 2017; van Butsic et al., 2015; Potapov et al., 2012; Zhuravleva et al., 2013). However, all these studies compare average deforestation inside PAs to either the national average or buffer zones around them. As Joppa et al. (2008) notes, protected land in the DRC tends to be established in remote areas with low settlement densities and accordingly little human interference. If the extent of remoteness further increases for areas that are located deeper inside PAs, the average pressure on ecosystems is expected to be lower regardless of protection (Joppa and Pfaff, 2010). Reduced forest loss in comparison to the national average or to buffer zones is then unlikely to be an outcome of protection, but of a higher level of remoteness of PAs. The RD approach that is adapted here suits better in assessing the efficiency of protection, since it identifies discontinuities. If protection works as a conservation policy, one would expect sharp cut-offs in deforestation rates as soon as crossing the boundaries. The findings here imply that this is not the case in the DRC.

A plausible explanation for the non-results on deforestation is that enforcement of PAs is low in DRC due to a generally high level of state fragmentation. Debroux et al. (2007) notes that years of inner conflicts in DRC have led to a state that is unable to fulfil its most basic functions. Levels of corruption are high and many fundamental governmental services lacking. This, they hold, also shows in the incapability of forest protection management. In combination with the remoteness of the DRC's PAs, it can explain why protection does not work and is in line with results from the literature indicating that weak institutions and remoteness are two important factors leading to inefficient PAs (Anderson et al., 2016; Bonilla-Mejía and Higuera-Mendieta, 2019). Therefore, PAs in the DRC can be referred to what Joppa et al. (2008) call *paper parks*: areas whose protection only exists de jure, but lacks de facto enforcement on the ground. The reason why the DRC has seen rising deforestation rates in the previous decades could then be explained with a combination of inefficient conservation policies and increasing pressure on ecosystems.

6.2 Poverty reducing factors in protected areas

The second result indicates that households inside PAs face less deprivations in life, especially in education and health. Naidoo et al. (2019) suggest two explanations for their findings of better health and lower poverty likelihood for PAs in the developing world: (1) superior environmental conditions, including more plants and animals for self-use and income generation, and (2) ecotourism. The first explanation finds support from other studies too, such as Bauch et al. (2015). Especially improved health outcomes are commonly explained with better environmental conditions inside PAs (Bauch et al., 2015; Naidoo et al., 2019). However, under the hypothesis stated above that PAs in the DRC are mere paper parks, it appears unlikely that this explanation holds for the findings in the DRC, as health improvements around the boundaries seem to show even in absence of effective forest conservation. To fully discard the claim of superior environmental conditions inside PAs, it would be necessary to consider other ecosystem indicators in the analysis, which is outside the scope of this work.

The second explanation in regard to ecotourism is more likely to play a role. Holmes and Brockington (2012) note that tourism generates income at the local level and induces development programs, and Balmford et al. (2015) provide evidence that there is a global tourism run on PAs. This can generate jobs and tourism-related market opportunities with the potential to increase income and well-being (Naidoo et al., 2019). Higher income for communities creates the financial abilities to build schools and health facilities, which would explain the fact that households inside PAs appear less deprived of education and health than those outside. Evidence for tourism related revenue sharing with local communities exists for instance for Uganda, where it lead to beneficial outcomes (Mackenzie et al., 2015).

Besides the two explanations offered by Naidoo et al. (2019), a third possible explanation for the effect could be integrated conservation and development programs (ICDPs). ICDPs are programs that reconcile the raising of awareness on conservation issues with the improvement of livelihoods and compensation for restricted forest access, often through education (Mackenzie et al., 2015). For example, in the Luo Scientific Reserve in the East of the DRC, community development programs have been implemented to reduce reliance on forest use (Nackoney et al., 2014). Amongst others, new schools were built and health facilities installed. The fact that the results identify education as being the main driver for the reduction in multidimensional poverty in the DRC supports this hypothesis. However, other evidence of ICDPs in the DRC is rare, and the DRC's low state capacity makes it seem unlikely that community development is pursued on a larger scale. Even though funding for PAs from external donors such as the EU or the African Development Bank is documented, lack of transparency on the usage of these funds is a common problem and it is doubted that much of it trickles down into local communities through ICDPs (Pyhälä et al., 2016).

If any of the three explanations is accurate in explaining potential improvements in livelihoods inside PAs can only be speculated at this stage and requires further investigation.

7 Conclusion

As deforestation pressure surges in the DRC, the implementation of effective forest conservation policies in the country becomes more urgent than ever. The interrelation between livelihoods and forest use make this a complex endeavour, but shows the necessity to create win-win scenarios where conservation and poverty alleviation are reconciled. The results from this thesis imply that the current state of PAs in the DRC instead engenders win-lose situations by enhancing livelihoods of local communities but not fulfilling the premise of protecting forests.

Whether or not a more rigorous protection enforcement would lead to win-win outcomes is unclear. Even though it would likely lower deforestation in PAs, it also has unforeseeable implications on forest dependent communities. A stricter enforcement at the cost of more ecoguards, for instance, would further increase the already high tension between communities and rangers (Pyhälä et al., 2016). Previous reports on physical clashes between patrols and locals as well as related human rights abuses make this scenario seem undesirable. Besides measurable impacts on poverty indicators such as health or education, potential loss of cultural identities that is induced by restricting people's ability to practice their traditional forest-connected lifestyles cannot be captured in these outcome variables but must crucially be taken into consideration when assessing the viability of conservation policies.

The 2014 enacted decree in the DRC that allows the transfer of forest concessions to local communities who have held the land customarily is a promising step towards more participatory forest management. Evidence from other parts of the world suggest that collective property rights and decentralisation can reduce deforestation rates and lead to desirable socio-economic outcomes (Romero and Saavedra, 2020; Baragwanath and Bayi, 2020; Tole, 2010), as indigenous and local communities can take responsibility themselves and provide valuable knowledge to synthesize with westernized scientific conservation rationales (Pyhälä et al., 2016). If the now commenced introduction of community forests can also lead to effective and equitable conservation outcomes in the DRC will have to be evaluated in the near future.

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Appendices

A Deforestation estimates for alternative radius lengths

Table 5: RD estimates for 2km deforestation radius

	<35km		<25km		<15km	
	(1)	(2)	(1)	(2)	(1)	(2)
PA	0.013**	0.046	0.030	0.051	0.077	0.058
	(0.003)	(0.021)	(0.039)	(0.056)	(0.062)	(0.438)
Latitude		0.114	0.225	0.053	0.509	1.162
		(0.110)	(0.193)	(0.050)	(0.441)	(4.201)
Longitude		0.023	-0.016	0.017	0.001	-0.059
		(0.018)	(0.026)	(0.031)	(0.005)	(0.771)
Latitude × Longitude		-0.004	-0.011	-0.001	-0.027	-0.062
		(0.006)	(0.011)	(0.002)	(0.025)	(0.225)
Growing season length		-0.034**		-0.019		-0.017
		(0.007)		(0.009)		(0.052)
Proximity to water		0.000*		0.000***		-0.000
		(0.000)		(0.000)		(0.000)
Slope		0.006		0.009*		0.009
		(0.006)		(0.002)		(0.073)
Precipitation		0.003		0.001		0.002
		(0.002)		(0.002)		(0.063)
Temperature		0.005		0.007		0.002
		(0.003)		(0.003)		(0.008)
Observations	29	29	22	22	16	16
R^2	0.59	0.87	0.51	0.85	0.92	0.94
Fixed effects	PA	PA	PA	PA	PA	PA
Controls	No	Yes	No	Yes	No	Yes

The table shows estimates for deforestation rates in a 2km radius around DHS clusters, with different bandwiths in each column. Standard errors are clustered at the PA level, where each observations is assigned to the cluster of the PA with the closest euclidean distance. Significance at 0.05, 0.01 and 0.001 level are indicated through *, ** and *** respectively. The control variables included are Growing season length, proximity to water, precipitation, slope and temperature. The coefficients PA indicate the treatment effect. Distance is specified as $latitude + longitude + (latitude \times longitude)$.

Table 6: RD estimates for 10km deforestation radius

	<35km		<25km		<15km	
	(1)	(2)	(1)	(2)	(1)	(2)
PA	-0.007	0.039	0.002	0.031	0.052	0.065
	(0.016)	(0.037)	(0.040)	(0.070)	(0.064)	(0.383)
Latitude		0.011	0.245	0.030	0.598	1.009
		(0.171)	(0.227)	(0.031)	(0.496)	(3.668)
Longitude		0.052	-0.030	0.013	-0.009	-0.023
		(0.030)	(0.033)	(0.039)	(0.008)	(0.673)
Latitude × Longitude		0.001	-0.012	0.000	-0.032	-0.054
		(0.009)	(0.013)	(0.001)	(0.028)	(0.196)
Growing season length		-0.025		-0.018		-0.027
		(0.026)		(0.023)		(0.176)
Proximity to water		0.000		0.000***		-0.000
		(0.000)		(0.000)		(0.000)
Slope		-0.005		0.008		0.022
		(0.009)		(0.006)		(0.064)
Precipitation		0.001		0.001		-0.004
		(0.003)		(0.003)		(0.055)
Temperature		0.001		0.008*		0.004
		(0.007)		(0.003)		(0.007)
Observations	29	29	22	22	16	16
R^2	0.38	0.67	0.50	0.83	0.93	0.97
Fixed effects	PA	PA	PA	PA	PA	PA
Controls	No	Yes	No	Yes	No	Yes

The table shows estimates for deforestation rates in a 10km radius around DHS clusters, with different bandwiths in each column. Standard errors are clustered at the PA level, where each observations is assigned to the cluster of the PA with the closest euclidean distance. Significance at 0.05, 0.01 and 0.001 level are indicated through *, ** and *** respectively. The control variables included are Growing season length, proximity to water, precipitation, slope and temperature. The coefficients PA indicate the treatment effect. Distance is specified as $latitude + longitude + (latitude \times longitude)$.

B One-dimensional regression discontinuity for different poverty dimensions

Table 7: RD estimates for different poverty dimensions as outcomes

	Education			Health			Standard of Living		
	<35km	<25km	<15km	<35km	<25km	<15km	<35km	<25km	<15km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A - Linear					
PA	-0.071	-0.098	-0.202	-0.086*	-0.076*	-0.127***	-0.140	-0.188*	-0.160
	(0.113)	(0.138)	(0.118)	(0.034)	(0.029)	(0.000)	(0.075)	(0.073)	(0.095)
R^2	0.10	0.07	0.09	0.03	0.03	0.04	0.30	0.37	0.40
				Panel B - Quadratic Polynomial					
PA	-0.077	-0.166	0.248$^+$	-0.086*	-0.065$^+$	-0.074	-0.153$^+$	-0.190$^+$	0.045
	(0.117)	(0.120)	(0.113)	(0.034)	(0.029)	(0.039)	(0.078)	(0.079)	(0.122)
R^2	0.10	0.08	0.11	0.03	0.03	0.04	0.30	0.37	0.42
				Panel C - Linear with spline					
PA	-0.076	-0.150	0.075	-0.084*	-0.072$^+$	-0.089**	-0.148	-0.197$^+$	-0.042
	(0.116)	(0.109)	(0.042)	(0.033)	(0.032)	(0.018)	(0.076)	(0.079)	(0.039)
R^2	0.10	0.08	0.11	0.03	0.03	0.04	0.30	0.37	0.42
				Panel D - Quadratic interaction					
PA	-0.173	-0.238**	-3.311***	-0.084*	-0.007	-6.377***	-0.188*	-0.227***	-10.509***
	(0.094)	(0.041)	(0.000)	(0.033)	(0.037)	(0.000)	(0.062)	(0.010)	(0.000)
R^2	0.11	0.09	0.13	0.03	0.04	0.04	0.32	0.40	0.54
Observations	0.11	0.09	0.13	4933	3610	2703	5014	3639	2713
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	PA	PA	PA	PA	PA	PA	PA	PA	PA

The table shows regression results with different poverty dimensions as dependent variables and different bandwiths in each column. Standard errors are clustered at the PA level, where each observations is assigned to the cluster of the PA with the closest euclidean distance. Significance at 0.1, 0.05, 0.01 and 0.001 level are indicated through $^+$, *, ** and *** respectively. The control variables included are Growing season length, proximity to water, precipitation, slope and temperature.

C Donut regression discontinuity

Table 8: Donut RD for five kilometre buffers and 35 kilometre bandwidth

	Mult. Poverty	Education	Health	Stand. of Living
	(1)	(2)	(3)	(4)
PA	-0.075***	-0.200***	-0.026***	0.005
	(0.001)	(0.018)	(0.004)	(0.016)
Latitude	0.142**	0.325*	0.016	0.073
	(0.034)	(0.107)	(0.082)	(0.051)
Longitude	-0.004	-0.125***	0.007	0.103***
	(0.004)	(0.004)	(0.009)	(0.016)
Latitude × Longitude	-0.007*	-0.015*	-0.001	-0.003
	(0.002)	(0.006)	(0.005)	(0.003)
Growing season length	-0.039***	-0.064***	0.005	-0.051***
	(0.004)	(0.006)	(0.007)	(0.005)
Proximity to water	-0.000***	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Slope	-0.020*	-0.010	-0.036	-0.010
	(0.008)	(0.000)	(0.025)	(0.026)
Precipitation	0.005**	0.008	-0.000	0.008***
	(0.001)	(0.004)	(0.002)	(0.001)
Temperature	0.014	0.011	0.040	-0.009
	(0.007)	(0.049)	(0.024)	(0.021)
Observations	3393	3461	3393	3468
R^2	0.13	0.12	0.04	0.21
Controls	Yes	Yes	Yes	Yes
Fixed effects	PA	PA	PA	PA

The respective outcomes are indicated in the panel heading. The bandwidth of the forcing variable amounts to 35km for all columns, with observations within 5km on each side of PA boundaries removed from the sample. Distance is specified as $latitude + longitude + (latitude \times longitude)$. Standard errors are clustered at the PA level, where each observations is assigned to the cluster of the PA with the closest euclidean distance. Significance at 0.05, 0.01 and 0.001 level are indicated through *, ** and *** respectively.