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"We Didn't Start the Fire"

The Impact of a Kenyan Logging Ban on Deforestation

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Declaration

I hereby declare that the content of this thesis is my own work and that, to the best of my knowledge, it contains no material published or written by any other author or authors, except where acknowledged. This thesis has not been submitted for award of any other degree or diploma at the University of New South Wales or any other educational institution.

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Nicholas Fransen
22 November 2019

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Abstract

This paper evaluates the effect of a logging ban on deforestation in Kenya and Uganda. In February 2018, the Kenyan Government introduced a command and control environmental policy, banning all logging in public and community forests. I employ a difference in differences strategy using a novel panel data set to determine the ban's effectiveness in Kenya and to identify spillover effects due to the ban in Uganda. Uniquely in the deforestation policy evaluation literature, I find that the protected area based implementation of the logging ban had no effect on deforestation in Kenya. Moreover, I find evidence of deforestation spillover effects in Uganda as a result of the logging ban. Although there are several data limitations, these results suggest that the environmental policy was ineffective in achieving its intended outcome while also creating negative unintended consequences. These findings suggest that policymakers should consider alternative solutions before implementing command and control environmental policy.

Chapter 1

Introduction

Households in developing countries are highly reliant on wood fuel for energy. In Kenya, the primary sources of energy for 82% of households are charcoal and firewood (KNBS 2018). These fuels are derived from timber, driving a forestry industry employing 900,000 people and valued at USD2016 \$1.6 billion a year. Although a valuable industry economically, the production of firewood and charcoal is responsible for approximately 18.7 million cubic metres of deforestation every year in Kenya (Wanjiru and Omedo 2016). As forests are essential for water conservation, the wood fuel market has adversely contributed to the drought affecting Kenya since 2014 (Sweeney et al. 2004; Njengere and Torma 2017).

By 2017, an estimated 2.7 million people were under threat of starvation due to food insecurity. In response to this crisis, the Kenyan Government declared a state of emergency, receiving USD2017 \$105 million in foreign aid. In an attempt to further alleviate the severity of the drought, the Kenyan Government imposed a 90-day ban on logging in public and community forests on the 24th of February 2018. The logging ban was extended twice, and is expected to be lifted on the 24th of November 2019 (Environment and Forestry 2018a).

This paper investigates the effectiveness of the logging ban on deforestation in Kenya, and whether the ban causes deforestation spillover effects in neighbouring Uganda. I use a novel panel data set containing hectare grid cell observations over six years between 2013 and 2018. The data is constructed by combining Global Forest Change data from Hansen et al. 2013 with other geographical, demographic, and socioeconomic variables.

To identify the effectiveness of the logging ban in Kenya, I employ a difference in differences strategy. I exploit spatial variation from the ban's implementation in Kenya's protected areas, and temporal variation from the ban's implementation in 2018. I find that for the average hectare grid cell after the ban, there is no additional reduction in deforestation within protected areas compared with non-protected areas. This suggests that the ban is not effective. I empirically test that the identifying assumptions of the difference in differences strategy hold using quadratic trend estimation and an event study, finding that the assumptions do hold. I lastly perform a series of robustness checks which do not change the conclusions taken from the main result.

In spite of the evidence that the ban is ineffective in Kenya, it is possible that the logging ban had an unintended impact on deforestation in neighbouring Uganda. The two nations share a fluid border and are economically integrated as part of the East Africa Community trade bloc (USCS 2019). Moreover, suggestive evidence shows that the price of charcoal in Kenya soared upon the onset of the ban in February 2018 (CEIC 2019). As the logging ban in Kenya did not impose any restrictions on logging imports, wood fuel producers in Uganda may choose to capture rents from the increased price of charcoal through higher exports. This would increase the amount of wood fuel production in Uganda, causing the logging ban in Kenya to have deforestation spillover effects.

To identify whether there are spillover effects in Uganda due to the logging ban in Kenya, I also employ a difference in differences strategy. I exploit spatial variation Euclidean distance to the Kenya border crossing, and temporal variation from the ban's implementation in 2018. I first employ a logarithmic and inverse function of distance to the Kenya border crossing as treatment, and find significant evidence of spillover effects. Specifically, the results from the logarithmic specification suggest that for the average hectare grid cell after the ban, there is an additional 0.021m^2 to 0.054m^2 of deforestation for every five kilometre increase in proximity to the Kenya border crossing. The results from the inverse specification suggest that for the average grid cell after the ban, there is an additional 37.27m^2 to 118.8m^2 of deforestation one kilometre away from the Kenya border crossing, compared with 505 kilometres away.

Using a continuous treatment variable has limitations for identification, so I exploit the same spatial and temporal variation using a non-parametric difference in differences strategy with 10 kilometre distance intervals. I find significant evidence of spillover effects within 70 kilometres of the Kenya border crossing. These spillover effects are most significant between 20 and 40 kilometres away from the border crossing, increasing the additional amount of deforestation by approximately 25m^2, or 30%, compared with these areas before the ban. I analyse the sample geographically to identify areas within 20 to 40 kilometres of the border which experience deforestation, and find that there is a significant amount of deforestation within important protected forests of Uganda, including around Mount Kadam and Mount Elgon National Park in 2018. Altogether with the initial specifications, these results present strong evidence of spillover effects in Uganda as a result of the logging ban in Kenya.

To check the robustness of these findings, I perform several empirical checks, which suggest that the main results should be interpreted with caution. First, I perform an event study using the logarithmic and inverse specifications to determine if the identifying assumptions of the difference in differences strategy hold. The results from the logarithmic specification suggests that the parallel trends assumption is not supported, and that there is a downward trend in the differential effect of distance from the border crossing on deforestation. The results from the inverse specification also suggest that the parallel trends assumption is not supported, but they do not suggest that there is any evidence of a pre-trend. Furthermore, I test for spatial correlation in the data and find that a spatial autoregressive model of the logarithmic and inverse specifications eliminates the significance of the treatment. This suggests that after the ban, the additional quantity of deforestation may be attributable to the quantity of deforestation in cells nearby and not distance from the Kenya border crossing. However, these results are attenuated by the fact that they have been obtained using a 3.4% sample of observations from the original random sample due to computational constraints.

These findings contribute to the literature on policy evaluations of deforestation by investigating the causal effect of a logging ban implemented within protected areas in Kenya. In the existing literature, Andam et al. 2008 apply matching methods to identify the causal effect of Costa Rica's protected-area system between 1960 and 1997 and find that approximately 10% of protected areas would have been deforested had they been unprotected. Oliveira et al. 2007 also evaluate the protected-area system as effective by comparing deforestation within 20 kilometres of roads inside and outside protected areas of the Peruvian Amazon. They assess that protected areas are effective, but the choice of protected areas is endogenous and thus correlated with factors which affect likelihood of deforestation. Although many studies within the literature address problems from causally including this one (Deininger and Minten 2002; Andam et al. 2008), other studies use descriptives to assess the effect of deforestation policies (Naughton-Treves et al. 2005; Oliveira et al. 2007). While protected area systems can be an effective means of reducing deforestation, this paper shows that a blanket ban on logging in Kenya may not achieve the desired outcomes and may generate negative unintended consequences for the environment.

I further contribute to the deforestation policy evaluation literature by investigating spillover effects in Uganda due to the Kenyan logging ban. This section of the literature demonstrates that policies designed to decrease deforestation can have unintended negative spillover effects on deforestation and the environment. Dou et al. 2018 evaluate the environmental effects of Amazon rainforest supply-chain agreements within the forest as well as in the surrounding Cerrado region. They find that although these agreements reduced Amazon rainforest deforestation by 80% in fifteen years up until 2015, it has caused the amount of deforestation in the surrounding region to nearly double. However, Andam et al. 2008 estimate whether protected areas cause spillovers in Costa Rica and do not find a significant result. Although inconclusive, the existing literature suggests that there could be region-specific economic mechanisms influencing whether a logging ban creates deforestation spillover effects in the surrounding regions. I find that there is evidence of deforestation spillover effects in Uganda caused by the ban in Kenya, supporting the hypothesis that East Africa may possess region-specific economic mechanisms for a logging ban to cause spillover effects into neighbouring countries.

Finally, this thesis contributes to the literature on command and control environmental policy through the empirical investigation of a command and control policy's effectiveness in Kenya. The majority of literature on this topic is theoretical, but Cole and Grossman 1999 analyse command and control environmental policy and show that these can be a feasible alternative when there are sufficient institutional or technological constraints. They apply their hypothesis to the Clear Air Act (1970) of the United States, which used a command and control approach between 1970 and 1990, and find that the net benefits over this period are USD1999 $21.7 trillion compounded at 5%. However, my results suggest that the policy does not achieve the desired outcomes and even causes adverse spillover effects. This is in line with other studies within the literature, hypothesising that command and control policy will result in a "zero-sum" mentality where environmental improvements must come at an economic cost (Stewart 1985; Ackerman and Stewart 1984).

The remainder of the paper is as follows. Section 2 provides context on Kenya's logging ban, wood fuel markets, and economic integration with Uganda. Section 3 explains the data construction and sample selection used for analysis. Section 4 analyses the logging ban's effectiveness in Kenya's protected areas. Section 5 whether there are spillover effects in Uganda due to the logging ban. Section 6 provides a discussion of the findings and potential limitations. Finally, section 7 concludes the paper with the overall findings.

Chapter 2

Context

2.1 Kenyan Logging Moratorium

Since 2014, Kenya has been experiencing drought. As 2.7 million Kenyans faced starvation if assistance was not provided, President Uhuru Kenyatta declared the drought a national emergency on the 10th of February 2017 (Njengere and Torma 2017). Although the Kenyan government received USD 2017 $105m in foreign aid to assist the 23 affected counties, the allocation of these funds was not made clear (Kenyatta 2017). In late 2017, a prolonged dry season worsened the drought and caused an acute shortage of water flows. The funding allocation had not improved the situation as water levels continued to fall and rivers, streams, and wells dried up (Njengere and Torma 2017).

Deforestation and low forest cover adversely contributes to this water shortage through the destruction of water towers and a reduction in rainfall (Sweeney et al. 2004). Currently, forest cover is 7% of total land in contrast to the government's imposed minimum of 10% which they aim to reach in 2022 (Onwonga 2019). In response to this, the Kenyan Government imposed a 90-day moratorium on logging and timber harvesting in all public and community forests on the 24th of February, 2018 (Environment and Forestry 2018b).

Shortly following the ban's implementation, the Secretary for Environment and Forestry appointed a Task Force on Forest Resources Management and Logging to assess the forest sector in Kenya (Environment and Forestry 2018b). To facilitate the appointment of a new board of the Kenya Forest Service (KFS) and the finalisation of the Task Force recommendations, the ban was extended for a further six months until the 24th of November 2018 (Environment and Forestry 2018a). The KFS board was appointed on the 6th of June 2018 and made significant progress in implementing the Task Force recommendations throughout 2018. Despite the progress made, the Ministry stated that inadequate institutional capacity and budget constraints had impeded implementation. Consequently, the ban was extended until the 24th of November 2019 (Environment and Forestry 2018a). There has not been any indication of whether the ban will be extended again as of the 22nd of November 2019.

The Kenyan Government and KFS board have been working to monitor deforestation activity and ensure enforcement of the logging moratorium. Statements from the Kenyan Government and KFS released at the start of the ban suggest that monitoring will involve investigating staff, employing new surveillance technologies, and labelling forest product with their origin (Environment and Forestry 2018b). To further ensure the ban is effectively monitored, they have introduced movement permits to track the supply of logs (Kalenda 2019). To enforce the ban, the KFS statements suggest that they are planning to mobilise the relevant administrative bodies, develop an elaborate control mechanism, and strengthen the capacity of the KFS Law Enforcement Unit (Environment and Forestry 2018b). It remains unclear whether these policies have been implemented and enforced in actuality.

Media reports suggest that there may be some issues surrounding the enforcement of the ban, including reports of corruption. On July 20, 2019, the Kenya News Agency reported that the Cabinet Secretary for Environment and Forestry accused KFS officers of colluding with businessmen to conduct illegal logging (Nyakundi and Kavoo 2019). These men were indicted over the incident, indicating that the logging moratorium was effectively enforced in this case. However, there are other news reports suggesting that deforestation is continuing throughout Kenya despite the ban (Mureithi 2019). Without understanding the ban's effectiveness empirically, it is impossible to determine whether Kenya will achieve ecological and agricultural sustainability through this policy.

2.2 Wood Fuel in Kenya

The wood fuel sector is one of the primary drivers of deforestation in Kenya, responsible for 18.7 million cubic metres of timber or 45% of the 41.7 million cubic metres harvested each year (Wanjiru and Omedo 2016). Firewood is the main source of energy in Kenya followed by charcoal. Firewood is the main fuel source in 65% of households in Kenya; 87% in rural areas and 32% in urban areas (Wanjiru and Omedo 2016; KNBS 2018). Moreover, charcoal is the main source of energy for 17% of households in Kenya; 8% in rural areas and 30% in urban areas (Wanjiru and Omedo 2016; KNBS 2018). The sector employs approximately 900,000 people in production and trade and had been estimated to contribute USD2016 $1.6 billion per year to Kenya's economy (Wanjiru and Omedo 2016). The logging ban does not diminish Kenya's demand for fuel, so an altered timber supply chain may transpire if alternative fuel sources are unaffordable or inaccessible.

2.3 Economic Integration of Kenya and Uganda

Kenya and Uganda are economically integrated through a fluid border and a strong trade relationship. Both nations belong to the East African Community (EAC) and the Common Market for Eastern and Southern Africa (COMESA) (USCS 2019). In pursuit of economic integration and regional cooperation, these organisations have established free trade policies to encourage higher trade volume between member states. Furthermore, as of 2017, Uganda was Kenya's second largest export partner with an export share of 10.4% (WITS 2017a). Similarly, Kenya was Uganda's largest export partner with an export share of 19.02% (WITS 2017b). The extent of economic integration between the two nations may cause the logging ban to have unintended consequences in Uganda.

Chapter 3

Data

3.1 Geographic Variables

I use a geographic information system (GIS) data set containing geophysical data in Kenya and Uganda. These data include deforestation, protected areas, distance to the Kenya border crossing, terrain ruggedness, maize productivity, and distances to other geographical features.

3.1.1 Sample Selection

The observations in the geographical information system are hectare grid cells. I use the Global Forest Change data set (2000 to 2018) from Hansen et al. 2013 to determine which grid cells will form the final sample.

Based on Landsat satellite imagery, the Hansen data contains data pixels with a spatial resolution of one arc-second, approximately 30m x 30m, or 900 square metres in size (Hansen et al. 2013). Each data pixel contains percentage of canopy closure in 2000 defined as canopy closure for all vegetation taller than five metres in height. A pixel is considered forested if its canopy closure is above 50%. This threshold is used as standard practice in the literature when analysing deforestation with the Global Forest Change data (Hansen et al. 2013).

The data pixels also contain information on forest gain and loss. Each data pixel contains a yearly binary variable indicating if there was forest loss for each year between 2000 and 2018. Each data pixel also contains a binary variable indicating if there was forest gain during the period between 2000 and 2012. The data set does not record forest gain after 2012 because a replacement satellite altered the data collection process.

The construction of the data set begins by drawing hectare-sized (100m x 100m)grid cells around data pixels with non-zero forest cover in 2000 [1]. From these grid cells, ten percent

[1] Credit to the consultant who constructed the cross-sectional GIS data set

are randomly selected to form the initial sample [2]. Each pixel's forest loss binary variable is aggregated at the grid cell level, defined as the hectares of forest lost in each year between 2000 and 2018. Similarly, each pixel's forest gain binary variable is aggregated at the grid cell level, defined as the hectares of forest gained between 2000 and 2012. Lastly, each pixel's canopy closure in 2000 is aggregated at the grid cell level, defined as the percentage of tree cover in 2000.

I extrapolate the forest definition from Hansen et al. 2013 and define a grid cell as forested if its canopy closure is above 50%. I drop all grid cells which are not forested under this definition, leaving only forested cells as of 2000 in the sample. I define hectares of forest in 2000 equal to one for every grid cell in this sample. Using hectares of forest in 2000 and net deforestation during the period of 2000 to 2012, I predict hectares of forest in each grid cell as of 2012. If the number of hectares within a grid cell is predicted to be above one, I normalise it to one. I keep grid cells which are predicted to contain strictly greater than zero hectares of forest in 2012.

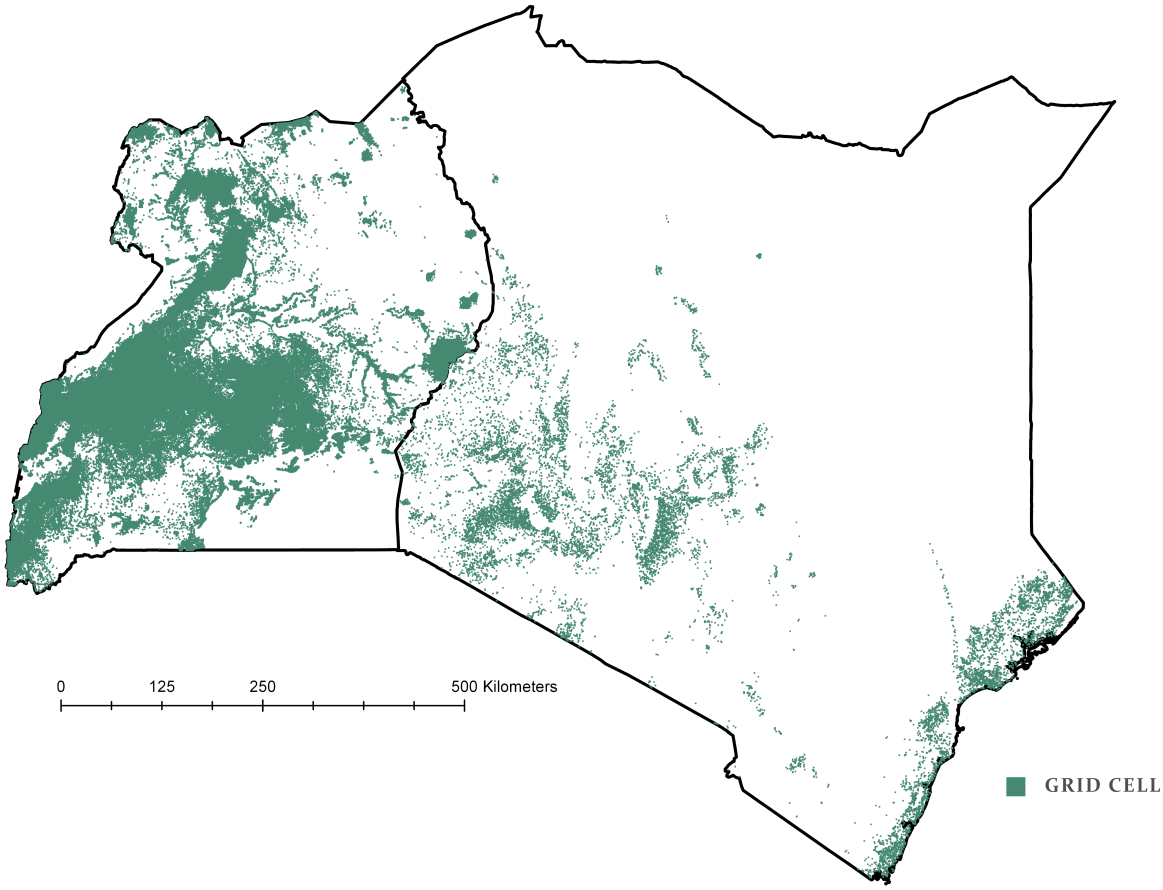


Figure 3.1: Final Sample of Grid Cells in Kenya and Uganda

My final sample contains completely forested cells as of 2000 which contain strictly greater

[2] 10% is a large sample of 290,905 cells

than zero hectares of forest as of 2012. I reshape the data into a panel and only keep observations between 2013 and 2018. In the final sample, there are 6,764 cells in Kenya and 284,186 cells in Uganda for a total of 290,950 hectare grid cells. The data set is a panel spanning six years such that there are a total of 1,745,700 observations.

3.1.2 Deforestation

I use yearly forest loss measured in hectares within each grid cell between 2013 and 2018 as my outcome variable. I convert yearly forest loss from hectares to square metres, interpreted as the number of square metres of forest loss within a hectare grid cell where there are 10,000 square metres in a hectare.

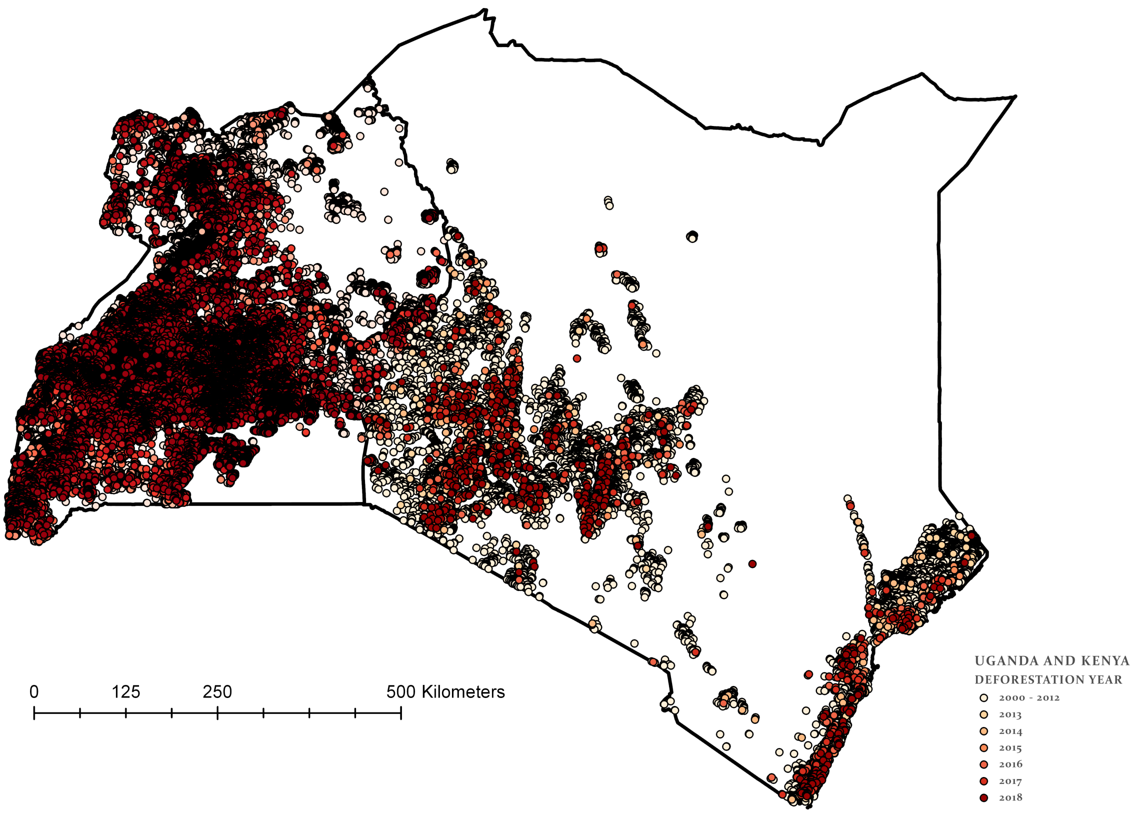


Figure 3.2: Most Recent Year of Deforestation in Kenya and Uganda

3.1.3 Protected Areas

Data on protected areas is extracted from the World Database on Protected Areas (WDPA) created by UN Environment and IUCN (Planet 2019). A protected area is defined by the IUCN as "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." (Dudley 2008)

Of the 6,764 cells in Kenya, 5,297 are non-protected areas and 1,467 are protected areas.

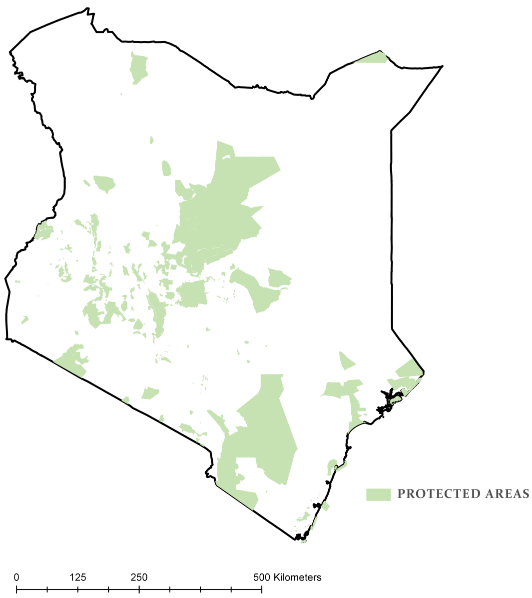


Figure 3.3: Protected Areas in Kenya

3.1.4 Terrain Ruggedness

I use the Terrain Ruggedness Index devised by Riley et al. 1999 and used by Nunn and Puga 2012 to quantify and control for relative topographic heterogeneity. This index is created using a global elevation data set developed through a collaborative effort led by staff at the US Geological Survey's Center for Earth Resources Observation and Science (EROS). Elevation data are regularly spaced at 30 arc-seconds across the entire surface of the Earth such that the sea-level surface distance between two adjacent grid points on a meridian is 926 metres. This means the cells created are 30 x 30 arc-seconds in area, just under one kilometre squared, where each cell has one data point on the the area's elevation.

To calculate the Terrain Ruggedness Index, let $e_{r,c}$ denote elevation at the point located in row r and column c of a grid of elevation points. The index at that point is then calculated as:

$$TRI_{r,c} = \sum_{i=r-1}^{i=r+1} \sum_{j=r-1}^{j=r+1} (e_{i,j} - e_{r,c})^2 \tag{3.1}$$

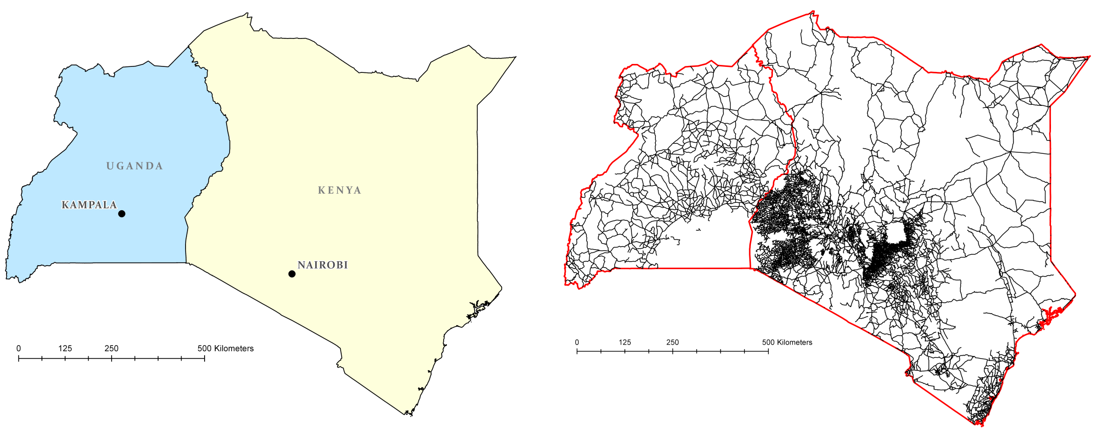
I scale ruggedness down by a factor of one million to normalise the coefficients. As an alternative measure of topographic heterogeneity, the data set also contains the slope of the land in each cell. For each elevation point on the grid, the absolute value of the difference in elevation between this point and the point 30 arc-seconds north of it is measured, and then this is divided by the sea-level distance between these two points. The data also contains elevation at each point in the grid, measured in metres above sea level.

3.1.5 Maize Productivity

The crop suitability index (value) for low input level rain-fed maize is extracted from the Food and Agriculture Organisation of the United Nations through the Global Agro-Ecological Zones data portal (Food and Organization 2019). I define this variable as m indicating the productivity of land for growing maize given low inputs and rain as the only water source within each grid cell, where $m \in M = [0, 10000]$. This index has been selected because Kenya and Uganda's agricultural land has low inputs where rain is the only water source.

3.1.6 Distance to Geographical Features

Data on distance to geographical features were extracted directly from the GIS by the consultant. For each grid cell g, this measures the Euclidean distance to the geographical feature from g in kilometres. Geographical features include the Kenya border crossing, the Kenya border, the closest city, the closest dirt road, the closest improved road, Nairobi (Kenya's capital city), and Kampala (Uganda's capital city). The data set also contains distance to the Kenyan border using distance via road rather than Euclidean distance.



(a) Kampala in Uganda & Nairobi in Kenya (b) Road Network (SEDAC 2010)

Figure 3.4: Geographical Features

3.2 Demographic Variables

3.2.1 Population

Part of the geographical information system, the Gridded Population of the World collection from the Socioeconomic Data and Applications Center (SEDAC) is used to extract data on population for each grid cell. Population input data are collected at the most detailed spatial resolution available from the results of the 2010 round of Population and Housing Censuses. The data is extrapolated by SEDAC to produce population estimates for 2010 and 2015. The population estimates are then matched to a raster data set constructed from national or sub-national input administrative units. This data is then mapped into the GIS with an output resolution of 30 arc-seconds or approximately one kilometre squared. Each hectare grid cell contains data on the population of the SEDAC kilometre squared grid cell it lies within, rather than the population of the hectare grid cell itself.

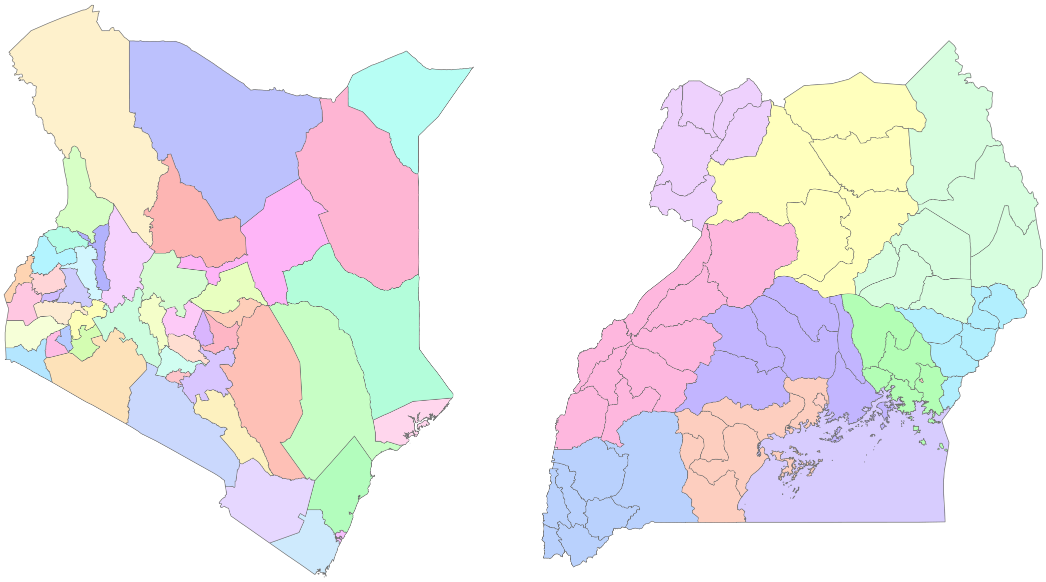
As the data is a panel spanning 2013 through 2018, I assign the population value in 2010 for observations in 2013 and 2014. Similarly, I assign the population value in 2015 for observations in 2015, 2016, 2017 and 2018. Although the true value of population within each grid cell changes for each year of the data, using both population values in the SEDAC data accounts for variation in population over time using the most updated value.

3.3 Socioeconomic Variables

I extract socioeconomic variables for Kenya from the Demographic Health Survey 2014 (DHS) and the Kenya Integrated Household Budget Survey 2015-2016 (KIHBS) (USAid 2015; KNBS 2018). Although these are two distinct surveys, they are both designed to provide data for the population of Kenya. Enumeration regions are constructed to survey representative strata, such that survey weights can be used to extract the parameter of interest for the population.

I extract socioeconomic variables for Uganda from the Living Standards Measurement Survey 2013-2014 (LSMS 13-14) and Living Standards Measurement Survey 2015-2016 (LSMS 15-16)(Bank 2017; Bank 2019). Applying the same survey techniques, these surveys are both designed to provide data for the population of Uganda.

I calculate the average of each socioeconomic variable for each of the forty-seven counties in Kenya and each of the ten sub-regions in Uganda. This is to merge the socioeconomic data with the geographical information system. For the purpose of simplifying the explanation, let counties and sub-regions be known in combination as regions.



(a) Kenya Counties (b) Uganda Sub-Regions

Figure 3.5: Regions in Kenya and Uganda

3.3.1 Education

The DHS contains data on each household member's years of education in 2014. KIHBS contains information on each household member's highest level of education reached and their highest grade completed within this level. I use these two variables and information on Kenya's education system to extrapolate each household member's years of education in 2016 (Clark 2015).

Both the LSMS 13-14 and LSMS 15-16 contain data on each household member's highest level of education reached and their highest grade completed within this level. Similarly to Kenya, I use these two variables and information on Uganda's education system to extrapolate each household member's years of education in 2014 and 2016 (Scholaro 2018; Masinde 2012). I drop all household members except the head of household.

I extract the years of education obtained by each head of household i within each region j across time t (where the two time periods are 2014 and 2016). Define this as $education_{ijt}$. To calculate the average years of education within each region j across each head of household i in time t, where each head of household has an assigned survey weight of w_{ijt}:

$$meaneducation_{jt} = \sum_{i=1}^{N_{jt}} \frac{education_{ijt}}{N_{jt}} w_{ijt} \quad \forall j \ \forall t \tag{3.2}$$

When extrapolating years of education I simply add the grade reported within each level to the number of years of education required to reach the level. However, several participants in the KIHBS survey reported a completed grade which exceeded the highest grade possible within their highest level of education reached. I constructed an artificial cap on the possible grade they could reach to determine if it affected the final variable. I perform a t-test to determine if this variable is significantly different, but I fail to reject the null hypothesis that they are the same. Therefore, I do not change my original method for extrapolating years of education.

3.3.2 Agricultural and Pastoral Employment

For Kenya, the DHS contains data on each household member's occupation in 2014 and the KIHBS contains data on each household member's primary and secondary occupation in 2016. For Uganda, both the LSMS 13-14 and LSMS 15-16 contain data on each household member's sector of employment in 2014 and 2016. I drop all household members except the head of household.

I extract the status of agricultural and pastoral employment for each head of household i within each region j across time t (where the two time periods are 2014 and 2016). Define this as a dummy variable, $agriemployed_{ijt}$. To calculate the percentage of head of households i in agricultural or pastoral employment within each region j in time t, where each head of household has an assigned survey weight of w_{ijt}:

$$meanagriemployed_{jt} = \sum_{i=1}^{N_{jt}} \frac{agriemployed_{ijt}}{N_{jt}} w_{ijt} \quad \forall j \ \forall t \tag{3.3}$$

3.3.3 Poverty

For Kenya, the DHS does not contain any information on the poverty status of households, so I am unable to determine poverty in 2014. The KIHBS contains data on each household's per-capita consumption and the per-capita consumption poverty threshold in 2016. If a household's per capita consumption is below the poverty threshold, I categorise them as poor.

For Uganda, the LSMS 13-14 contains data indicating poverty status under per-capita consumption for every household. Similarly to Kenya, if a household's per capita consumption is below the poverty threshold, I categorise them as poor. The LSMS 15-16 does not contain any information on the poverty status of households, so I am unable to determine the poverty status of households in 2016 within Uganda.

To calculate the percentage of households h in poverty within each region j, where each household has an assigned survey weight of w_{hj}:

$$meanpoverty_j = \sum_{h=1}^{N_j} \frac{poor_{hj}}{N_j} w_{hj} \quad \forall j \tag{3.4}$$

The KIHBS also contains data on each household's nutritional consumption and the nutritional consumption poverty threshold in 2016. As households may be affected differently if their occupants are malnourished compared to having very low consumption, I calculate this as another socioeconomic variable for Kenya only. I extract the nutritional poverty status for each household h within each region j in Kenya for 2016. Define this as a dummy variable $nupoverty_{ij}$. To calculate the percentage of households h in nutritional poverty within each region j, where each household has an assigned survey weight of w_{hj}:

$$meannupoverty_j = \sum_{h=1}^{N_j} \frac{nupoverty_{hj}}{N_j} w_{hj} \quad \forall j \tag{3.5}$$

3.3.4 Merging Socioeconomic Variables to the Panel Data

To construct time-variant socioeconomic controls for the panel data set, I assign the value for 2014 to observations in 2013 and 2015, and the value for 2016 to observations in 2017 and 2018. Note that poverty status is time-invariant for every region j in both Kenya and Uganda. I then merge these data with the deforestation data and geographical covariates discussed above.

3.4 Summary Statistics

I have constructed a summary statistics table for the panel data presented in Appendix Table A.2. I have also constructed a table for a cross section of the data by collapsing the variables by grid cell to display the mean of each variable across years, presented in Appendix Table A.3. As I analyse the data in Kenya and Uganda separately, I have constructed the cross section table but include data for Kenya and Uganda separately. These are presented in Appendix Table A.4 and A.5.

Chapter 4

Kenya

4.1 Identification Strategy

I model the effect of the logging ban on the average square metres of deforestation within a hectare grid cell in Kenya by employing a difference in differences identification strategy. I exploit spatial variation using the ban's implementation in Kenya's protected areas and temporal variation using the ban's implementation in 2018 to identify this effect.

The logging ban is implemented in public and community forests while private forests, the only other type of forest in Kenya, are unaffected by the ban. In theory, if a grid cell lies within a public and community forest and therefore affected by the ban, it should be considered a treated grid cell. If a grid cell lies within a private forest, it should be considered a control grid cell. However, I observe protected public forests but not community forests, and therefore community forests constitute the control group when they should constitute the treatment group.

The distribution of private and community forests within non-protected areas is not disclosed by the Kenyan Government and has not been analysed by academic research to the best of my knowledge. Private forests are any forest owned privately by an individual, institution or body corporate. Conversely, community forests were only introduced in 2005 and require an intensive application to engage in conservation (Government 2005). Although the exact distribution is unknown, it is safe to assume that there will be a substantially larger amount of private forests than community forests in non-protected areas. Therefore, there will be a substantially larger amount of control grid cells than treated grid cells in the control group.

Temporal variation is derived from the implementation of the ban in February 2018. The pre-treatment period is therefore 2013 to 2017, while the treatment period is 2018.

4.2 Balance of Covariates

Grid cell characteristics between protected and non-protected areas may affect deforestation differently over time. If this is the case, the estimated average treatment effect will be estimating the differential effect of observable characteristics on deforestation over time, rather than the effect of the ban. If observable characteristics are significantly different between protected and non-protected areas, these may affect deforestation differently over time. To determine if this is the case, I perform a difference in means test for all variables presented in Table 4.1. The results suggest that there is a significant difference between protected and non-protected areas in most observable characteristics such that this could affect deforestation differently over time.

Table 4.1: Kenya Balance of Covariates

	Non-Protected Areas		Protected Areas		Difference in Means	
	Count	Mean	Count	Mean	Difference	P-Value
Loss (m^2)	5297	34.63	1467	21.85	12.79***	(0.008)
Loss 2013 (m^2)	5297	45.95438	1467	35.54932	10.41	(0.397)
Loss 2014 (m^2)	5297	23.52468	1467	12.59935	10.93	(0.258)
Loss 2015 (m^2)	5297	26.15326	1467	23.31028	2.843	(0.799)
Loss 2016 (m^2)	5297	32.57794	1467	13.61819	18.96*	(0.083)
Loss 2017 (m^2)	5297	41.41247	1467	33.55322	7.859	(0.578)
Loss 2018 (m^2)	5297	38.18283	1467	12.46486	25.72**	(0.019)
Loss 2013 - 2017 (m^2)	5297	169.6227	1467	118.6304	50.99*	(0.056)
Forest 2012	5297	.9051785	1467	.9236424	-0.0185***	(0.001)
Distance to Border Crossing (km)	5297	97.73401	1467	125.1712	-27.44***	(0.000)
Distance to Border (km)	5297	92.28542	1467	116.9947	-24.71***	(0.000)
Distance to Border via Road (km)	4656	156.6811	992	205.6679	-48.99***	(0.000)
Ruggedness	5297	100146.8	1467	138376.6	-38229.8***	(0.000)
Slope (%)	5297	8.450194	1467	5.355025	3.095**	(0.027)
Maize Productivity	5297	4179.484	1467	2788.57	1390.9***	(0.000)
Distance to Dirt Road (km)	5297	2.028855	1467	3.88708	-1.858***	(0.000)
Distance to Improved Road (km)	5297	4.610992	1467	9.72305	-5.112***	(0.000)
Distance to Closest City (km)	5297	37.6671	1467	43.05871	-5.392***	(0.000)
Distance to Kampala (km)	5297	523.9264	1467	563.0355	-39.11***	(0.000)
Distance to Nairobi (km)	5297	259.3137	1467	274.505	-15.19***	(0.000)
Population	5297	296.1115	1467	92.6069	203.5***	(0.000)
Years of Education	5119	7.717883	1391	7.753268	-0.0354	(0.343)
Agricultural Employment (%)	5119	.3858542	1391	.3711309	0.0147***	(0.000)
Poverty (%)	5119	.3038188	1391	.3182601	-0.0144***	(0.000)
Nutritional Poverty (%)	5119	.2592968	1391	.247959	0.0113***	(0.000)
N	6764					

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

4.3 Results

I specify the difference in differences equation as:

$$d_{gt} = \beta_1 P_g * T_t + \beta_2 P_g + \beta_3 T_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \tag{4.1}$$

The outcome variable, d_{gt}, is square metres deforested within grid cell g in year t. P_g is the treatment variable equal to one if the grid cell is located within a protected area and zero otherwise. T_t is the treatment period dummy variable equal to one if the observation is in 2018 and zero otherwise. The interaction of P_g and T_t identifies the treatment effect where β_1 is the difference in differences estimator. To control for geographical, demographic and socioeconomic covariates, I incorporate time-invariant controls (X_g) and a vector of time-varying controls ($\mu\prime X_{gt}$). I also incorporate grid cell and year fixed effects, γ_g and ϕ_t, in some specifications.

I estimate the average treatment effect using the difference in differences model specified in Equation 4.1, clustering standard errors at the grid cell level. Clustering at the grid cell level accounts for autocorrelated errors within each grid cell. This produces a more robust estimate reflective of the treatment effect within the population of interest. I present the results of the estimation in Table 4.2.

Table 4.2: Impact of Logging Ban in Kenya

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)	(6) Loss (m^2)
Protected Area x Logging Ban (t = 2018)	-15.52*	-13.67	-13.34	-13.43	-13.12	-7.992
	(9.133)	(9.420)	(9.543)	(9.437)	(9.550)	(8.881)
Protected Area	-10.20**	-3.296		-3.009		
	(5.004)	(5.397)		(5.373)		
Logging Ban (t = 2018)	4.258	6.521	5.466			29.73
	(6.060)	(6.471)	(6.442)			(86.85)
Constant	33.92***	79.54***	31.56*	97.76***	45.72***	39.41***
	(2.539)	(16.18)	(16.32)	(18.18)	(17.11)	(5.151)
N	40584	39060	39060	39060	39060	39060
Controls	No	Yes	Yes	Yes	Yes	No
Grid Cell Fixed Effect	No	No	Yes	No	Yes	Yes
Year Fixed Effect	No	No	No	Yes	Yes	Yes
Year FE x Controls	No	No	No	No	No	Yes

Controls: Ruggedness, Slope, Maize Productivity, Distance to Dirt Road, Distance to Nairobi, Distance to Closest City, Distance to Kenya Border, Population, Years of Education, Agricultural Employment, Poverty, Nutritional Poverty
Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) estimates the regression without controls or fixed effects. The result suggest that for the average grid cell after the logging ban, deforestation in protected areas is an additional 15.52m^2 lower than in non-protected areas. This is marginally significant at the 10% level. Prior to the ban however, the estimated average effect of protecting an area is 10.20m^2 less deforestation than non-protected areas on average, significant at the 5% level. Comparing these two effects suggests that the logging ban may have an economically significant impact in Kenya.

To account for the observable characteristics which may affect deforestation differently over time as a function of distance, I incorporate time-invariant controls and a vector of time-varying controls. Note that time-invariant controls will not affect the difference in differences estimate. The results, presented in column (2) of Table 4.2, suggest that for the average grid cell after the ban, deforestation is 13.67m^2 lower than non-protected areas. However, the coefficient is statistically insignificant.

Next, I incorporate grid cell fixed effects to control for any time-invariant unobservable characteristics which may be correlated with deforestation. Note that this regression omits the average effect of protected areas on deforestation because it is time invariant and therefore partialled out by the grid cell fixed effects. The results, presented in column (3), suggest that for the average grid cell after the ban, deforestation in protected areas is an additional 13.34m^2 lower than non-protected areas. However, the coefficient remains statistically insignificant.

Then, I introduce year fixed effects in column (4) to control for time-varying unobservable factors that affect all grid cells equally. Note that this regression omits the average effect of the treatment period on deforestation because it is has perfect collinearity with the year fixed effects. I incorporate both grid cell and year fixed effects and present the results in column (5). Together, these results suggest that for the average grid cell after the logging ban, deforestation in protected areas decreases by an additional 13.43m^2 to 13.12m^2, relative to non-protected areas. However the coefficients remain statistically insignificant.

The estimation strategy up until this point relies on time variation in the control variables. This is because the difference in differences strategy is identifying whether these control variables affect deforestation differently over time. As explained in the data section, only population, education, and agricultural employment vary over time. This does not incorporate the fact that time-invariant controls may have a differential effect on deforestation within each year. However, this can not be estimated under the original specification, Equation 4.1. To account for this, I interact time-invariant controls with year dummies and present the result in column (6) of Table 4.2. The results suggest that for the average grid cell after the logging ban, deforestation in protected areas is an additional 7.992m^2 lower than in non-protected areas. However, the estimate remains statistically insignificant.

Altogether, these results suggest that the logging ban has not had a statistically significant effect on the additional amount of deforestation occurring in protected areas within Kenya.

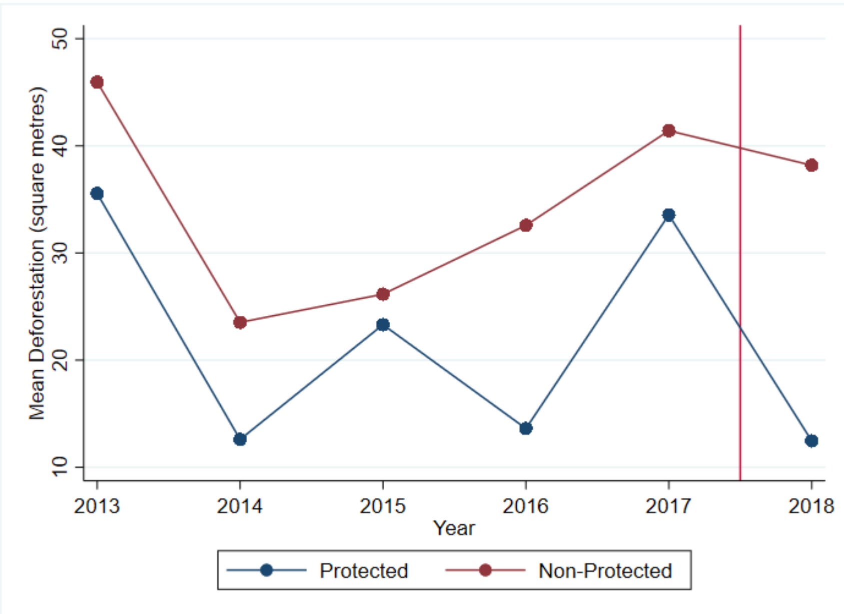
4.4 Pre-Trends

The difference in differences identification strategy assumes parallel trends in the outcome between treated and control grid cells before the treatment period. In this case, we would expect deforestation to have changed by the same amount for both protected and non-protected areas in 2018 had the ban not been implemented. This is expressed mathematically in Equation 4.2 where $d^0_{g,t}$ is the square metres of deforestation in grid cell g in year t without treatment.

$$\begin{aligned} &E(E(d^0_{g,t}|P_g = 1, T_t = 1) - E(d^0_{g,t}|P_g = 1, T_t = 0)) - \\ &E(E(d^0_{g,t}|P_g = 0, T_t = 1) - E(d^0_{g,t}|P_g = 0, T_t = 0)) = 0 \end{aligned} \tag{4.2}$$

As a preliminary assessment of whether the parallel trends assumption holds, I plot the mean deforestation within each year for both protected and non-protected areas in Figure 4.1.

Figure 4.1: Trends in Protected and Non-Protected Areas



The plot suggests that there is some evidence that the parallel trends assumption holds. There are parallel trends between 2013 and 2015, and this continues if the trends are extrapolated to 2017. However there is a significant divergence between the protected and non-protected areas in 2016. Based on this preliminary analysis, we can not be certain if there are parallel trends between protected and non-protected areas.

4.4.1 Quadratic Trend Estimation

To better understand whether there are pre-trends in deforestation before the ban, I regress deforestation on a quadratic function of year and a treatment period dummy. I perform this separately for protected and non-protected areas. This regression modelled in Equation 4.3 and the results are presented in Table 4.3. I apply the same methodology with a linear and cubic trend displayed in Appendix Table B.4, but the estimates are insignificant for these specifications.

$$d_{gt} = \beta_1 T_t + \beta_2 year + \beta_3 year^2 \tag{4.3}$$

Table 4.3: Kenya Deforestation Pre-Trends

	Non-Protected	Protected
	(1)	(2)
	Loss (m^2)	Loss (m^2)
Year	-28.43***	-28.31*
	(9.306)	(16.69)
Year x Year	4.737***	4.669*
	(1.551)	(2.752)
Logging Ban (t = 2018)	-28.89**	-43.05*
	(14.64)	(24.10)
Constant	67.10***	57.30**
	(12.26)	(22.55)
N	31782	8802

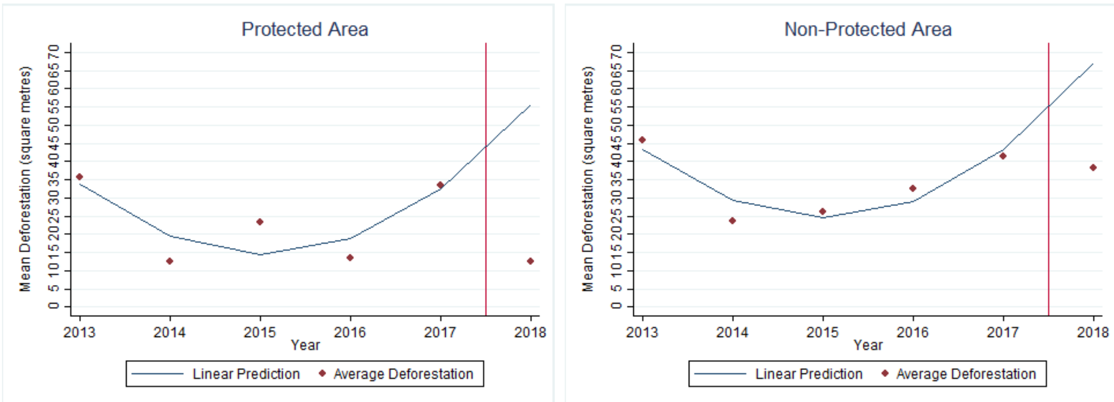
Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All coefficients are significant in both regressions at the 10% level or higher. This suggests that deforestation follows a quadratic trend in both protected and non-protected areas prior to the treatment. Moreover, these estimated quadratic trends are very similar for protected and non-protected areas, supporting the parallel trends assumption. It also suggests that there is a statistically significant deforestation reduction in 2018 compared to the estimated quadratic trend for both protected and non-protected areas. This is what we expect in protected areas given the logging ban's implementation, but it is a surprise to also see this effect in non-protected areas.

However, the magnitude of the estimated reduction in 2018 is 43.05m^2 in protected areas compared with 28.89m^2 in non-protected areas. This suggests that the break in the trend is more economically significant in protected areas. I perform a Chow test to determine if the separate regressions for protected and non-protected areas are statistically different from a pooled regression. The test statistic is significant at the 10% level. As the year coefficients are so similar across protected and non-protected areas, this provides some evidence that the coefficients on the treatment period dummy are statistically different for protected and non-protected areas.

I plot the quadratic trend regression and yearly mean deforestation for both protected and non-protected areas in Figure 4.2 to illustrate the effect of the ban.

Figure 4.2: Deforestation Pre-Trends in Kenya



(a) Protected Areas (b) Non-Protected Areas

4.4.2 Event Study

To further analyse trends prior to the treatment, I perform an event study excluding observations in 2018. This will estimate the differential amount of deforestation due to an area being protected in every year between 2013 and 2016, relative to 2017; the period just before the ban. This will identify whether the estimated average treatment effect is biased due to an existing pre-trend, such that deforestation in protected areas changes differently to deforestation in non-protected areas over time without treatment.

I specify the event study equation as:

$$d_{gt} = \sum_{t=2013}^{2016} \beta_{1,t} Y_t * P_g + \beta_2 P_g + \sum_{t=2013}^{2016} \beta_{3,t} Y_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \tag{4.4}$$

The outcome variable, d_{gt}, is square metres deforested within grid cell g in year t. P_g is the treatment unit variable equal to one if the grid cell is located within a protected area and zero otherwise. Y_t is a year dummy variable equal to one if the observation is in year t and zero otherwise. To control for geographical, demographic and socioeconomic covariates, I include time-invariant controls (X_g) and a vector of time-varying controls ($\mu' X_{gt}$). I also incorporate year fixed effects, ϕ_t, and grid cell fixed effects, γ_g, in some specifications. I present the results in Table 4.4.

Column (1) estimates the event study with year fixed effects, accounting for any contemporaneous factors affecting all grid cells equally. The differential effect of protected areas on deforestation in each year is not significant relative to the differential effect of protected areas in 2017. I incorporate controls and grid cell fixed effects in column (2) and (3) to account for omitted grid cell characteristics. This does not change the significance of the interaction coefficients. Note that incorporating grid cell fixed effects partials out the effect of protected areas because it is time-invariant.

I also estimate the event study using time-invariant controls interacted with year dummies. The results, presented in column (4), show that the significance of the interaction coefficients does not change. I conclude that there are no trends in the effect of protected areas on deforestation in the period before the ban and hence the parallel trends assumption is supported. Therefore, the difference in differences strategy will identify the effect of the logging ban in Kenya, rather than an existing pre-trend affecting protected areas differently to non-protected areas over time.

4.5 Robustness Checks

4.5.1 Deforested Sample

The estimated logging ban treatment effect may be affected by the proportion of grid cells which do not experience any deforestation in the sample. If wood fuel producers do not have a high propensity to deforest these grid cells prior to the ban, the ban's enforcement will likely not focus on these grid cells. To analyse whether this changes the average treatment effect, I estimate the difference in differences strategy modelled in Equation 4.1 using a sample of grid cells which experience any deforestation between 2013 and 2018. The results are shown in Appendix Table C.1. Although the magnitude of the coefficients change, the estimated average treatment effect of the logging ban remains insignificant. Incorporating controls, grid cell fixed effects and year fixed effects does not change the significance of the estimate. This supports the evidence that the logging ban has not had a statistically significant effect on the additional amount of deforestation occurring in protected areas within Kenya.

Table 4.4: Kenya Event Study

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
Protected Area x 2013 Year Dummy	-2.546	2.895	1.939	12.75
	(18.19)	(18.73)	(19.12)	(19.90)
Protected Area x 2014 Year Dummy	-3.066	3.053	2.097	1.477
	(15.20)	(15.40)	(15.81)	(17.21)
Protected Area x 2015 Year Dummy	5.016	10.69	9.357	9.712
	(17.38)	(17.91)	(18.06)	(19.38)
Protected Area x 2016 Year Dummy	-11.10	-9.909	-9.909	-15.42
	(15.06)	(14.95)	(14.95)	(17.79)
Protected Area	-7.859	-5.137		
	(13.35)	(13.79)		
2013 Year Dummy	4.542	-3.239	-3.154	184.0*
	(8.873)	(9.230)	(10.23)	(110.7)
2014 Year Dummy	-17.89**	-27.10***	-27.01***	-38.95
	(8.319)	(9.172)	(9.759)	(59.84)
2015 Year Dummy	-15.26*	-23.30**	-22.65**	-12.33
	(8.468)	(9.610)	(9.627)	(74.26)
2016 Year Dummy	-8.835	-9.652	-9.652	-54.74
	(8.496)	(8.747)	(8.746)	(67.43)
Constant	41.41***	105.7***	54.61***	39.29***
	(6.722)	(22.54)	(19.99)	(5.109)
N	33820	32550	32550	32550
Controls	No	Yes	Yes	No
Grid Cell Fixed Effect	No	No	Yes	Yes
Year FE x Controls	No	No	No	Yes

Controls: Ruggedness, Slope, Maize Productivity, Distance to Dirt Road, Distance to Nairobi, Distance to Closest City, Distance to Kenya Border, Population, Years of Education, Agricultural Employment, Poverty, Nutritional Poverty
Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Event study estimation excludes observations in 2018 from the sample
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5.2 Tobit Model

The sample used for analysis contains gross deforestation measured in square metres for every year between 2013 and 2018. However, in each year, the majority of grid cells in this sample do not experience any deforestation. These grid cells could potentially experience a gain in forest cover, which could also be interpreted as negative gross deforestation. However, the gross deforestation variable does not take on negative values and is therefore censored at zero. To account for these censored values, I estimate the difference in differences equation using a tobit model specified in Equation 4.5. This incorporates controls and year fixed effects, but I am unable to include grid cell fixed effects due to computational constraints.

$$d^*_{gt} = \beta_1 P_g * T_t + \beta_2 P_g + \beta_3 T_t + X_g + \mu\prime X_{gt} + \phi_t + \epsilon_{gt} \tag{4.5}$$

$$d_{gt} = d^*_{gt} \text{ if } d^*_{gt} \geq 0, \quad d_{gt} = 0 \text{ if } d^*_{gt} < 0 \tag{4.6}$$

I present the results in Appendix Table C.2. The magnitude of the coefficients have changed significantly compared to the original results due to the number of cells which do not experience deforestation. However, the estimated average treatment effect of the logging ban remains insignificant. This further supports the evidence that the logging ban has not had a statistically significant effect on the additional amount of deforestation occurring in protected areas within Kenya.

The tobit results with year fixed effects should be treated with caution because the maximum likelihood estimator is biased and inconsistent (Greene 2004). It is econometrically sound to estimate a panel tobit regression incorporating random effects instead. However, the assumption for the random effects model does not hold because there is correlation between the unobserved grid cell heterogeneity and the independent variables I use. For example, the distance from the city centre could be correlated with the presence of higher quality tress which I do not observe in the data.

4.5.3 Probability Model

If the ban is enforced by monitoring the amount of deforestation within certain areas, producers may deforest the same area of logs but do so over a larger area and hence a larger number of grid cells. This would enable the producer to avoid detection while maintaining a consistent supply of timber. This could create unintended adverse consequences because it is more difficult to replenish forest cover over larger areas. To test whether the ban affects the probability that a grid cell is deforested, I estimate the main difference in differences strategy using a linear probability model specified as:

$$P(df_{gt} = 1) = \beta_1 P_g * T_t + \beta_2 P_g + \beta_3 T_t + X_g + \mu \prime X_{gt} + \phi_t + \epsilon_{gt} \tag{4.7}$$

$$\text{where } df_{gt} = \begin{cases} 1 \text{ if } d_{gt} > 0 \\ 0 \text{ otherwise} \end{cases} \tag{4.8}$$

I present the results in Appendix Table C.3. They suggest that for the average grid cell after the ban, the probability of deforestation decreases by an additional 0.259 percentage points in protected areas compared with non-protected areas. However, this coefficient is statistically insignificant. Incorporating controls or fixed effects does not change the coefficient's significance. Therefore, the logging ban does not have any impact on the additional probability that a protected area experiences deforestation. This falsifies the hypothesis that there could be a greater chance of a grid cell experiencing deforestation as a result of the ban. However, it further supports the evidence that the logging ban has not had a statistically significant effect on the additional amount of deforestation occurring in protected areas within Kenya.

4.5.4 Spatial Autoregressive Model

The models I have used for estimation assume that each observation is independent of each other across grid cells and time. However, this assumption is unlikely to hold because wood fuel producers do not choose to deforest grid cells randomly but rather to deforest large areas at once. Therefore, the square metres deforested within a grid cell will be dependent on the square metres deforested in surrounding grid cells. This motivates the use of a spatial autoregressive model which estimates spatial dependence by incorporating a spatially lagged dependent variable. The spatial autoregressive difference in differences model incorporating fixed effects is specified as:

$$d_{gt} = \lambda \boldsymbol{W} d_{gt} + \beta_1 P_g * T_t + \beta_2 P_g + \beta_3 T_t + \mu \prime X_{gt} + \gamma_g + u_{gt} \tag{4.9}$$

$$u_{gt} = \rho \boldsymbol{M} u_{gt} + v_{nt} \tag{4.10}$$

In this specification, u_{gt} is a spatially lagged error and $v_{n,t}$ is a vector of disturbances independent and identically distributed (i.i.d.) across grid cells and time with mean zero and variance σ^2. **W** and **M** are spatial weighting matrices constructed using the inverse Euclidean distance from grid cell g to every other kth grid cell for all g grid cells in the sample. I estimate this model and present the results in Appendix Table C.4.

The results suggest that for the average grid cell after the logging ban, deforestation in protected areas is an additional 14.42m^2 lower than in non-protected areas. However, the estimate is statistically insignificant. Moreover, the spatially lagged dependent variable is statistically significant at the 1% level, suggesting that deforestation within grid cells surrounding grid cell g have significant explanatory power for deforestation in grid cell g. Incorporating controls, year fixed effects, and time invariant controls interacted with year dummies, does not change the significance of the average treatment effect. This further supports the evidence that the logging ban has not had a statistically significant effect on the additional amount of deforestation occurring in protected areas within Kenya.

There is strong evidence that the logging ban implemented by the Kenyan Government in 2018 has not had a significant effect on deforestation in targeted areas. This could be because the ban is ineffective in actuality due to poor monitoring, limited enforcement, and possibly corruption. However, the evidence may be skewed by measurement error in the treatment variable because theoretically treated grid cells constitute non-protected areas. This is unable to be identified in the data and attenuates the logging ban's impact in Kenya.

Chapter 5

Uganda

5.1 Identification Strategy

I model the spillover effect of the logging ban on the average square metres of deforestation within a hectare grid cell in Uganda. I apply a difference in differences identification strategy. I exploit exogenous temporal variation using the ban's implementation in 2018 and spatial variation using distance from the closest Kenya border crossing.

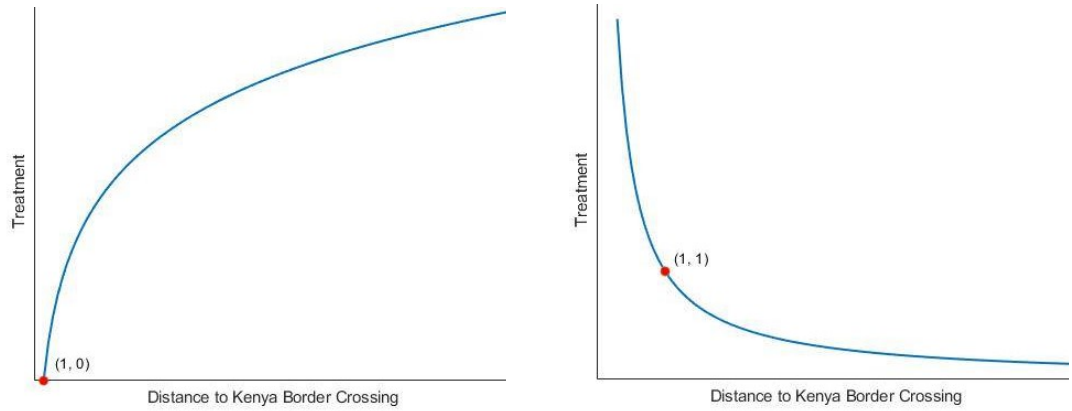
This spatial variation is measured as the Euclidean distance to the closest Kenya border crossing (access points into Kenya from Uganda by road as shown in F.6). Wood fuel producers in Uganda have a higher marginal cost of production due to higher transportation costs for every extra kilometre they must travel to access wood fuel markets in Kenya. I anticipate that producers will target forests closest to the border to keep production costs low, resulting in a greater likelihood of these forests being deforested due to the logging ban in Kenya.

To model this empirically, I assume that a forested grid cell in Uganda is treated to the largest extent at the Kenya border crossing where the marginal cost of production is lowest. The extent of treatment for a grid cell then decreases as a function of its Euclidean distance to the Kenya border crossing. To estimate this treatment as a linear function would be unrealistic because this assumes that a grid cell's deforestation due to the ban responds to the same extent for every extra kilometre away it is from the border crossing.

As I anticipate that deforestation in Uganda will mainly be affected within grid cells close to the Kenya border crossing, I use a natural logarithmic and inverse transformation of the treatment variable. This is represented graphically in Figure 5.1. The logarithmic function increases at a decreasing rate while the inverse function decreases at a decreasing rate. These two functions both exhibit the same second order property, such that grid cells are treated to a lesser extent for every extra kilometre they are away from the Kenya border crossing.

Temporal variation is derived from the implementation of the ban in February 2018. The

Figure 5.1: Treatment Functions of Distance to the Kenya Border Crossing



(a) Logarithmic Treatment

(b) Inverse Treatment

pre-treatment period is therefore 2013 to 2017, while the treatment period is 2018.

5.2 Balance of Covariates

Grid cell characteristics may affect deforestation differently over time as a function of distance from the Kenya border crossing. If this is the case, the estimated average treatment effect is biased, because it is identifying the differential effect of grid cell characteristics which affect deforestation differently over time, rather than the effect of the ban itself.

If observable characteristics are significantly different between protected and non-protected areas, these may affect deforestation differently over time. To determine if this is the case, I could perform a difference in means test as I did for Kenya's protected and non-protected areas. However, the treatment variable is continuous and every grid cell in the sample is treated as a function of distance, so to define a treatment and control group would not be reflective of the identification strategy. If $g(D_g)$ defines treatment equal to one based on an arbitrary distance to the Kenya border H then

$$g(D_g) = \begin{cases} 0 \text{ if } D_g \geq H \\ 1 \text{ if } D_g < H \end{cases} \tag{5.1}$$

but then $\lim_{D_g \to H^-} f(D_g) = \lim_{D_g \to H^+} f(D_g)$.

Although the difference in means test requires the use of an arbitrary threshold, it could provide insight as to whether observable characteristics are a function of distance to the Kenya border crossing. I therefore perform a difference in means test using both a 10th percentile threshold and 25th percentile threshold, and present the results in Table 5.1

and Appendix Table D.1. The results suggest that there is a significant difference between all observable characteristics as a function of distance and this could affect deforestation differently over time.

Table 5.1: Uganda Difference in Means Tests at the 10th Percentile

	Below 10%		Above 10%		Difference in Means	
	Count	Mean	Count	Mean	Difference	P-Value
Loss (m^2)	28418	21.16467	255768	35.10259	-13.94***	(0.000)
Loss 2013 (m^2)	28418	78.74559	255768	103.5037	-24.76***	(0.000)
Loss 2014 (m^2)	28418	3.751897	255768	7.434207	-3.682*	(0.012)
Loss 2015 (m^2)	28418	8.617094	255768	14.88333	-6.266**	(0.002)
Loss 2016 (m^2)	28418	7.586665	255768	29.23288	-21.65***	(0.000)
Loss 2017 (m^2)	28418	16.61517	255768	36.7724	-20.16***	(0.000)
Loss 2018 (m^2)	28418	11.67162	255768	18.78896	-7.117**	(0.003)
Loss 2013 - 2017 (m^2)	28418	115.3164	255768	191.8266	-76.51***	(0.000)
Forest 2012	28418	.9416026	255768	.928663	0.0129***	(0.000)
Protected Area	28418	.5898022	255768	.3492657	0.241***	(0.000)
Ruggedness	28418	215699.1	255768	100776.6	114922.4***	(0.000)
Slope (%)	28418	9.046278	255768	10.74016	-1.694***	(0.001)
Maize Productivity	28418	2189.225	255768	2581.055	-391.8***	(0.000)
Distance to Dirt Road (km)	28418	45.75616	255768	145.9092	-100.2***	(0.000)
Distance to Improved Road (km)	28418	48.64664	255768	147.0479	-98.40***	(0.000)
Distance to Closest City (km)	28418	32.6086	255768	33.3519	-0.743***	(0.000)
Distance to Kampala (km)	28418	175.9	255768	196.8518	-20.95***	(0.000)
Distance to Nairobi (km)	28418	430.298	255768	673.7056	-243.4***	(0.000)
Population	28418	193.3739	255768	123.7255	69.65***	(0.000)
Years of Education	27909	5.862993	254645	6.296129	-0.433***	(0.000)
Agricultural Employment (%)	27909	.3257013	254645	.2841124	0.0416***	(0.000)
Poverty (%)	27909	.2973199	254645	.2099332	0.0874***	(0.000)
N	284186					

Data is separated by the 10th percentile of Euclidean distance to Kenya border crossing
126.32km is the 10th percentile Euclidean distance to Kenyan border crossing
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Results

I specify the logarithmic difference in differences equation as:

$$d_{gt} = \beta_1 ln(D_g) * T_t + \beta_2 ln(D_g) + \beta_3 T_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \quad (5.2)$$

I specify the inverse difference in differences equation as:

$$d_{gt} = \beta_1 (D_g)^{-1} * T_t + \beta_2 (D_g)^{-1} + \beta_3 T_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \quad (5.3)$$

The outcome variable, d_{gt}, is square metres deforested within grid cell g in year t. D_g is the treatment variable, continuous Euclidean distance to the Kenya border crossing. T_t is the treatment period dummy variable equal to one if the observation is in 2018 and zero otherwise. The interaction of a function of D_g and T_t identifies the treatment effect where β_1 is the difference in differences estimator. To control for geographical, demographic and socioeconomic covariates, I include time-invariant controls (X_g) and a vector of time-variant controls ($\mu\prime X_{gt}$). I have also incorporated grid cell and year fixed effects, γ_g and ϕ_t, in some specifications.

I estimate the average treatment effect using the difference in differences models specified in Equations 5.2 and 5.3, clustering standard errors at the grid cell level. Clustering at the grid cell level accounts for autocorrelated errors within each grid cell. This produces a more robust estimate reflective of the treatment effect within the population of interest. I present the results of the estimation in Table 5.2.

Table 5.2: Impact of Logging Ban in Uganda

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)	(6) Loss (m^2)
Log Specification						
ln(Distance to Kenya Crossing) x Logging Ban	-1.007	-2.475***	-2.498***	-3.252***	-2.170***	-5.387***
	(0.757)	(0.782)	(0.808)	(0.799)	(0.816)	(1.498)
ln(Distance to Kenya Border Crossing)	-5.802***	-3.934***		-3.117***		
	(0.405)	(0.792)		(0.799)		
Logging Ban (t = 2018)	-13.20***	-5.055	-0.501			57.17***
	(4.505)	(4.551)	(4.706)			(24.99)
Constant	68.85***	105.1***	88.38***	99.21***	47.05***	34.62***
	(2.351)	(7.805)	(14.47)	(7.754)	(13.65)	(0.865)
Inverse Specification						
(Distance to Kenya Border Crossing)$^{-1}$ x Logging Ban	87.97***	109.5***	117.7***	118.8***	106.7***	37.27*
	(18.67)	(20.57)	(21.28)	(21.32)	(20.64)	(1.498)
(Distance to Kenya Border Crossing)$^{-1}$	-134.9***	-17.32		-26.57**		
	(17.44)	(12.46)		(12.75)		
Logging Ban (t = 2018)	-19.31***	-19.48***	-15.02***			32.45
	(0.840)	(0.876)	(0.885)			(24.70)
Constant	37.68***	91.75***	89.77***	86.52***	46.04***	34.62***
	(0.439)	(6.677)	(14.29)	(6.772)	(13.70)	(0.865)
N	1705116	1695324	1695324	1695324	1695324	1695324
Controls	No	Yes	Yes	Yes	Yes	No
Grid Cell Fixed Effect	No	No	Yes	No	Yes	Yes
Year Fixed Effect	No	No	No	Yes	Yes	Yes
Year FE x Controls	No	No	No	No	No	Yes

Controls: Ruggedness, Slope, Maize Productivity, Distance to Dirt Road, Distance to Kampala, Distance to Closest City, Population, Years of Education, Agricultural Employment, Poverty
Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) estimates the regression without controls or fixed effects. Interpreting the logarithmic treatment function, the results suggest that after the ban, there is an additional 0.010m^2 of deforestation for every five kilometre increase in proximity to the Kenya border crossing. Note that five kilometres is one percent of the maximum distance from the Kenya border crossing within the data. However, this result is not statistically significant. Interpreting the inverse treatment function, the results suggest that for the average grid cell after the ban, there is an additional 87.97m^2 of deforestation for every unit increase in the inverse treatment. This can be interpreted as the additional amount of deforestation, after the ban, one kilometre away from the Kenya border crossing compared with the maximum distance, 505 kilometres. Thus, for the average grid cell after the ban, there is an additional 87.97m^2 of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. This is statistically significant at the 1% level.

To account for the observable characteristics which may affect deforestation differently over time as a function of distance from the border crossing, I incorporate time-invariant controls and a vector of time-varying controls. Note that time-invariant controls will not affect the difference in differences estimate. The results are presented in column (2) of Table 5.2. Interpreting the logarithmic treatment function, the results suggest that for the average grid cell after the ban, there is an additional 0.025m^2 of deforestation for every five kilometre increase in proximity to the Kenya border crossing. Interpreting the inverse treatment function, the results suggest that for the average grid cell after the ban, there is an additional 109.5m^2 of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. The results are statistically significant at the 1% level for both the logarithmic and the inverse treatment functions.

Next, I incorporate grid cell fixed effects to control for any time-invariant unobservable characteristics which may be correlated with deforestation. The results are presented in column (3) of Table 5.2. Note that this regression omits the effect of the respective treatment functions on deforestation because they are time invariant and therefore partialled out by the grid cell fixed effects. Interpreting the logarithmic treatment function, the results suggest that for the average grid cell after the ban, there is an additional 0.025m^2 of deforestation for every five kilometre increase in proximity to the Kenya border crossing. Interpreting the inverse treatment function, the results suggest that for the average grid cell after the ban, there is an additional 117.7m^2 of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. The results are statistically significant at the 1% level for both the logarithmic and the inverse treatment functions.

Then, I introduce year fixed effects in column (4) to control for time-varying unobservable factors that affect all grid cells equally. Note that this regression omits the average effect of the treatment period on deforestation because it is has perfect collinearity with the year fixed effects. I incorporate both grid cell and year fixed effects and present the results in column (5). Interpreting the logarithmic treatment function, the results suggest that for the average grid cell after the ban, there is an additional $0.022m^2$ to $0.033m^2$ in deforestation for every five kilometre increase in proximity to the Kenya border crossing. Interpreting the inverse treatment function, the results suggest that for the average grid cell after the ban, there is an additional $106.7m^2$ to $118.8m^2$ of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. The results are statistically significant at the 1% level for both the logarithmic and the inverse treatment functions.

The estimation strategy up until this point relies on time variation in the control variables. This is because the difference in differences strategy is identifying whether these control variables affect deforestation differently over time. As explained in the data section, only population, education, and agricultural employment vary over time. However, time-invariant controls may have a differential effect on deforestation within each year which can not be estimated under the original specifications. To account for this, I interact time-invariant controls with year dummies and present the result in column (6).

Interpreting the logarithmic treatment function, the results suggest that for the average grid cell after the ban, there is an additional 0.054^2 in deforestation for every five kilometre increase in proximity to the Kenya border crossing. The results for the logarithmic treatment function are statistically significant at the 1% level. Interpreting the inverse treatment function, the results suggest that for the average grid cell after the ban, there is an additional $37.27m^2$ of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. The results for the inverse treatment function are statistically significant at the 10% level.

The logarithmic treatment function results suggest that for the average grid cell after the ban, there is an additional $0.0224m^2$ to $0.054m^2$ reduction in deforestation for every five kilometre increase in distance from the Kenya border crossing. The inverse treatment function results suggest that for the average grid cell after the ban, there is an additional $37.27m^2$ to $118.8m^2$ of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. Altogether, these results present strong evidence for spillover effects in Uganda as a result of the logging ban in Kenya.

5.4 Non-Parametric Estimation

5.4.1 Model

Although the difference in differences analysis using continuous treatment functions provides strong evidence of spillover effects, using a continuous function has limitations. The first ten kilometres may be very heavily affected but areas beyond ten kilometres may not be affected at all, for example. However, the continuous treatment function is unable to identify this stark treatment effect between different distances. To alleviate this limitation and further investigate the spillover effects, I estimate a non-parametric difference in differences strategy using ten kilometre distance intervals to the Kenya border crossing.

To do this, I firstly construct a set of ten kilometre intervals for distance to the Kenya border crossing, $I = \{i \,|\, i \in \mathbb{N}^* \,,\, i \leq 50\}$. I then construct dummy variables $D_{g,i}$ equal to one if grid cell g lies within interval i and zero otherwise. The maximum value of distance to the Kenya border crossing is 505km, so I have estimated intervals up until 500km to avoid perfect collinearity. I interact every dummy variable with the treatment variable to identify, after the ban, the additional square metres of deforestation within each interval i compared with the omitted grid cells. I specify the non-parametric difference in differences equation as:

$$d_{gt} = \sum_{i \in I} D_{g,i} * T_t + \sum_{i \in I} \beta_{2,i} D_{g,i} + \beta_{3,i} T_t + X_g + \mu\prime X_{gt} + \phi_t + \epsilon_{gt} \tag{5.4}$$

A plot of the the estimated treatment coefficients using the interval set I shows that the treatment effects within the intervals farthest from the border are insignificant (Figure D.1). I define a set of interval sets $I_p = \{i \mid i \in \mathbb{N}^* \,,\; i \in p\}$ where p is the percentage of grid cells closest to the Kenya border crossing and an element of the set $P = \{10,$ $25,\ 50,\ 75,\ 90\}$. Each interval set estimates with a different base group, changing the estimated treatment coefficients for every $i \in I_p \; \forall p$ compared with each $i \in I$. I specify the non-parametric difference in differences equation with percentile restrictions as:

$$d_{gt} = \sum_{i \in I_p} D_{g,i} * T_t + \sum_{i \in I_p} \beta_2 D_{g,i} + \beta_3 T_t + X_g + \mu\prime X_{gt} + \phi_t + \epsilon_{gt} \quad \forall p \in P \tag{5.5}$$

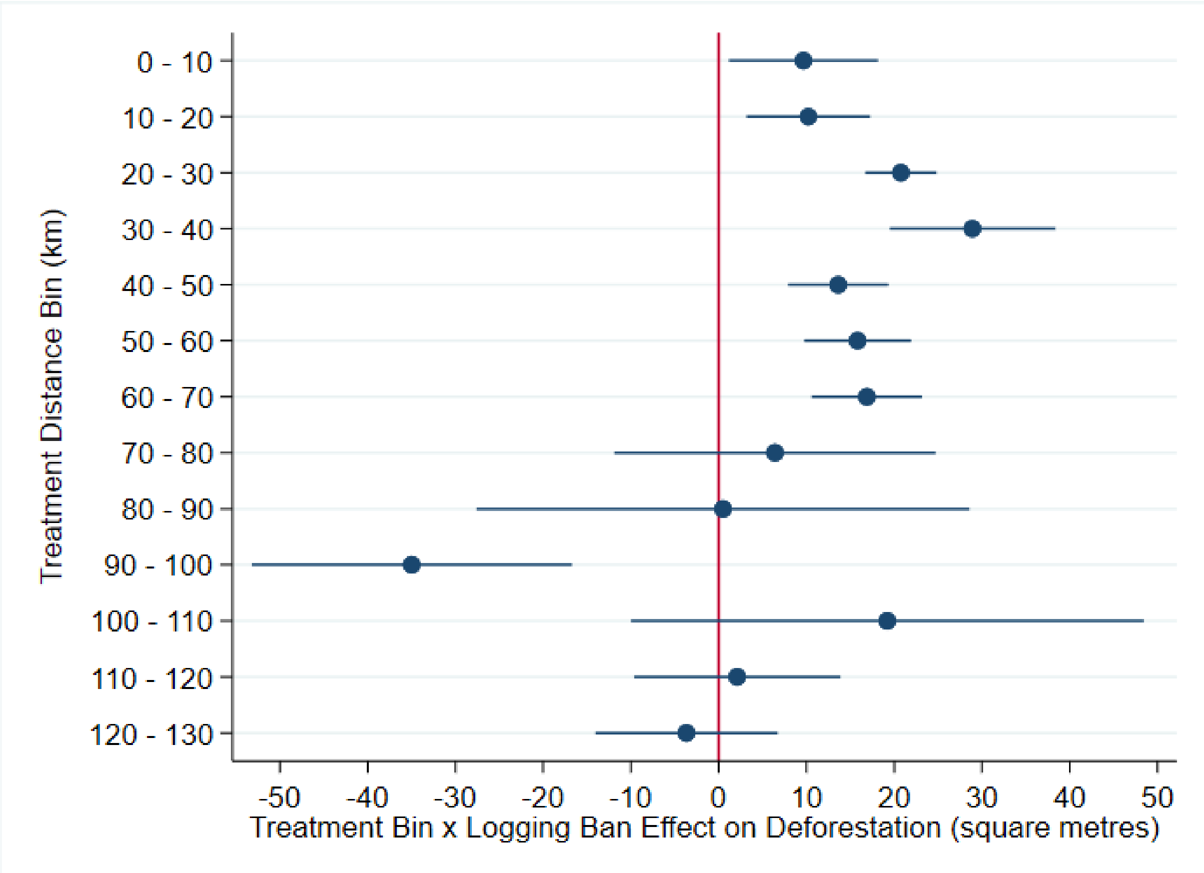
I do not incorporate grid cell fixed effects due to computational constraints.

5.4.2 Results

A plot of the estimated coefficients using the interval set I_p with $p \in P = \{10, 25, 50, 75, 90\}$ shows that the treatment effect within the intervals farthest from the border crossing remain mostly insignificant (Figure D.2 - D.5). However, there are some significant negative coefficients for intervals farther than 100km from the Kenya border crossing. This could be because producers are choosing to switch their deforestation from forests farther away from the border to forests closer to the border. Although a possibility, there are very few negative significant coefficients and they do not exhibit any trends to support the hypothesis that producers are switching in a consistent manner. It is therefore more likely that there is an exogenous event occurring within the interval during the treatment period or that it is estimated as significant by chance due to the random sample of grid cells.

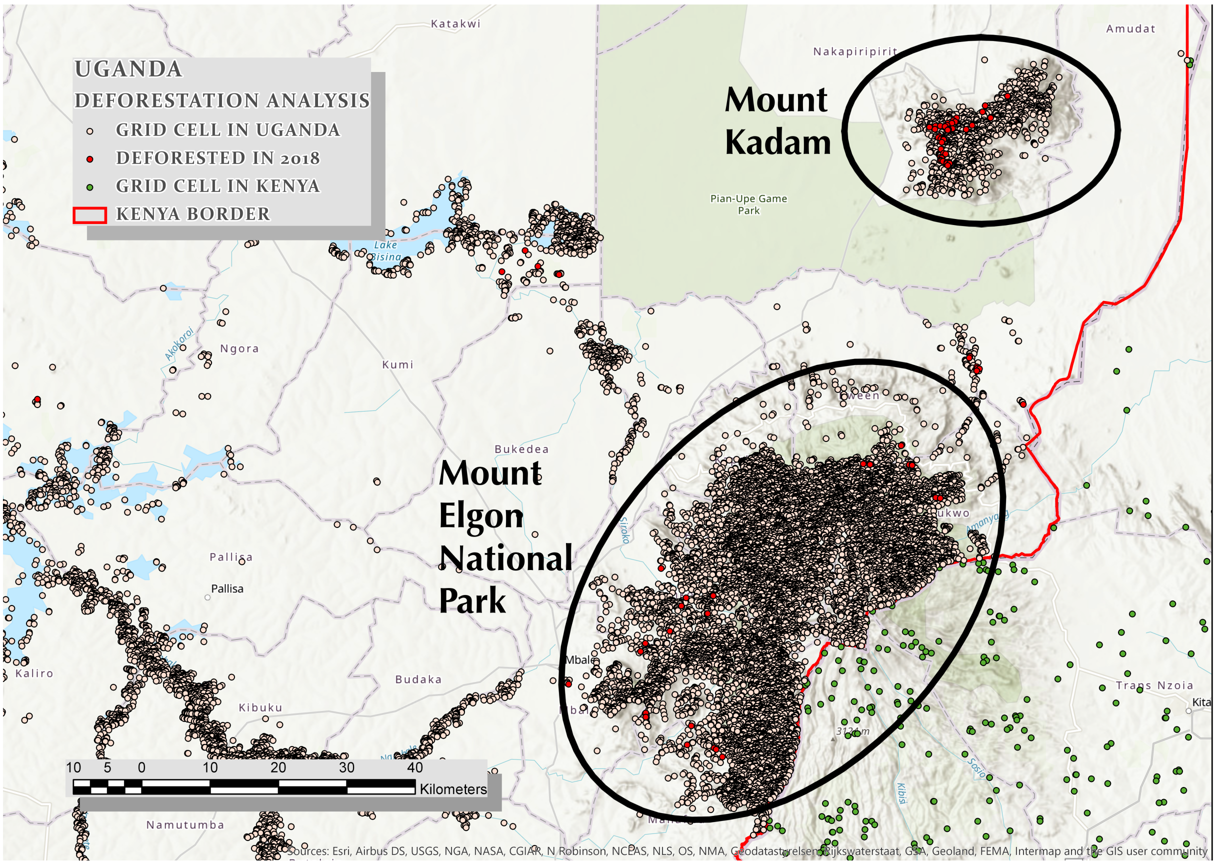
In light of weak evidence for spillover effects beyond 100km from the Kenya border crossing, I report my main non-parametric specification using the the closest 10% of cells to the Kenya border crossing; the interval set I_p where $p = 10$. This is shown in Figure 5.2. The graph presents, after the ban, the additional square metres of deforestation within each interval i compared with the grid cells further than 130 kilometres from the border. The estimated coefficients are plotted for each bin with a 95% confidence interval.

Figure 5.2: Impact of Logging Ban in Uganda (Interval Estimation)



The results show that, after the ban, there are additional square metres of deforestation within 70 kilometres of the Kenya border crossing, compared with the grid cells further than 130 kilometres away. This is strongest in magnitude within the 20 to 40 kilometre intervals from the border crossing. I investigate these intervals geographically and find that there is a substantial amount of deforestation on the outskirts of Mount Elgon National Park and on Mount Kadam. These are both protected areas within Uganda, and it is therefore unlikely to experience deforestation in the absence of spillover effects from the logging ban in Kenya (Planet 2019). A map of deforestation in 2018 within Uganda highlighting Mount Kadam and Mount Elgon National Park is displayed in Figure 5.3.

Figure 5.3: Uganda Deforestation: Mount Kadam and Mount Elgon National Park



The results also show that the estimated average treatment effect is insignificant for all intervals beyond 70 kilometres within the closest 10% of grid cells, except between 90 and 100 kilometres. Within this interval, the average treatment effect of the logging ban is, after the ban, a 35 square metre additional reduction in deforestation, relative to grid cells further than 130km away. Although this interval is relatively close to the border crossing and we hypothesise that there could be positive spillover effects, the result within this interval contradicts this hypothesis. This specification is unable to identify the mechanism behind this effect, but it does validate the use of the non-parametric identification strategy alongside the use of continuous treatment functions.

The non-parametric difference in differences strategy identifies positive spillover effects in Uganda within seventy kilometres of the Kenya border crossing on Mount Kadam and in Mount Elgon National Park. This supports the results from the difference in differences using continuous treatment functions. Altogether, these results support the strong evidence for spillover effects in Uganda as a result of the logging ban in Kenya.

5.5 Pre-Trends

The difference in differences identification strategy assumes parallel trends in the outcome for every extent of treatment before the treatment period. In this case, we would expect deforestation to have changed by the same amount for any function of two different distances D_g, $f(D_g) = x$ and $f(D_g) = y$ where $D_g \in D = [0, 505]$, without the treatment. This is expressed mathematically in equation 5.6 where $d^0_{g,t}$ is the square metres of deforestation in grid cell g in year t without treatment.

$$\begin{aligned} E(E(d^0_{g,t}|f(D_g) = x, T_t = 1) - E(d^0_{g,t}|f(D_g) = x, T_t = 0)) - \\ E(E(d^0_{g,t}|f(D_g) = y, T_t = 1) - E(d^0_{g,t}|f(D_g) = y, T_t = 0)) = 0 \end{aligned} \tag{5.6}$$

I am unable to perform a preliminary assessment of the parallel trends assumption by plotting mean deforestation for treated and control units. As previously discussed, the treatment variable is continuous and every grid cell in the sample is treated as a function of distance, so to define a treatment and control group would not reflect the identification strategy.

5.5.1 Event Study

To analyse trends prior to the treatment, I perform an event study excluding observations in 2018. This will estimate the differential amount of deforestation as a continuous function of distance to the Kenya border crossing in every year between 2013 and 2016, relative to 2017; the period just before the ban. This will identify whether the estimated average treatment effect is biased due to an existing pre-trend, such that deforestation changes differently as a function of distance to the Kenya border crossing over time without treatment.

I specify the logarithmic event study as:

$$d_{gt} = \sum_{t=2013}^{2016} \beta_{1,t} Y_t * ln(D_g) + \beta_2 ln(D_g) + \sum_{t=2013}^{2016} \beta_{3,t} Y_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \tag{5.7}$$

The outcome variable, d_{gt}, is square metres deforested within grid cell g in year t. D_g is the treatment variable, continuous Euclidean distance to the Kenya border crossing. Y_t is a year dummy variable equal to one the observation is in year t and zero otherwise.

To control for geographical, demographic and socioeconomic covariates, I include time-invariant controls (X_g) and a vector of time-variant controls ($\mu\prime X_{gt}$). I also incorporate year fixed effects, ϕ_t, and grid cell fixed effects, γ_g, in some specifications. I present the results in Table 5.3.

Table 5.3: Uganda Event Study (Log Specification)

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
ln(Distance to Kenya Border Crossing) x 2013 Year Dummy	5.348***	11.59***	8.264***	23.07***
	(1.549)	(1.588)	(1.595)	(3.139)
ln(Distance to Kenya Border Crossing) x 2014 Year Dummy	8.247***	14.22***	10.90***	10.10***
	(1.032)	(1.192)	(1.279)	(2.195)
ln(Distance to Kenya Border Crossing) x 2015 Year Dummy	5.279***	11.10***	6.845***	8.338***
	(1.147)	(1.298)	(1.378)	(2.413)
ln(Distance to Kenya Border Crossing) x 2016 Year Dummy	3.163***	3.438***	3.438***	12.66***
	(1.163)	(1.167)	(1.167)	(2.579)
ln(Distance to Kenya Border Crossing)	-10.21***	-10.57***		
	(0.929)	(1.254)		
2013 Year Dummy	36.77***	3.089	16.09*	-97.64**
	(8.967)	(8.856)	(8.834)	(42.24)
2014 Year Dummy	-73.19***	-105.2***	-92.25***	-107.2***
	(6.042)	(6.586)	(7.034)	(25.30)
2015 Year Dummy	-49.62***	-79.96***	-57.98***	-89.15***
	(6.709)	(7.209)	(7.569)	(27.63)
2016 Year Dummy	-25.14***	-26.82***	-26.82***	-22.74
	(6.873)	(6.895)	(6.895)	(30.07)
Constant	91.08***	123.1***	43.77***	34.62***
	(5.471)	(10.00)	(16.98)	(0.855)
N	1420930	1412770	1412770	1412770
Controls	No	Yes	Yes	No
Grid Cell Fixed Effect	No	No	Yes	Yes
Year FE x Controls	No	No	No	Yes

Controls: Ruggedness, Slope, Maize Productivity, Distance to Dirt Road, Distance to Kampala, Distance to Closest City, Population Years of Education, Agricultural Employment, Poverty
Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Estimation excludes observations in 2018 from the sample
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) estimates the event study with year fixed effects, accounting for any contemporaneous factors affecting all grid cells equally. The coefficients on the interaction of year and treatment are significant at the 1% level in each year relative to 2017, suggesting that the parallel trends assumption may not hold. The estimates also show a declining differential effect of logarithmic distance from the border crossing in the period between 2014 and 2017. I incorporate controls and grid cell fixed effects in columns (2) and (3) to account for omitted grid cell characteristics. However, the coefficients on the interaction of year and treatment remain significant at the 1% level in each year relative to 2017. Furthermore, the declining differential effect of logarithmic distance to the Kenya border crossing in the period between 2014 and 2017 persists in both cases.

I also estimate the event study using time-invariant controls interacted with year dummies and present the results in column (4) of Table 5.3. The coefficients on the interaction of year and treatment remain significant at the 1% level in each year relative to 2017. Furthermore, the estimates show a declining differential effect of logarithmic treatment in the period between 2013 and 2015, relative to 2017. However, there is now an increase in the differential effect of logarithmic treatment in 2016, relative to 2017, which breaks the declining differential trend estimated in preceding specifications.

The extent of treatment is affecting deforestation significantly differently at the 1% level in each year relative to 2017 for all specifications. Therefore treatment affects deforestation differently over time as a function of distance to the Kenya border crossing before the implementation of the ban. This suggests that the parallel trends assumption does not hold. There is also mixed evidence of a declining differential effect of logarithmic treatment prior to the implementation of the ban. In this case, the estimated average treatment effect for the logarithmic difference in differences is overestimated because it is identifying the existing pre-trend rather than spillover effects due to the logging ban.

I specify the inverse event study in Equation 5.8 and present the results in Table 5.4.

$$d_{gt} = \sum_{t=2013}^{2016} \beta_{1,t} Y_t * (D_g)^{-1} + \beta_2 (D_g)^{-1} + \sum_{t=2013}^{2016} \beta_{3,t} Y_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \quad (5.8)$$

Column (1) estimates the event study with year fixed effects. The differential effect of inverse treatment on deforestation is statistically significant at the 1% level in the period between 2013 and 2015 relative to 2017, providing a further lack of support for the parallel trends assumption. The estimates also show no evidence of a pre-trend preceding the ban, and could be picking up spurious correlation on the basis on the substantial volatility in the coefficients.

I incorporate controls and grid cell fixed effects in columns (2) and (3) to account for omitted grid cell characteristics. The differential effect of the treatment becomes less statistically significant in some periods relative to 2017. I also estimate the event study using time-invariant controls interacted with year dummies and present the results in column (4) of Table 5.4. The differential effect of the treatment changes statistical significance in some periods relative to 2017. However, the conclusions regarding the parallel trends assumption, no pre-trends, and spurious correlation from column (1), all remain supported.

Table 5.4: Uganda Event Study (Inverse Specification)

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
(Distance to Kenya Border Crossing)$^{-1}$ x 2013 Year Dummy	-484.0***	-541.9***	-510.5***	-333.1***
	(62.02)	(69.00)	(65.74)	(60.52)
(Distance to Kenya Border Crossing)$^{-1}$ x 2014 Year Dummy	82.16***	25.00	56.38*	-44.34
	(28.74)	(29.22)	(30.31)	(31.69)
(Distance to Kenya Border Crossing)$^{-1}$ x 2015 Year Dummy	122.2***	70.57*	122.6***	8.571
	(38.01)	(37.72)	(39.84)	(38.82)
(Distance to Kenya Border Crossing)$^{-1}$ x 2016 Year Dummy	-12.75	-14.57	-14.57	-112.3***
	(33.43)	(33.52)	(33.52)	(42.14)
(Distance to Kenya Border Crossing)$^{-1}$	-76.42***	82.76***		
	(24.62)	(26.30)		
2013 Year Dummy	69.32***	69.92***	64.61***	4.662
	(1.711)	(1.840)	(1.970)	(39.85)
2014 Year Dummy	-28.21***	-27.43***	-32.74***	-60.31**
	(1.128)	(1.248)	(1.440)	(23.71)
2015 Year Dummy	-21.27***	-19.68***	-21.33***	-49.54*
	(1.203)	(1.311)	(1.331)	(25.82)
2016 Year Dummy	-7.608***	-7.745***	-7.745***	34.85
	(1.301)	(1.301)	(1.301)	(28.25)
Constant	35.24***	85.60***	61.26***	34.62***
	(1.036)	(8.610)	(16.13)	(0.855)
N	1420930	1412770	1412770	1412770
Controls	No	Yes	Yes	No
Grid Cell Fixed Effect	No	No	Yes	Yes
Year FE x Controls	No	No	No	Yes

Controls: Ruggedness, Slope, Maize Productivity, Distance to Dirt Road, Distance to Kampala, Distance to Closest City, Population, Years of Education, Agricultural Employment, Poverty

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)

Estimation excludes observations in 2018 from the sample

Standard errors are clustered at the grid cell level

Standard errors in parentheses

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

Altogether, the event study suggests that deforestation does change differently over time as a function of distance to the Kenya border crossing. Thus, the parallel trends assumption is unlikely to hold. Furthermore, there is mixed evidence of a pre-trend using the logarithmic treatment function, suggesting that this specification could be overestimating the treatment effect. Thus, the estimated spillover effects should be interpreted with care.

5.6 Robustness Checks

5.6.1 Treatment Variable

I use Euclidean distance to the Kenya border crossing opposed to the Kenya border to define the continuous treatment function for analysis. This is because using Euclidean distance to the Kenya border does not incorporate the distance which Ugandan wood fuel producers actually travel to access markets in Kenya. The average treatment effect estimated using a logarithmic and inverse function of distance to the Kenya border will therefore be attenuated by measurement error, potentially reducing magnitude and significance. To determine if this is the case, I estimate the model specified in Equation 5.2 and Equation 5.3. However, I replace D_g, Euclidean distance to the Kenya border crossing, with Euclidean distance to the Kenya border incorporating controls and fixed effects.

The results for the logarithmic specification incorporating the full specification are presented in column (5) of Appendix Table E.1. They suggest that after the ban, there is an additional 0.020m^2 in deforestation for every five kilometre increase in proximity to the Kenya border crossing. This is statistically significant at the 1% level. The final result for the inverse specification is presented in column (5) of Appendix Table E.2. They suggest that after the ban, there is an additional 11.51m^2 of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. The results are statistically significant at the 1% level for both the logarithmic and the inverse treatment functions. Although using a variable which is less accurate for identifying the spillover effects reduces the magnitude of the estimates as hypothesised, these results support the evidence that there are deforestation spillover effects in Uganda due to the logging ban in Kenya.

I also estimate the non-parametric models specified in Equation 5.4 and Equation 5.5, but similarly, I define treatment using the Euclidean distance to the border. The treatment coefficients are presented graphically in Appendix Figures E.1 - E.6. The specification estimates a positive and significant average treatment effect for intervals between 0 and 40 kilometres, as well as between 50 and 60 kilometres. Although the estimated average treatment effects change when using a different treatment variable, these results also support the evidence that there are deforestation spillover effects in Uganda due to the logging ban in Kenya.

5.6.2 Deforested Sample

The estimated average treatment effect of the logging ban may be affected by the proportion of grid cells which do not experience any deforestation in the sample. To analyse whether this changes the average treatment effect, I estimate the difference in differences strategy modelled in Equation 5.2 and Equation 5.3 using a sample of grid cells which experience any deforestation in the sample period, incorporating controls and fixed effects. The results are shown in Appendix Table E.3 and Appendix Table E.4.

The logarithmic specification estimates an average treatment effect which is only significant at the 10% level. Furthermore, the inverse specification estimates an average treatment effect which is not statistically significant. For comparison, the estimated treatment effect for both specifications using the original sample were significant at the 1% level. Although this tentatively provides evidence against the main result, it does not necessarily defy the strong evidence that there are deforestation spillover effects in Uganda due to the logging ban in Kenya. There may be a tendency for grid cells deforested in the pre-period to be unaffected by the logging ban spillovers. This could be due to a limited amount of wood available or because there is a tendency to switch to different grid cells as a result of the ban. The statistical significance of the estimates could also be affected by the restricted sample size. However, this result suggests that the estimated spillover effects should be interpreted with care.

5.6.3 Tobit Model

The sample used for analysis contains gross deforestation measured in square metres for every year between 2013 and 2018. However, in each year, the majority of grid cells in this sample do not experience any amount of gross deforestation. These grid cells could potentially experience a gain in forest cover, which could also be interpreted as negative gross deforestation. However, the gross deforestation variable does not take on negative values and is therefore censored at zero. To account for these censored values, I estimate a difference in differences for the logarithmic and inverse specifications using a tobit model specified in Equations 5.9 and 5.10. This incorporates controls and year fixed effects for reasons previously discussed, but I am unable to include grid cell fixed effects due to computational constraints.

$$d^*_{gt} = \beta_1 ln(D_g) * T_t + \beta_2 ln(D_g) + \beta_3 T_t + X_g + \mu\prime X_{gt} + \phi_t + \epsilon_{gt} \tag{5.9}$$

$$d^*_{gt} = \beta_1 (D_g)^{-1} * T_t + \beta_2 (D_g)^{-1} + \beta_3 T_t + X_g + \mu\prime X_{gt} + \phi_t + \epsilon_{gt} \tag{5.10}$$

$$d_{gt} = d^*_{gt} \text{ if } d^*_{gt} \geq 0, \quad d_{gt} = 0 \text{ if } d^*_{gt} < 0 \tag{5.11}$$

I present the results in Appendix Table E.5 and E.6. As expected, the magnitude of the coefficients have changed significantly for both specifications compared to the original results because of the amount of cells which do not experience deforestation. The estimated average treatment effect of the logging ban remains significant at the 1% level for all specifications. These results support the evidence that there are deforestation spillover effects in Uganda due to the logging ban in Kenya. As previously discussed, the tobit results with year fixed effects should be treated with caution because the maximum likelihood estimator is biased and inconsistent (Greene 2004).

5.6.4 Spatial Autoregressive Model

The presence of spatial correlation in the data set motivates the use of a spatial autoregressive model (SAR). This characterises spatial dependence by incorporating a spatially lagged dependent variable into the estimation. I estimate the spatial autoregressive difference in differences model incorporating fixed effects specified in Equations 5.12 and 5.13.

$$d_{gt} = \lambda \boldsymbol{W} d_{gt} + \beta_1 ln(D_g) * T_t + \beta_2 ln(D_g) + \beta_3 T_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \tag{5.12}$$

$$d_{gt} = \lambda \boldsymbol{W} d_{gt} + \beta_1 (D_g)^{-1} * T_t + \beta_2 (D_g)^{-1} + \beta_3 T_t + X_g + \mu\prime X_{gt} + \gamma_g + \phi_t + \epsilon_{gt} \tag{5.13}$$

$$u_{gt} = \rho \boldsymbol{M} u_{gt} + v_{nt} \tag{5.14}$$

In this specification, u_{gt} is a spatially lagged error and $v_{n,t}$ is a vector of disturbances and is independent and identically distributed (i.i.d.) across grid cells and time with mean zero and variance σ^2. **W** and **M** are spatial weighting matrices constructed using the inverse Euclidean distance from grid cell g to every other kth grid cell for all g grid cells in the sample. I take a random sample of 10,000 grid cells due to computational constraints and estimate this model. The results are presented in Table 5.5.

Column (1) estimates the regression with fixed effects. Interpreting the logarithmic treatment function, the results suggest that after the ban, there is an additional 0.020m^2 of deforestation for every five kilometre increase in distance from the Kenya border crossing. Using the inverse treatment function, Thus, after the ban, there is an additional 87.97m^2 of deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. Thus, after the ban, there is an additional 24.16m^2 reduction in deforestation one kilometre away from the Kenya border crossing compared with 505 kilometres away. However, both treatment function coefficients are not statistically significant. Furthermore, the spatially lagged dependent variable is statistically significant at the 1% level, suggesting that deforestation within grid cells surrounding grid cell g have significant explanatory power for deforestation in grid cell g.

Table 5.5: Impact of Logging Ban in Uganda (Spatial Autoregressive Model)

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
Log Specification				
ln(Distance to Kenya Crossing) x Logging Ban	1.994	1.183	7.547	4.005
	(7.209)	(7.409)	(7.381)	(12.47)
Logging Ban (t = 2018)	1.220	5.101	-8.548	-111.1
	(40.01)	(41.07)	(41.14)	(198.0)
Inverse Specification				
(Distance to Kenya Border Crossing)$^{-1}$ x Logging Ban	-24.16	-14.52	-181.8	-30.78
	(294.0)	(294.8)	(293.6)	(322.7)
Logging Ban (t = 2018)	12.35**	11.70**	34.16***	-92.17
	(5.349)	(5.442)	(6.661)	(188.4)
Spatial Matrix				
Loss (m^2)	1.555***	1.561***	2.706***	3.436***
	(0.0457)	(0.0466)	(0.0495)	(0.0179)
Constant	451.6***	451.6***	449.8***	448.4***
	(1.420)	(1.420)	(1.415)	(1.410)
N	60000	60000	60000	60000
Controls	No	Yes	Yes	No
Grid Cell Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes
Year FE x Controls	No	No	No	Yes

Controls: Population, Years of Education, Agricultural Employment
Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I incorporate time-varying controls, year fixed effects, and time-invariant controls interacted with year dummy variables. The estimated average treatment effect remains insignificant for both the logarithmic and the inverse specification. Moreover, the spatially lagged dependent variable remains statistically significant at the 1% level. This result suggests that additional deforestation after the ban is attributed to spatial correlation between deforested grid cells rather than a function of distance from the Kenya border crossing.

Although the treatment effect has been estimated as insignificant using a SAR model, the previous evidence for spillover effects should not be disregarded. The analysis uses a 10% sample of available grid cells, and the SAR model is estimated using approximately 3.4% of these grid cells (or 0.34% of the available sample). There is the potential for the random sample to omit observations which exhibit a diminishing differential amount of deforestation in the ban period as a function of distance to the Kenya border crossing, relative to other years. However, the grid cells which do form the sample may still exhibit strong spatial correlation in the dependent variable, and hence drive the observed result.

We should therefore err on the side of caution when discussing the previous evidence which supports the presence of spillovers in Uganda as a result of the logging ban in Kenya.

Chapter 6

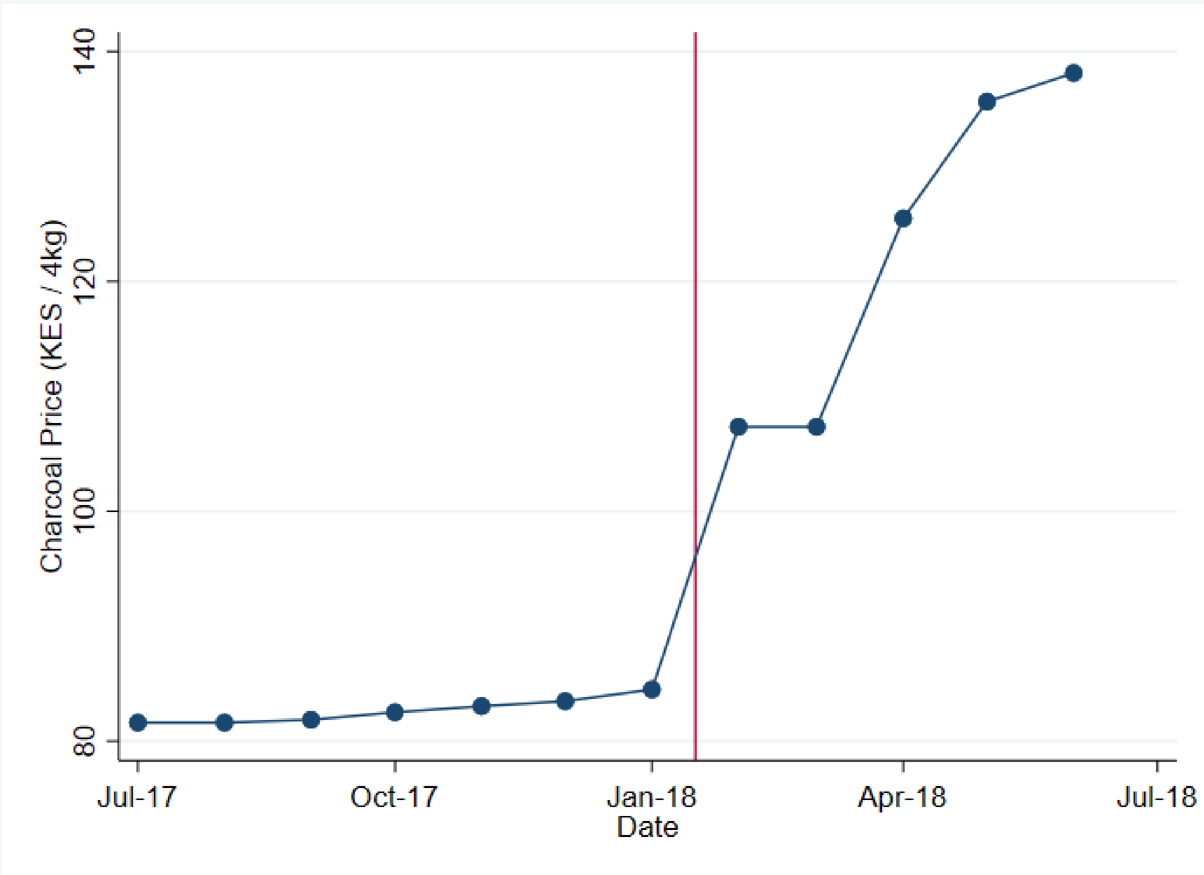
Discussion

Implemented by the Kenyan Government in 2018, the logging ban has been estimated to have no statistically significant effect on deforestation in protected areas. However, after the ban, there is strong evidence of deforestation spillover effects in Uganda. If wood fuel producers and other economic agents in Kenya are not changing their deforestation behaviour in response to the logging ban, there must be an explanation for the spillover effects in Uganda. It is possible that the ban's enforcement mechanisms are not changing the quantity of deforestation, but are increasing the cost of wood fuel production in Kenya. This would make production relatively cheaper in Uganda, increasing the likelihood of higher export volumes into Kenya. Theoretically, this also increases the price of wood fuel in the Kenyan market, providing the incentive for Ugandan wood fuel producers to increase their volume of exports to capture rents. Although an interesting explanation, it is also possible that data restrictions are attenuating the results.

The logging ban's enforcement mechanisms could have changed the cost of wood fuel production in Kenya, affecting the incentive to deforest in Uganda. To monitor and enforce the logging ban, the Kenyan Government and KFS planned to employ new surveillance technologies, monitor the origin of timber production, and strengthen law enforcement (Kalenda 2019; Environment and Forestry 2018b). This was intended to decrease deforestation and increase tree cover, alleviating the drought's adverse consequences for agriculture and food security. However, evidence from the media suggests that corruption may affect the forestry industry in Kenya (Nyakundi and Kavoo 2019). The monitoring and enforcement mechanisms may be ineffective as a result of corruption, leading wood fuel producers to incorporate any costs associated with avoiding the ban as costs of production. If wood fuel producers in Kenya can avoid the ban and deforest to the same extent as prior to the ban, there would be no significant effect of the ban on deforestation in Kenya, supporting the empirical evidence.

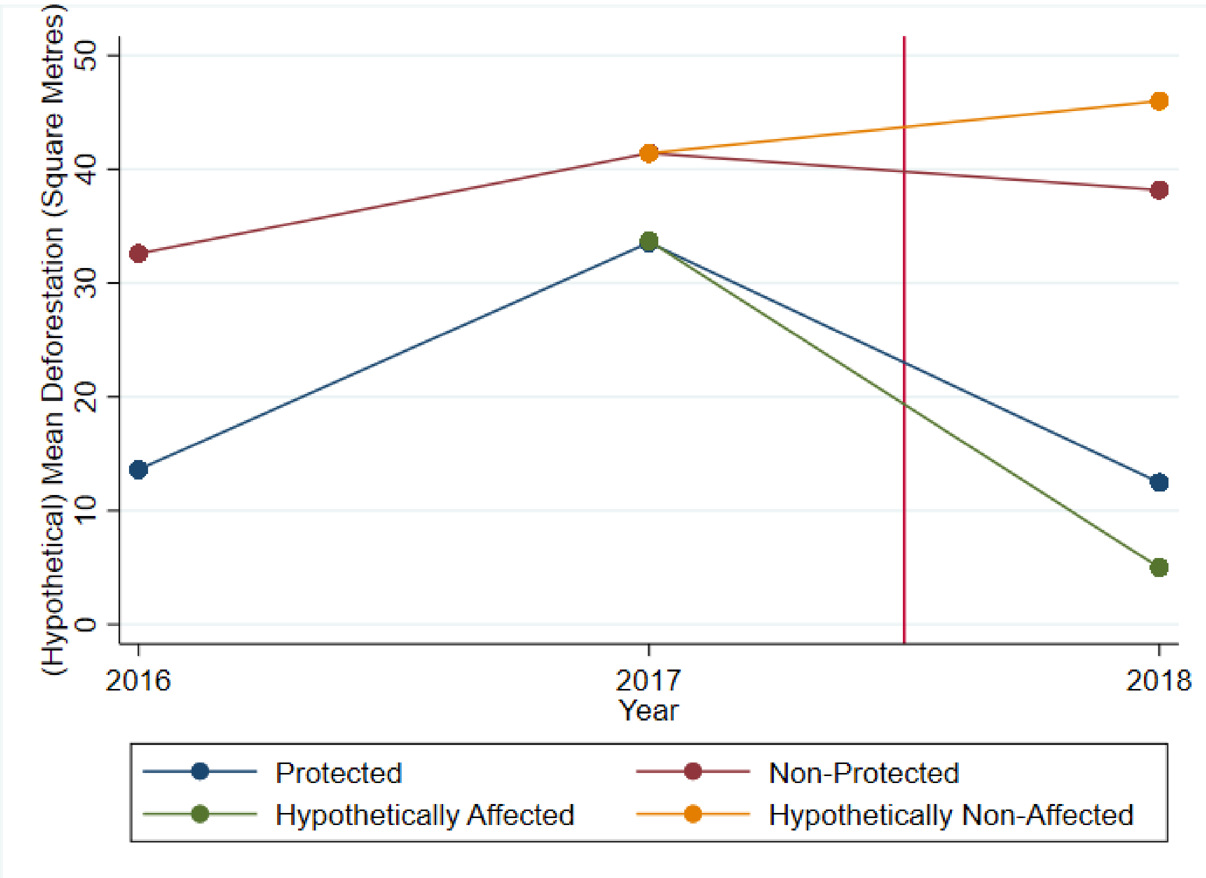
Furthermore, increasing the cost of wood fuel production in Kenya makes it relatively cheaper for producers in Uganda, likely increasing the amount of deforestation in Uganda close to the border. Theoretically, a rise in the cost of wood fuel production in Kenya will also be passed on to consumers in the form of higher prices. To provide evidence for this, I collect charcoal price data measured in Kenyan Shillings between July 2017 and June 2018, presented in Figure 6.1 (CEIC 2019). The data shows that there is a clear spike in charcoal prices in February 2018 when the logging ban was implemented, suggesting that the ban did in fact increase the cost of wood fuel production. Higher charcoal prices in Kenya will incentivise Ugandan wood fuel producers to increase their volume of logging production as they seek to capture rents from the Kenyan market. The deforestation in Uganda in response to charcoal price changes in Kenya is likely to be concentrated within close proximity of the Kenya border crossing. This, alongside the relatively cheaper cost of production in Uganda, could be the mechanism driving deforestation spillover effects in Uganda after the ban's implementation.

Figure 6.1: Kenya Retail Price of Charcoal July-17 to June-18



Although ineffective monitoring and enforcement could explain the insignificant effect of the ban on deforestation in protected areas, there may be problems with the data and identification affecting the result. The evidence for the insignificant effect of the logging ban in Kenya may be skewed by measurement error in the treatment variable because theoretically treated cells constitute non-protected areas. This attenuates the identification strategy because the ban will reduce deforestation in both protected and non-protected areas. This, taking the difference in differences will not identify the exact additional amount of deforestation in protected areas compared to non-protected areas due to the ban. This is illustrated graphically in Figure 6.2. Protected and non-protected areas reflect the data, while affected and non-affected areas are hypothetical quantities of deforestation we might observe if the ban's affected areas were exactly identified. Applying the difference in differences strategy to actually affected and non-affected areas could identify a significant effect of the logging ban on deforestation. While there could be economic mechanisms causing the logging ban to be ineffective, it may also be an identification problem affecting the result.

Figure 6.2: Deforestation in Protected and Non-Protected Areas Compared with Hypothetical Deforestation in Areas Affected and Non-Affected By the Logging Ban



There are other data limitations which may also attenuate the findings in both Kenya and Uganda. The data has been constructed using 900 square metre data pixels from the Global Forest Change data (Hansen et al. 2013). Each of these data pixels do not have information on the square metres of forest loss within each year, but rather a binary variable indicating if the data pixel experienced any forest loss for each year. If a hectare grid cell contains approximately ten data pixels and one experiences forest loss in a given year, the hectare grid cell will experience 900 square metres of forest loss in that year. The imputed quantity of deforestation could therefore be overestimated because the calculation assumes that the entirety of a data pixel is deforested if it experiences any deforestation in any given year. If actual square metres of forest loss was observed at the grid cell level and used for the analysis, it is possible that the spillover effects in Uganda due to the ban would not be identified.

The Global Forest Change data is also limited to one yearly observation such that there is only one observation for each grid cell during the treatment period (Hansen et al. 2013). It is possible that the ban had the desired effect on deforestation when it was initially implemented, but lack of enforcement over time meant that deforestation did not change over the entire year compared with deforestation prior to the ban. It is also possible that spillover effects in Uganda did not occur at the onset of the ban, but rather several months later. As Figure 6.1 suggests, the price of charcoal in Kenya was much higher in May that February of 2018. Ugandan wood fuel producers may have only responded to much higher prices months later because the marginal benefit of exporting only became higher than the marginal cost at this time. Higher frequency data would provide the opportunity for a greater depth of analysis, but this is not feasible with the current data.

Although the results are attenuated by the limitations of the data, it does create the opportunity for further research into the logging ban's effect on deforestation. Firstly, acquiring geographical data on all the areas affected by the logging ban would better identify the policy's effect. Secondly, applying the same methods for analysis using higher density deforestation data will improve the accuracy of the results. Thirdly, the ban has been implemented for 21 months as of November 2019, so applying the same methods for analysis using updated data from 2019 will provide a deeper insight into the ban's effect. Furthermore, access to higher frequency data and local charcoal prices could be used to further explore the mechanisms driving the results over time. If feasible, field work could also be used to understand the ban's monitoring and enforcement mechanisms, and whether they reflect the statements released by the Kenyan Government. Altogether, these recommendations can be applied to further understand the effect of the Kenyan logging ban and command and control environmental policy in general.

Chapter 7

Conclusion

Evaluating the effect of the logging ban implemented by the Kenyan Government in 2018, I find that there is no significant effect on deforestation in Kenya's protected areas. Furthermore, I find evidence of spillover effects in Uganda as a result of the logging ban. These results suggest that Kenya's decision to implement the ban has not improved tree cover and the drought by extension. Furthermore, the ban may have caused an unintended negative environmental outcome in Uganda. Although the policy was implemented with the best intentions, outcomes have only worsened in both Kenya and Uganda.

More generally, these results suggest that command and control environmental policy can have negative unintended consequences while failing to achieve the intended outcome. Policymakers should consider the economic and institutional landscape of their state to ensure that a command and control policy is appropriate, as ineffective policies may worsen the outcomes they were attempting to improve. If there is evidence that a command and control policy is appropriate, policymakers should still consider market-based or democratic approaches to environmental management and sustainability.

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Appendix A

Summary Statistics

Table A.1: Description of Variables

Variable	Description
Object ID	Grid Cell ID
Year	Year
Loss (m^2)	Forest Loss (m^2)
Loss 2013 (m^2)	Forest Loss in 2013 (m^2)
Loss 2014 (m^2)	Forest Loss in 2014 (m^2)
Loss 2015 (m^2)	Forest Loss in 2015 (m^2)
Loss 2016 (m^2)	Forest Loss in 2016 (m^2)
Loss 2017 (m^2)	Forest Loss in 2017 (m^2)
Loss 2018 (m^2)	Forest Loss in 2018 (m^2)
Loss 2013 - 2017 (m^2)	Total forest loss in the period between 2013 and 2017 (m^2)
Forest 2012	Predicted forest cover in 2012 (m^2)
Protected Area	Protected Area
Distance to Border Crossing (km)	Euclidean distance to the Kenya border crossing (km)
Distance to Border (km)	Euclidean distance to the Kenya border (km)
Distance to Border via Road (km)	Road distance to the Kenya border (km)
Ruggedness	Ruggedness Index from Nunn & Puga (2012)
Slope (%)	Elevation change within cell as a percentage (%)
Maize Productivity	GAEZ Maize Productivity Index
Distance to Dirt Road (km)	Euclidean distance to a dirt road (km)
Distance to Improved Road (km)	Euclidean distance to an improved road (km)
Distance to Closest City (km)	Euclidean distance to the closest city (km)
Distance to Kampala (km)	Euclidean distance to Kampala (km)
Distance to Nairobi (km)	Euclidean distance to Nairobi (km)
Population	Population of SEDAC grid cell (Population / 1km^2)
Years of Education	Average years of education attained by the head of household within each county (Kenya) or sub-region (Uganda)
Agricultural Employment (%)	Percentage (%) of head of households employed in agriculture within each county (Kenya) or sub-region (Uganda)
Poverty (%)	Percentage (%) of households in poverty under the aggregate consumption definition within each county (Kenya) or sub-region (Uganda)
Nutritional Poverty (%)	Percentage (%) of households in poverty under the nutritional consumption definition within each county (Kenya only)
County	County (Kenya)
Sub-region	Sub-region (Uganda)

Table A.2: Panel Summary Statistics

	Count	Mean	Variance	SD	Min	Max
Year	1745700	-	-	-	2013	2018
Loss 2013 (m^2)	1745700	99.69516	447232	668.7541	0	10000
Loss 2014 (m^2)	1745700	7.393529	56708.07	238.1346	0	9948.326
Loss 2015 (m^2)	1745700	14.51896	107664.7	328.123	0	9948.326
Loss 2016 (m^2)	1745700	27.10079	214134.6	462.7467	0	9948.329
Loss 2017 (m^2)	1745700	34.87182	282810.8	531.7996	0	9948.329
Loss 2018 (m^2)	1745700	18.41499	148833.5	385.7894	0	9948.329
Loss 2013 - 2017 (m^2)	1745700	183.5803	1209022	1099.555	0	10000
Forest 2012	1745700	.929474	.0342947	.1851882	.0000534	1
Protected Area	1745700	.3696821	.2330174	.4827187	0	1
Distance to Border Crossing (km)	1745700	284.9534	14061.28	118.5803	.2905214	504.7889
elevation	1745700	1289.061	231543	481.1892	1	4518
Distance to Border (km)	1745700	276.2149	13862.5	117.7391	.0012607	487.1337
Distance to Border via Road (km)	1290390	874.8898	118352.9	344.0245	.187516	1832.292
Ruggedness	1745700	112179.6	2.09e+10	144545.3	0	2059514
Slope (%)	1745700	10.50587	6425.527	80.15938	.0068098	1211.37
Maize Productivity	1745700	2572.931	1864127	1365.33	0	9967
Distance to Dirt Road (km)	1745700	132.7914	4484.228	66.96438	.0000686	248.7292
Distance to Improved Road (km)	1745700	134.1512	4389.138	66.25057	.0005312	249.3055
Distance to Closest City (km)	1745700	33.4068	284.593	16.86988	.1939307	144.8557
Distance to Kampala (km)	1745700	202.6064	12618.86	112.3337	5.755363	1031.812
Distance to Nairobi (km)	1745700	640.374	16067.58	126.758	1.675018	858.0328
Population	1745700	133.5098	32088.34	179.1322	0	21211.04
Years of Education	1734384	6.2865	.4968356	.7048657	.9649687	10.84299
Agricultural Employment (%)	1734384	.2903483	.0063107	.07944	.0067352	.7956914
Poverty (%)	1734384	.2205542	.0069907	.0836107	.0303886	.7080883
Nutritional Poverty (%)	39060	.2568743	.0108518	.104172	.1076129	.5594001
N	1745700					

Table A.3: Grid Cell Summary Statistics

	Count	Mean	Variance	SD	Min	Max
Object ID	290950	-	-	-	263179	1034765
Loss 2013 (m^2)	290950	99.69516	447233.3	668.755	0	10000
Loss 2014 (m^2)	290950	7.393529	56708.23	238.1349	0	9948.326
Loss 2015 (m^2)	290950	14.51896	107665	328.1235	0	9948.326
Loss 2016 (m^2)	290950	27.10079	214135.2	462.7474	0	9948.329
Loss 2017 (m^2)	290950	34.87182	282811.6	531.8003	0	9948.329
Loss 2018 (m^2)	290950	18.41499	148833.9	385.79	0	9948.329
Loss 2013 - 2017 (m^2)	290950	183.5803	1209025	1099.557	0	10000
Forest 2012	290950	.929474	.0342947	.1851884	.0000534	1
Protected Area	290950	.3696821	.233018	.4827194	0	1
Distance to Border Crossing (km)	290950	284.9534	14061.32	118.5804	.2905214	504.7889
Distance to Border (km)	290950	276.2149	13862.54	117.7393	.0012607	487.1337
Distance to Border via Road (km)	215065	874.8898	118353.3	344.0252	.187516	1832.292
Ruggedness	290950	112179.6	2.09e+10	144545.5	0	2059514
Slope (%)	290950	10.50587	6425.545	80.1595	.0068098	1211.37
Maize Productivity	290950	2572.931	1864133	1365.332	0	9967
Distance to Dirt Road (km)	290950	132.7914	4484.241	66.96448	.0000686	248.7292
Distance to Improved Road (km)	290950	134.1512	4389.151	66.25067	.0005312	249.3055
Distance to Closest City (km)	290950	33.4068	284.5938	16.86991	.1939307	144.8557
Distance to Kampala (km)	290950	202.6064	12618.9	112.3339	5.755363	1031.812
Distance to Nairobi (km)	290950	640.374	16067.63	126.7581	1.675018	858.0328
Population	290950	133.5098	31697.56	178.0381	0	19983.56
Years of Education	289064	6.2865	.3504395	.5919793	4.738654	10.40178
Agricultural Employment (%)	289064	.2903483	.0022944	.0479003	.0067352	.6648331
Poverty (%)	289064	.2205542	.0069908	.0836108	.0303886	.7080883
Nutritional Poverty (%)	6510	.2568743	.0108532	.1041787	.1076129	.5594001
N	290950					

Table A.4: Grid Cell Summary Statistics in Kenya

	Count	Mean	Variance	SD	Min	Max
Object ID	6764	-	-	-	263179	1034765
Loss 2013 (m^2)	6764	43.69769	173512	416.5477	0	9974.558
Loss 2014 (m^2)	6764	21.15515	107033.2	327.1593	0	9948.326
Loss 2015 (m^2)	6764	25.53667	142650.4	377.6908	0	9948.324
Loss 2016 (m^2)	6764	28.46589	137483.4	370.7875	0	9948.329
Loss 2017 (m^2)	6764	39.70793	229729.8	479.3013	0	9948.328
Loss 2018 (m^2)	6764	32.60503	137500.2	370.8102	0	9892.645
Loss 2013 - 2017 (m^2)	6764	158.5633	816923.2	903.838	0	9974.558
Forest 2012	6764	.909183	.035389	.1881196	.0014041	1
Protected Area	6764	.2168835	.1698702	.4121531	0	1
Distance to Border Crossing (km)	6764	103.6847	5849.703	76.48335	.2905214	347.6233
Distance to Border (km)	6764	97.64445	6519.692	80.74461	.0012607	347.3262
Distance to Border via Road (km)	5648	165.285	8084.961	89.91641	.187516	419.2818
Ruggedness	6764	108438.2	2.74e+10	165581.3	0	1512193
Slope (%)	6764	7.778903	2251.301	47.44788	.0068098	806.9447
Maize Productivity	6764	3877.818	5213710	2283.355	0	9967
Distance to Dirt Road (km)	6764	2.431873	20.53573	4.531637	.0000686	36.08249
Distance to Improved Road (km)	6764	5.719713	74.40792	8.626003	.0007461	49.92909
Distance to Closest City (km)	6764	38.83645	696.9447	26.39971	.2332647	141.9686
Distance to Kampala (km)	6764	532.4085	71440	267.2826	155.1175	1031.812
Distance to Nairobi (km)	6764	262.6084	18812.4	137.1583	1.675018	540.7311
Population	6764	251.9747	319422	565.1743	0	19983.56
Years of Education	6510	7.725444	1.522424	1.233865	4.738654	10.40178
Agricultural Employment (%)	6510	.3827083	.0163455	.1278495	.0067352	.6648331
Poverty (%)	6510	.3069045	.0177136	.1330924	.1295851	.7080883
Nutritional Poverty (%)	6510	.2568743	.0108532	.1041787	.1076129	.5594001
N	6764					

Table A.5: Grid Cell Summary Statistics in Uganda

	Count	Mean	Variance	SD	Min	Max
Object ID	284186	-	-	-	277888	1033167
Loss 2013 (m^2)	284186	101.028	453672.4	673.5521	0	10000
Loss 2014 (m^2)	284186	7.065984	55506.18	235.5975	0	9948.326
Loss 2015 (m^2)	284186	14.25672	106829.9	326.8484	0	9948.326
Loss 2016 (m^2)	284186	27.0683	215960	464.715	0	9948.329
Loss 2017 (m^2)	284186	34.75672	284075.2	532.9871	0	9948.329
Loss 2018 (m^2)	284186	18.07724	149099.2	386.1337	0	9948.329
Loss 2013 - 2017 (m^2)	284186	184.1757	1218345	1103.787	0	10000
Forest 2012	284186	.9299569	.0342588	.1850913	.0000534	1
Protected Area	284186	.3733189	.2339527	.4836866	0	1
Distance to Border Crossing (km)	284186	289.2679	13456.1	116.0004	.4206638	504.7889
Distance to Border (km)	284186	280.4651	13260.31	115.1534	.1053417	487.1337
Distance to Border via Road (km)	209417	894.028	107380.5	327.6896	5.184158	1832.292
Ruggedness	284186	112268.6	2.07e+10	144006.6	0	2059514
Slope (%)	284186	10.57077	6524.725	80.77577	.0111494	1211.37
Maize Productivity	284186	2541.873	1742934	1320.202	0	9029
Distance to Dirt Road (km)	284186	135.8941	4176.385	64.62496	.0000759	248.7292
Distance to Improved Road (km)	284186	137.208	4089.908	63.95239	.0005312	249.3055
Distance to Closest City (km)	284186	33.27757	274.0633	16.55486	.1939307	144.8557
Distance to Kampala (km)	284186	194.7567	8568.641	92.56696	5.755363	456.8516
Distance to Nairobi (km)	284186	649.3653	12524.9	111.9147	346.0392	858.0328
Population	284186	130.6902	24508.46	156.5518	0	8842.307
Years of Education	282554	6.253347	.2746377	.5240589	5.419979	7.311189
Agricultural Employment (%)	282554	.2882203	.0017697	.0420678	.1875849	.3559921
Poverty (%)	282554	.2185647	.006568	.0810433	.0303886	.5215632
N	284186					

Appendix B

Kenya Results

Table B.1: Kenya Difference in Differences Incorporating Controls

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
Protected Area	-10.20**	-6.389	-1.426	-3.296
	(5.004)	(5.012)	(5.279)	(5.397)
Logging Ban (t = 2018)	4.258	4.258	4.258	6.521
	(6.060)	(6.060)	(6.060)	(6.471)
Protected Area x Logging Ban (t = 2018)	-15.52*	-15.52*	-15.52*	-13.67
	(9.133)	(9.133)	(9.133)	(9.420)
Ruggedness		-10.83	-0.546	-2.387
		(10.59)	(10.74)	(12.67)
Slope (%)		-0.00317	-0.00306	0.00229
		(0.0415)	(0.0412)	(0.0470)
Maize Productivity		0.00245**	0.00176	0.00202*
		(0.00109)	(0.00112)	(0.00114)
Distance to Dirt Road			-0.778**	-0.756**
			(0.326)	(0.382)
Distance to Nairobi			-0.0657***	-0.0633**
			(0.0220)	(0.0302)
Distance to Closest City			-0.128**	-0.188**
			(0.0575)	(0.0753)
Distance to Kenya Border			-0.129***	-0.130***
			(0.0321)	(0.0408)
Population				-0.0103***
				(0.00369)
Years of Education				-1.269
				(0.938)
Agricultural Employment (%)				3.097
				(15.41)
Poverty (%)				-29.90
				(51.27)
Nutritional Poverty (%)				14.05
				(62.66)
Constant	33.92***	24.80***	61.98***	79.54***
	(2.539)	(5.125)	(9.722)	(16.18)
N	40584	40584	40584	39060
Grid Cell Fixed Effect	No	No	No	No
Year Fixed Effect	No	No	No	No

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Kenya Difference in Differences Incorporating Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
Protected Area	-3.296		-3.009	
	(5.397)		(5.373)	
Logging Ban (t = 2018)	6.521	5.466		
	(6.471)	(6.442)		
Protected Area x Logging Ban (t = 2018)	-13.67	-13.34	-13.43	-13.12
	(9.420)	(9.543)	(9.437)	(9.550)
Ruggedness	-2.387		-1.664	
	(12.67)		(12.67)	
Slope (%)	0.00229		0.00239	
	(0.0470)		(0.0469)	
Maize Productivity	0.00202*		0.00195*	
	(0.00114)		(0.00113)	
Distance to Dirt Road	-0.756**		-0.774**	
	(0.382)		(0.383)	
Distance to Nairobi	-0.0633**		-0.0720**	
	(0.0302)		(0.0301)	
Distance to Closest City	-0.188**		-0.209***	
	(0.0753)		(0.0770)	
Distance to Kenya Border	-0.130***		-0.135***	
	(0.0408)		(0.0410)	
Population	-0.0103***	-0.00171	-0.00990***	-0.00777
	(0.00369)	(0.0490)	(0.00368)	(0.0542)
Years of Education	-1.269	-0.824	-2.801**	-2.374**
	(0.938)	(0.902)	(1.195)	(1.178)
Agricultural Employment (%)	3.097	17.23	1.449	17.78
	(15.41)	(25.36)	(15.29)	(25.41)
Poverty (%)	-29.90		-29.66	
	(51.27)		(51.29)	
Nutritional Poverty (%)	14.05		10.01	
	(62.66)		(63.00)	
Constant	79.54***	31.56*	97.76***	45.72***
	(16.18)	(16.32)	(18.18)	(17.11)
N	39060	39060	39060	39060
Grid Cell Fixed Effect	No	Yes	No	Yes
Year Fixed Effect	No	No	Yes	Yes

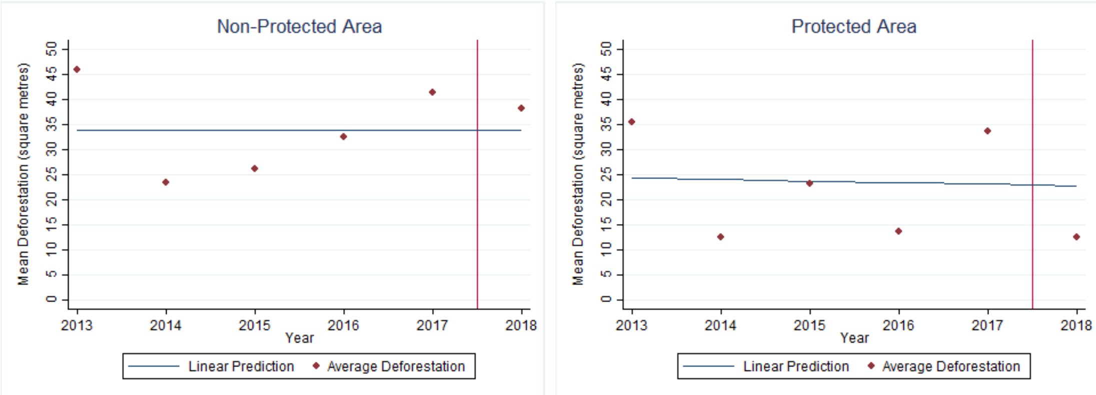
Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Kenya Difference in Differences Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1) Loss (m^2)	Year t = 2018	t = 2016	t = 2015	t = 2014	t = 2013
Protected Area						
Logging Ban (t = 2018)	29.73 (86.85)					
Protected Area x Logging Ban (t = 2018)	-7.992 (8.881)					
t Year Dummy			-53.26 (67.02)	-13.26 (73.95)	-39.09 (59.53)	182.7* (110.5)
Ruggedness x t Year Dummy		-16.23 (53.95)	12.15 (43.93)	62.72 (53.78)	22.76 (43.48)	-4.027 (44.46)
Slope (%) x t Year Dummy		0.293 (0.238)	0.00700 (0.0405)	0.0515* (0.0313)	-0.0128 (0.0405)	0.223 (0.156)
Maize Productivity x t Year Dummy		-0.00297 (0.00408)	-0.00135 (0.00376)	-0.00347 (0.00406)	0.0000214 (0.00353)	0.00365 (0.00407)
Distance to Dirt Road (km) x t Year Dummy		1.316 (1.477)	-0.580 (1.141)	-0.644 (1.199)	1.115 (1.481)	-0.263 (1.295)
Distance to Nairobi (km) x t Year Dummy		-0.128 (0.122)	0.101 (0.0900)	-0.0322 (0.0744)	0.131 (0.0870)	0.0433 (0.0820)
Distance to Closest City (km) x t Year Dummy		0.164 (0.296)	0.427* (0.251)	0.330 (0.253)	0.253 (0.219)	-0.0353 (0.257)
Distance to Kenya Border (km) x t Year Dummy		0.0102 (0.141)	0.156 (0.121)	-0.0830 (0.109)	0.107 (0.0915)	0.139 (0.140)
Population x t Year Dummy		0.0248** (0.0115)	0.0260* (0.0143)	0.00831 (0.00868)	0.0245* (0.0139)	0.00394 (0.0105)
Years of Education x t Year Dummy		-3.690 (5.105)	-4.055 (2.974)	-1.770 (3.115)	-5.855** (2.768)	-4.532 (3.274)
Agricultural Employment (%) x t Year Dummy		40.37 (38.40)	16.41 (32.65)	72.96 (44.79)	21.33 (29.97)	20.64 (34.68)
Poverty (%) x t Year Dummy		-169.9 (234.8)	-148.5 (218.4)	-14.96 (234.5)	-186.0 (217.8)	-93.32 (248.1)
Nutritional Poverty (%) x t Year Dummy		272.2 (258.2)	-19.88 (247.1)	-56.70 (255.8)	10.31 (247.4)	55.33 (270.7)
Constant	39.41*** (5.151)					
N	39060					
Grid Cell Fixed Effect	Yes					

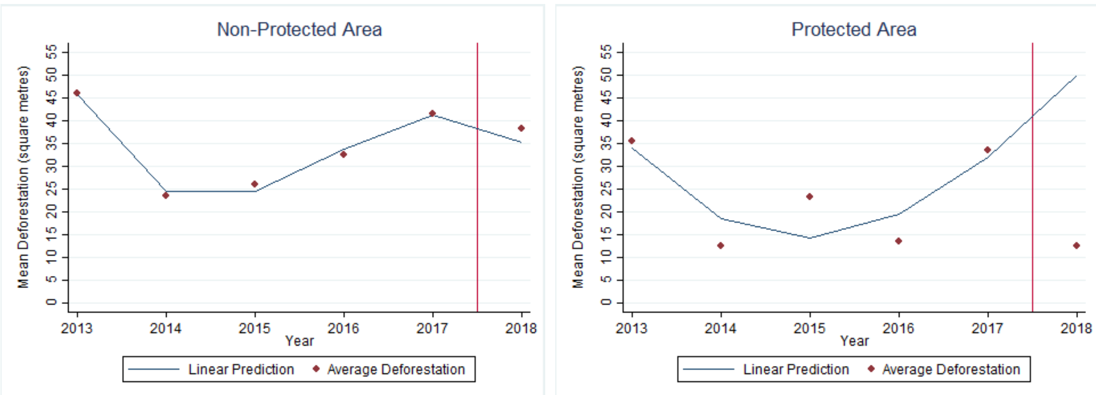
Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B.1: Kenya Deforestation Pre-Trends (Linear Estimation)



(a) Non-Protected Areas (b) Protected Areas

Figure B.2: Kenya Deforestation Pre-Trends (Cubic Estimation)



(a) Non-Protected Areas (b) Protected Areas

Table B.4: Kenya Deforestation Pre-Trends

	Non-Protected			Protected		
	(1)	(2)	(3)	(4)	(5)	(6)
	Loss (m^2)	Loss (m^2)	Loss (m^2)	Loss (m^2)	Loss (m^2)	Loss (m^2)
Year	-0.00305	-28.43***	-72.97**	-0.297	-28.31*	-36.24
	(1.913)	(9.306)	(34.31)	(3.268)	(16.69)	(48.20)
Year x Year		4.737***	21.72*		4.669*	7.694
		(1.551)	(12.79)		(2.752)	(17.05)
Year x Year x Year			-1.887			-0.336
			(1.428)			(1.887)
Logging Ban (t = 2018)	4.267	-28.89**	2.813	-10.37	-43.05*	-37.41
	(8.590)	(14.64)	(29.71)	(12.19)	(24.10)	(44.33)
Constant	33.93***	67.10***	98.80***	24.62**	57.30**	62.95
	(5.960)	(12.26)	(26.72)	(10.40)	(22.55)	(41.91)
N	31782	31782	31782	8802	8802	8802

Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Kenya Event Study Incorporating Controls and Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
Protected Area	-7.859	-5.137		-5.137	
	(13.35)	(13.79)		(13.79)	
2013 Year Dummy	4.542	-3.239	-3.154		
	(8.873)	(9.230)	(10.23)		
2014 Year Dummy	-17.89**	-27.10***	-27.01***		
	(8.319)	(9.172)	(9.759)		
2015 Year Dummy	-15.26*	-23.30**	-22.65**		
	(8.468)	(9.610)	(9.627)		
2016 Year Dummy	-8.835	-9.652	-9.652		
	(8.496)	(8.747)	(8.746)		
Protected Area x 2013 Year Dummy	-2.546	2.895	1.939	2.895	1.939
	(18.19)	(18.73)	(19.12)	(18.73)	(19.12)
Protected Area x 2014 Year Dummy	-3.066	3.053	2.097	3.053	2.097
	(15.20)	(15.40)	(15.81)	(15.40)	(15.81)
Protected Area x 2015 Year Dummy	5.016	10.69	9.357	10.69	9.357
	(17.38)	(17.91)	(18.06)	(17.91)	(18.06)
Protected Area x 2016 Year Dummy	-11.10	-9.909	-9.909	-9.909	-9.909
	(15.06)	(14.95)	(14.95)	(14.95)	(14.95)
Ruggedness		4.806		4.806	
		(13.35)		(13.35)	
Slope (%)		-0.0375		-0.0375	
		(0.0322)		(0.0322)	
Maize Productivity		0.00232*		0.00232*	
		(0.00121)		(0.00121)	
Distance to Dirt Road (km)		-1.061***		-1.061***	
		(0.407)		(0.407)	
Distance to Nairobi (km)		-0.0416		-0.0416	
		(0.0321)		(0.0321)	
Distance to Closest City (km)		-0.224***		-0.224***	
		(0.0865)		(0.0865)	
Distance to Kenya Border (km)		-0.131***		-0.131***	
		(0.0459)		(0.0459)	
Population		-0.0117***	-0.0267	-0.0117***	-0.0267
		(0.00418)	(0.0584)	(0.00418)	(0.0584)
Years of Education		-2.836**	-2.931**	-2.836**	-2.931**
		(1.349)	(1.364)	(1.349)	(1.364)
Agricultural Employment (%)		11.46	46.34	11.46	46.34
		(16.42)	(32.06)	(16.42)	(32.06)
Poverty (%)		-14.17		-14.17	
		(56.92)		(56.92)	
Nutritional Poverty (%)		-42.06		-42.06	
		(70.93)		(70.93)	
Constant	41.41***	105.7***	54.61***	93.01***	42.11**
	(6.722)	(22.54)	(19.99)	(20.21)	(17.83)
N	33820	32550	32550	32550	32550
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Kenya Event Study Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1)	Year			
	Loss (m^2)	t = 2016	t = 2015	t = 2014	t = 2013
Protected Area					
Protected Area x t Year Dummy		-15.42	9.712	1.477	12.75
		(17.79)	(19.38)	(17.21)	(19.90)
t Year Dummy		-54.74	-12.33	-38.95	184.0*
		(67.43)	(74.26)	(59.84)	(110.7)
Ruggedness x t Year Dummy		5.172	59.70	16.42	23.74
		(46.71)	(56.38)	(46.33)	(47.70)
Slope (%) x t Year Dummy		0.00600	0.0539*	-0.0110	0.218
		(0.0422)	(0.0327)	(0.0420)	(0.155)
Maize Productivity x t Year Dummy		-0.00109	-0.00303	0.000572	0.00163
		(0.00385)	(0.00406)	(0.00339)	(0.00391)
Distance to Dirt Road (km) x t Year Dummy		-0.431	-0.682	1.153	-0.551
		(1.156)	(1.235)	(1.509)	(1.359)
Distance to Nairobi (km) x t Year Dummy		0.161	-0.0289	0.164	-0.127
		(0.121)	(0.117)	(0.114)	(0.127)
Distance to Closest City (km) x t Year Dummy		0.562*	0.355	0.344	-0.472
		(0.306)	(0.310)	(0.281)	(0.386)
Distance to Kenya Border (km) x t Year Dummy		0.230	-0.0799	0.147	-0.0682
		(0.175)	(0.166)	(0.142)	(0.163)
Population x t Year Dummy		0.0244*	0.00989	0.0251*	0.00376
		(0.0147)	(0.00858)	(0.0143)	(0.0106)
Years of Education x t Year Dummy		-0.946	-1.274	-3.834	-14.38**
		(4.083)	(4.548)	(3.895)	(7.308)
Agricultural Employment (%) x t Year Dummy		23.99	74.33*	26.40	-3.829
		(31.43)	(43.44)	(27.62)	(37.77)
Poverty (%) x t Year Dummy		-142.6	-23.18	-190.8	-84.73
		(216.6)	(230.8)	(215.1)	(243.2)
Nutritional Poverty (%) x t Year Dummy		-1.341	-36.63	38.51	-54.08
		(261.7)	(269.5)	(259.6)	(281.8)
Constant	39.29***				
	(5.109)				
N	32550				
Grid Cell Fixed Effect	Yes				

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C

Kenya Robustness Checks

Table C.1: Kenya Difference in Differences Incorporating Controls and Fixed Effects Using Deforested Sample

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
Protected Area	77.26	72.16		74.87	
	(69.66)	(72.97)		(72.96)	
Logging Ban (t = 2018)	47.79	69.92	66.20		
	(68.06)	(74.69)	(74.78)		
Protected Area x Logging Ban (t = 2018)	-265.2*	-242.3	-242.5	-247.6	-250.0
	(146.6)	(155.6)	(155.2)	(155.4)	(154.6)
Ruggedness		-8.499		0.918	
		(111.5)		(111.7)	
Slope (%)		0.222		0.209	
		(0.492)		(0.489)	
Maize Productivity		-0.00817		-0.00856	
		(0.00892)		(0.00895)	
Distance to Dirt Road (km)		-1.925		-2.216	
		(5.021)		(5.016)	
Distance to Nairobi (km)		-0.0677		-0.178	
		(0.310)		(0.305)	
Distance to Closest City (km)		-1.325		-1.650*	
		(0.916)		(0.943)	
Distance to Kenya Border (km)		-0.756		-0.745	
		(0.496)		(0.496)	
Population		-0.0794*	-0.0000715	-0.0735*	-0.125
		(0.0407)	(0.565)	(0.0389)	(0.626)
Years of Education		-13.64	-13.56	-34.37*	-40.71**
		(14.21)	(14.95)	(17.78)	(19.75)
Agricultural Employment (%)		92.16	231.5	40.87	150.9
		(171.6)	(333.9)	(171.2)	(327.8)
Poverty(%)		53.85		64.14	
		(417.7)		(419.2)	
Nutritional Poverty (%)		-756.1		-799.2	
		(531.3)		(537.1)	
Constant	380.7***	820.6***	408.0*	1059.6***	695.1***
	(23.10)	(205.8)	(216.2)	(235.0)	(263.0)
N	3288	3132	3132	3132	3132
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Kenya Difference in Differences Tobit Incorporating Controls and Year Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
Protected Area	-1001.0***	-376.7	-1009.6***	-359.6
	(280.3)	(312.0)	(282.8)	(314.3)
Logging Ban (t = 2018)	200.2	529.2*	266.1	300.9
	(272.0)	(295.2)	(344.0)	(356.2)
Protected Area x Logging Ban (t = 2018)	-595.3	-631.6	-583.6	-637.4
	(709.7)	(751.3)	(709.4)	(750.6)
Ruggedness		36.07		86.91
		(793.7)		(797.4)
Slope (%)		-1.607		-1.867
		(2.355)		(2.407)
Maize Productivity		0.0989**		0.0938**
		(0.0458)		(0.0461)
Distance to Dirt Road (km)		-128.8***		-129.7***
		(38.99)		(39.14)
Distance to Nairobi (km)		-5.090***		-5.161***
		(1.429)		(1.455)
Distance to Closest City (km)		-15.62***		-15.63***
		(5.087)		(5.160)
Distance to Kenya Border (km)		-9.228***		-9.322***
		(2.268)		(2.282)
Population		-0.709**		-0.645**
		(0.323)		(0.319)
Years of Education		-196.4***		-249.6***
		(56.09)		(71.96)
Agricultural Employment (%)		-229.7		-260.4
		(680.2)		(689.8)
Poverty (%)		-6315.6***		-6668.8***
		(2184.6)		(2205.9)
Nutritional Poverty (%)		6433.2**		6484.4**
		(2686.8)		(2708.2)
2013 Year Dummy			1514.1***	939.0***
			(305.9)	(362.5)
2014 Year Dummy			-971.8***	-1607.2***
			(362.4)	(421.7)
2015 Year Dummy			-823.4**	-1454.3***
			(357.3)	(415.7)
2016 Year Dummy			-167.8	-204.1
			(336.1)	(350.6)
Constant	-12870.0***	-8507.7***	-12908.5***	-7630.1***
	(481.5)	(976.5)	(529.6)	(1189.8)
Variance	36524632.2***	36723291.1***	36370999.5***	36482297.7***
	(2591199.7)	(2669695.3)	(2579821.2)	(2651128.9)
N	40584	39060	40584	39060
Controls	No	Yes	No	Yes
Year Fixed Effect	No	No	Yes	Yes

Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Kenya Difference in Differences Linear Probability Model Incorporating Controls and Fixed Effects

	(1) P($df = 1$)	(2) P($df = 1$))	(3) P($df = 1$)	(4) P($df = 1$)	(5) P($df = 1$)
Protected Area	-0.00599***	-0.00195		-0.00190	
	(0.00161)	(0.00175)		(0.00174)	
Logging Ban (t = 2018)	0.00136	0.00318	0.00375*		
	(0.00194)	(0.00201)	(0.00202)		
Protected Area x Logging Ban (t = 2018)	-0.00259	-0.00228	-0.00278	-0.00225	-0.00249
	(0.00325)	(0.00327)	(0.00329)	(0.00328)	(0.00329)
Ruggedness		-0.000467		-0.000404	
		(0.00531)		(0.00530)	
Slope (%)		-0.00000982		-0.00000990	
		(0.0000115)		(0.0000115)	
Maize Productivity		0.000000899**		0.000000891**	
		(0.000000400)		(0.000000400)	
Distance to Dirt Road (km)		-0.000396***		-0.000396***	
		(0.000142)		(0.000142)	
Distance to Nairobi (km)		-0.0000273***		-0.0000281***	
		(0.00000882)		(0.00000899)	
Distance to Closest City (km)		-0.0000622**		-0.0000635**	
		(0.0000273)		(0.0000272)	
Distance to Kenya Border (km)		-0.0000459***		-0.0000464***	
		(0.0000123)		(0.0000124)	
Population		-0.00000296**	-0.0000599**	-0.00000274*	-0.0000383
		(0.00000142)	(0.0000240)	(0.00000142)	(0.0000264)
Years of Education		-0.00107***	-0.000943***	-0.00122***	-0.00132***
		(0.000290)	(0.000311)	(0.000368)	(0.000408)
Agricultural Employment (%)		-0.00118	0.00318	-0.00131	0.00339
		(0.00481)	(0.00779)	(0.00478)	(0.00780)
Poverty (%)		-0.0345**		-0.0345**	
		(0.0153)		(0.0153)	
Consumption Poverty (%)		0.0388**		0.0385*	
		(0.0198)		(0.0198)	
Constant	0.0168***	0.0371***	0.0356***	0.0392***	0.0337***
	(0.000843)	(0.00516)	(0.00667)	(0.00585)	(0.00761)
N	40584	39060	39060	39060	39060
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

P($df = 1$) is the probability that deforestation will occur in a grid cell
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Kenya Spatial Auto-Regressive Difference in Differences Incorporating Controls and Year Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)
Protected Area			
Logging Ban (t = 2018)	3.845	4.934	2.691
	(5.866)	(6.127)	(7.247)
Protected Area x Logging Ban (t = 2018)	-14.82	-14.55	-14.47
	(12.60)	(12.62)	(12.62)
Population		-0.000861	-0.00298
		(0.0435)	(0.0462)
Years of Education (%)		-0.773	-1.472
		(1.107)	(1.468)
Agricultural Employment (%)		7.765	8.066
		(24.52)	(24.52)
2013 Year Dummy			-3.011
			(7.937)
2014 Year Dummy			-5.209
			(7.999)
2015 Year Dummy			-6.905
			(7.738)
2016 Year Dummy			-1.629
			(6.719)
Spatial Matrix			
Loss (m^2)	0.874***	0.874***	0.869***
	(0.0419)	(0.0420)	(0.0436)
σ_e			
Constant	389.7***	389.7***	389.7***
	(1.500)	(1.500)	(1.500)
N	40584	40584	40584
Controls	No	Yes	Yes
Grid Cell Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes

Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)

Standard errors in parentheses

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

Table C.5: Kenya Spatial Auto-regressive Difference in Differences Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1)			Year		
	Loss (m^2)	t = 2018	t = 2016	t = 2015	t = 2014	t = 2013
Protected Area						
Logging Ban (t = 2018)	18.78					
	(75.24)					
Protected Area x Logging Ban (t = 2018)	-10.09					
	(13.56)					
t Year Dummy			-42.21	-1.949	-15.51	159.5**
			(75.23)	(75.23)	(75.23)	(75.23)
Ruggedness x t Year Dummy		-39.25	-29.45	3.423	-17.22	-1.369
		(48.01)	(47.98)	(47.98)	(47.98)	(47.98)
Slope (%) x t Year Dummy		0.274*	0.0233	0.0595	-0.0101	0.158
		(0.144)	(0.143)	(0.143)	(0.143)	(0.144)
Maize Productivity x t Year Dummy		-0.00171	-0.0000491	-0.00224	0.00172	0.00116
		(0.00324)	(0.00321)	(0.00321)	(0.00321)	(0.00321)
Distance to Dirt Road (km) x t Year Dummy		0.976	-0.370	-0.196	1.019	-0.245
		(1.913)	(1.911)	(1.911)	(1.911)	(1.911)
Distance to Nairobi (km) x t Year Dummy		-0.135	0.0917	-0.0506	0.0454	-0.118
		(0.0983)	(0.0978)	(0.0977)	(0.0978)	(0.0977)
Distance to Closest City (km) x t Year Dummy		0.00975	0.399	0.211	0.123	-0.427
		(0.341)	(0.341)	(0.341)	(0.341)	(0.341)
Distance to Kenya Border (km) x t Year Dummy		-0.0265	0.165	-0.0569	0.0632	-0.0440
		(0.140)	(0.139)	(0.139)	(0.139)	(0.139)
Population x t Year Dummy		0.0106	0.0146	0.00411	0.0131	-0.00213
		(0.0140)	(0.0139)	(0.0139)	(0.0139)	(0.0139)
Years of Education x t Year Dummy		-2.489	0.431	-0.604	-1.080	-12.21**
		(4.808)	(4.800)	(4.800)	(4.803)	(4.800)
Agricultural Employment (%) x t Year Dummy		37.45	21.70	62.51	24.79	-9.316
		(44.73)	(44.73)	(44.73)	(44.73)	(44.73)
Poverty (%) x t Year Dummy		-76.44	-86.47	8.110	-69.67	-40.12
		(144.0)	(143.6)	(143.6)	(143.7)	(143.6)
Nutritional Poverty (%) x t Year Dummy		194.6	4.560	-20.91	-0.837	-67.37
		(184.4)	(183.7)	(183.7)	(183.7)	(183.7)
Spatial Matrix						
Loss (m^2)	0.855***					
	(0.0463)					
σ_e						
Constant	389.5***					
	(1.499)					
Grid Cell Fixed Effect	Yes					

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D

Uganda Results

Table D.1: Uganda Difference in Means Tests at the 25th Percentile

	Below 25%		Above 25%		Difference in Means	
	Count	Mean	Count	Mean	Difference	P-Value
Loss (m^2)	71046	55.11673	213140	26.57292	28.54***	(0.000)
Loss 2013 (m^2)	71046	147.8527	213140	85.41988	62.43***	(0.000)
Loss 2014 (m^2)	71046	10.87308	213140	5.796963	5.076***	(0.000)
Loss 2015 (m^2)	71046	23.5304	213140	11.16552	12.36***	(0.000)
Loss 2016 (m^2)	71046	51.29341	213140	18.99334	32.30***	(0.000)
Loss 2017 (m^2)	71046	60.50581	213140	26.17377	34.33***	(0.000)
Loss 2018 (m^2)	71046	36.64499	213140	11.88806	24.76***	(0.000)
Loss 2013 - 2017 (m^2)	71046	294.0554	213140	147.5495	146.5***	(0.000)
Forest 2012	71046	.9303211	213140	.9298356	0.000486	(0.545)
Protected Area	71046	.3326577	213140	.3868725	-0.0542***	(0.000)
Ruggedness	71046	110895.2	213140	112726.5	-1831.3**	(0.003)
Slope (%)	71046	8.609712	213140	11.22445	-2.615***	(0.000)
Maize Productivity	71046	2432.981	213140	2578.17	-145.2***	(0.000)
Distance to Dirt Road (km)	71046	101.2408	213140	147.4451	-46.20***	(0.000)
Distance to Improved Road (km)	71046	103.5555	213140	148.4254	-44.87***	(0.000)
Distance to Closest City (km)	71046	29.30259	213140	34.60255	-5.300***	(0.000)
Distance to Kampala (km)	71046	118.6237	213140	220.1341	-101.5***	(0.000)
Distance to Nairobi (km)	71046	494.4265	213140	701.0111	-206.6***	(0.000)
Population	71046	183.1957	213140	113.1885	70.01***	(0.000)
Years of Education	69609	5.971787	212945	6.345385	-0.374***	(0.000)
Agricultural Employment (%)	69609	.3312661	212945	.2741492	0.0571***	(0.000)
Poverty (%)	69609	.2143283	212945	.2199496	-0.00562***	(0.000)
N	284186					

Data is separated by the 25th percentile of Euclidean distance to Kenya border crossing

211.81km is the 25th percentile Euclidean distance to Kenyan border crossing

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

Table D.2: Uganda Difference in Differences (Log Specification) Incorporating Controls and Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
log(Distance to Kenya Border Crossing)	-5.802***	-3.934***		-3.117***	
	(0.405)	(0.792)		(0.799)	
Logging Ban (t = 2018)	-13.20***	-5.055	-0.501		
	(4.505)	(4.551)	(4.706)		
log(Distance to Kenya Crossing) x Logging Ban	-1.007	-2.475***	-2.498***	-3.252***	-2.170***
	(0.757)	(0.782)	(0.808)	(0.799)	(0.816)
Ruggedness		2.463		2.748	
		(2.032)		(2.035)	
Slope (%)		0.0201***		0.0193***	
		(0.00241)		(0.00241)	
Maize Productivity		-0.00509***		-0.00525***	
		(0.000257)		(0.000255)	
Distance to Dirt Road (km)		0.0240***		0.0299***	
		(0.00898)		(0.00902)	
Distance to Kampala (km)		-0.188***		-0.185***	
		(0.00766)		(0.00769)	
Distance to Closest City (km)		0.220***		0.237***	
		(0.0230)		(0.0230)	
Population		-0.0477***	-0.508***	-0.0413***	-0.182***
		(0.00246)	(0.0214)	(0.00232)	(0.0234)
Years of Education		2.605***	1.740	1.702**	1.170
		(0.677)	(1.860)	(0.664)	(1.727)
Agricultural Employment (%)		31.79***	11.48	44.94***	17.54*
		(6.711)	(10.02)	(7.378)	(9.996)
Poverty (%)		-124.6***		-121.3***	
		(7.449)		(7.475)	
Constant	68.85***	105.1***	88.38***	99.21***	47.05***
	(2.351)	(7.805)	(14.47)	(7.754)	(13.65)
N	1705116	1695324	1695324	1695324	1695324
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.3: Uganda Difference in Differences (Log Specification) Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1)	Year				
	Loss (m^2)	t = 2018	t = 2016	t = 2015	t = 2014	t = 2013
log(Distance to Kenya Crossing)						
Logging Ban (t = 2018)	57.17***					
	(24.99)					
log(Distance to Kenya Crossing) x Logging Ban	-5.387***					
	(1.498)					
t Year Dummy			37.14	-49.72*	-59.40**	11.46
			(28.25)	(25.82)	(23.71)	(39.86)
Ruggedness x *t*		16.93***	5.018	20.38***	22.43***	97.10***
		(5.534)	(5.524)	(5.160)	(4.914)	(9.065)
Slope (%) x *t* Year Dummy		-0.0103***	0.000927	-0.00671***	-0.0109***	0.0447***
		(0.00199)	(0.00208)	(0.00199)	(0.00194)	(0.0141)
Maize Productivity x *t* Year Dummy		0.00688***	0.00410***	0.00803***	0.0103***	0.00547***
		(0.000838)	(0.000882)	(0.000794)	(0.000759)	(0.00115)
Distance to Dirt Road (km) x *t* Year Dummy		-0.0795**	-0.154***	-0.111***	-0.154***	0.0954**
		(0.0344)	(0.0338)	(0.0313)	(0.0297)	(0.0463)
Distance to Kampala (km) x *t* Year Dummy		0.0843***	-0.0637**	0.0344	0.0853***	-0.120***
		(0.0290)	(0.0277)	(0.0252)	(0.0243)	(0.0391)
Distance to Closest City (km) x *t* Year Dummy		-0.261***	-0.259***	-0.270***	-0.407***	-0.0495
		(0.0698)	(0.0751)	(0.0696)	(0.0667)	(0.0997)
Population x *t* Year Dummy		0.0323***	0.0172***	0.0391***	0.0501***	0.0134
		(0.00596)	(0.00611)	(0.00454)	(0.00457)	(0.00954)
Years of Education x *t* Year Dummy		-5.377**	1.230	3.924	4.573*	8.457**
		(2.439)	(2.871)	(2.616)	(2.439)	(3.991)
Agricultural Employment (%) x *t* Year Dummy		-93.85***	-107.2***	-95.27***	-115.5***	159.9***
		(26.71)	(28.42)	(26.60)	(25.35)	(38.34)
Poverty (%) x *t* Year Dummy		-20.81	24.31	93.71***	80.01***	-261.6***
		(19.97)	(20.36)	(19.57)	(16.99)	(27.64)
Constant	34.62***					
	(0.865)					
N	1695324					
Grid Cell Fixed Effect	Yes					

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.4: Uganda Difference in Differences (Inverse Specification) Incorporating Controls and Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$	-134.9***	-17.32		-26.57**	
	(17.44)	(12.46)		(12.75)	
Logging Ban (t = 2018)	-19.31***	-19.48***	-15.02***		
	(0.840)	(0.876)	(0.885)		
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x Logging Ban	87.97***	109.5***	117.7***	118.8***	106.7***
	(18.67)	(20.57)	(21.28)	(21.32)	(20.64)
Ruggedness		6.253***		6.070***	
		(1.867)		(1.866)	
Slope (%)		0.0211***		0.0202***	
		(0.00241)		(0.00240)	
Maize Productivity		-0.00516***		-0.00531***	
		(0.000258)		(0.000256)	
Distance to Dirt Road (km)		0.00386		0.0123	
		(0.00745)		(0.00754)	
Distance to Kampala (km)		-0.217***		-0.210***	
		(0.00555)		(0.00570)	
Distance to Closest City (km)		0.219***		0.236***	
		(0.0230)		(0.0230)	
Population		-0.0468***	-0.508***	-0.0404***	-0.182***
		(0.00242)	(0.0214)	(0.00228)	(0.0234)
Years of Education		1.862***	1.593	1.037	1.063
		(0.677)	(1.840)	(0.665)	(1.713)
Agricultural Employment (%)		30.99***	9.621	43.60***	15.97*
		(6.579)	(9.746)	(7.195)	(9.707)
Poverty (%)		-103.2***		-102.9***	
		(6.058)		(6.060)	
Constant	37.68***	91.75***	89.77***	86.52***	46.04***
	(0.439)	(6.677)	(14.29)	(6.772)	(13.70)
N	1705116	1695324	1695324	1695324	1695324
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)

Standard errors are clustered at the grid cell level

Standard errors in parentheses

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

Table D.5: Uganda Difference in Differences (Inverse Specification) Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1)	Year				
	Loss (m^2)	t = 2018	t = 2016	t = 2015	t = 2014	t = 2013
$\frac{1}{\text{Distance to Kenya Border Crossing}}$						
Logging Ban (t = 2018)	32.45					
	(24.70)					
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x Logging Ban	37.27*					
	(1.498)					
t Year Dummy			37.14	-49.72*	-59.40**	11.46
			(28.25)	(25.82)	(23.71)	(39.86)
Ruggedness x *t*		20.64***	5.018	20.38***	22.43***	97.10***
		(5.331)	(5.524)	(5.160)	(4.914)	(9.065)
Slope (%) x *t* Year Dummy		-0.00906***	0.000927	-0.00671***	-0.0109***	0.0447***
		(0.00197)	(0.00208)	(0.00199)	(0.00194)	(0.0141)
Maize Productivity x *t* Year Dummy		0.00681***	0.00410***	0.00803***	0.0103***	0.00547***
		(0.000842)	(0.000882)	(0.000794)	(0.000759)	(0.00115)
Distance to Dirt Road (km) x *t* Year Dummy		-0.100***	-0.154***	-0.111***	-0.154***	0.0954**
		(0.0322)	(0.0338)	(0.0313)	(0.0297)	(0.0463)
Distance to Kampala (km) x *t* Year Dummy		0.0537**	-0.0637**	0.0344	0.0853***	-0.120***
		(0.0263)	(0.0277)	(0.0252)	(0.0243)	(0.0391)
Distance to Closest City (km) x *t* Year Dummy		-0.263***	-0.259***	-0.270***	-0.407***	-0.0495
		(0.0697)	(0.0751)	(0.0696)	(0.0667)	(0.0997)
Population x *t* Year Dummy		0.0335***	0.0172***	0.0391***	0.0501***	0.0134
		(0.00592)	(0.00611)	(0.00454)	(0.00457)	(0.00954)
Years of Education x *t* Year Dummy		-5.831**	1.230	3.924	4.573*	8.457**
		(2.441)	(2.871)	(2.616)	(2.439)	(3.991)
Agricultural Employment (%) x *t* Year Dummy		-91.26***	-107.2***	-95.27***	-115.5***	159.9***
		(26.79)	(28.42)	(26.60)	(25.35)	(38.34)
Poverty (%) x *t* Year Dummy		3.859	24.31	93.71***	80.01***	-261.6***
		(18.19)	(20.36)	(19.57)	(16.99)	(27.64)
Constant	34.62***					
	(0.865)					
N	1695324					
Grid Cell Fixed Effect	Yes					

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure D.1: Uganda Difference in Differences (Interval Specification) Including Full Sample

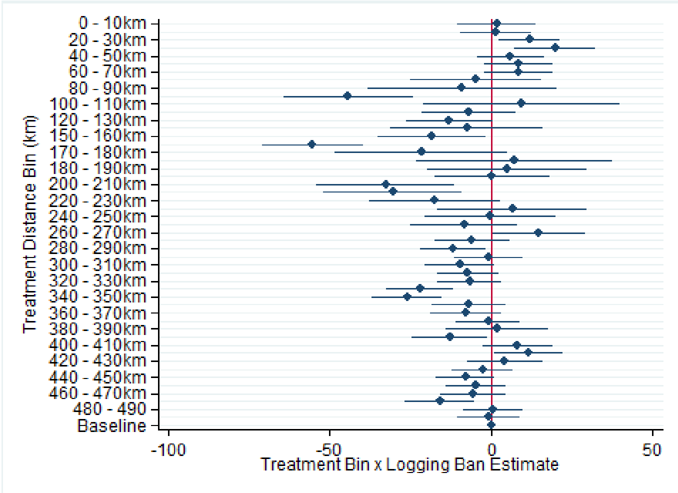


Figure D.2: Uganda Difference in Differences (Interval Specification) Excluding Furthest 10% of Observations by Distance to Border Crossing

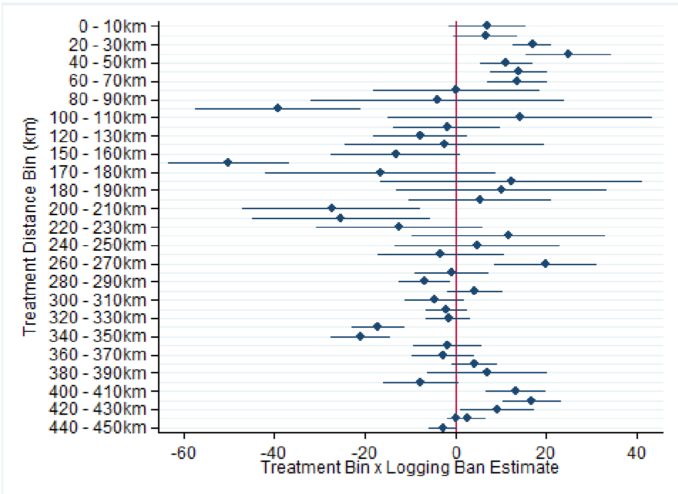


Figure D.3: Uganda Difference in Differences (Interval Specification) Excluding Furthest 25% of Observations by Distance to Border Crossing

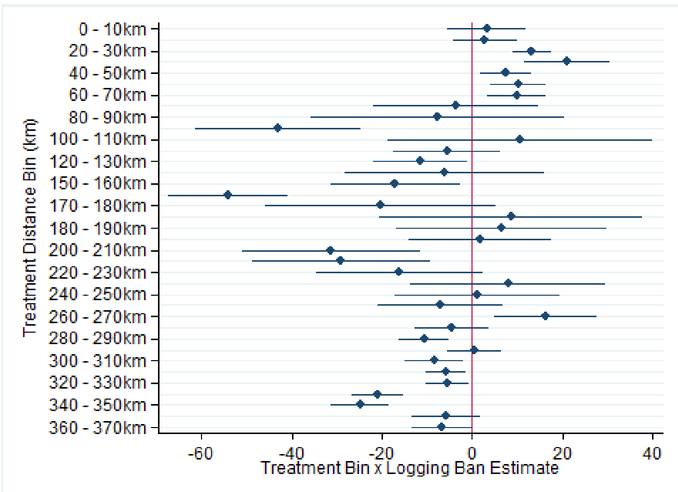


Figure D.4: Uganda Difference in Differences (Interval Specification) Excluding Furthest 50% of Observations by Distance to Border Crossing

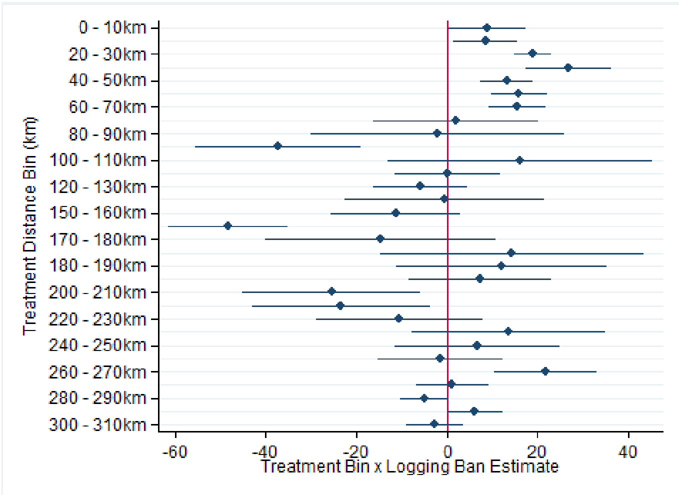


Figure D.5: Uganda Difference in Differences (Interval Specification) Excluding Furthest 75% of Observations by Distance to Border Crossing

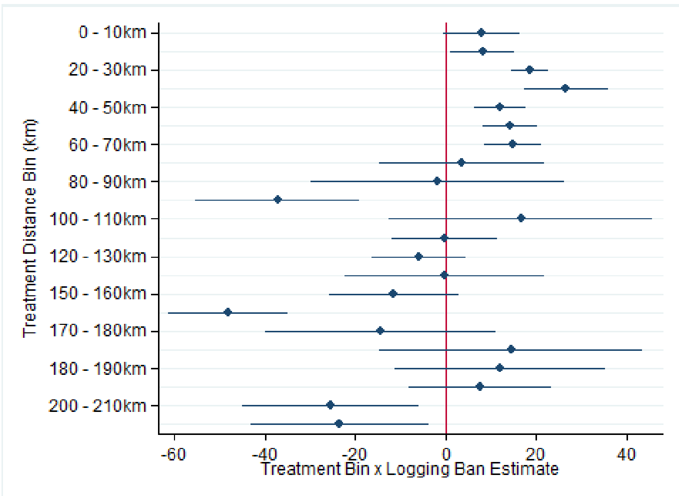


Table D.6: Uganda Event Study (Log Specification) Incorporating Controls and Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
log(Distance to Kenya Border Crossing)	-10.21***	-10.57***		-10.57***	
	(0.929)	(1.254)		(1.254)	
2013 Year Dummy	36.77***	3.089	16.09*		
	(8.967)	(8.856)	(8.834)		
2014 Year Dummy	-73.19***	-105.2***	-92.25***		
	(6.042)	(6.586)	(7.034)		
2015 Year Dummy	-49.62***	-79.96***	-57.98***		
	(6.709)	(7.209)	(7.569)		
2016 Year Dummy	-25.14***	-26.82***	-26.82***		
	(6.873)	(6.895)	(6.895)		
log(Distance to Kenya Border Crossing) x 2013 Year Dummy	5.348***	11.59***	8.264***	11.59***	8.264***
	(1.549)	(1.588)	(1.595)	(1.588)	(1.595)
log(Distance to Kenya Border Crossing) x 2014 Year Dummy	8.247***	14.22***	10.90***	14.22***	10.90***
	(1.032)	(1.192)	(1.279)	(1.192)	(1.279)
log(Distance to Kenya Border Crossing) x 2015 Year Dummy	5.279***	11.10***	6.845***	11.10***	6.845***
	(1.147)	(1.298)	(1.378)	(1.298)	(1.378)
log(Distance to Kenya Border Crossing) x 2016 Year Dummy	3.163***	3.438***	3.438***	3.438***	3.438***
	(1.163)	(1.167)	(1.167)	(1.167)	(1.167)
Ruggedness		4.953**		4.953**	
		(2.288)		(2.288)	
Slope (%)		0.0215***		0.0215***	
		(0.00287)		(0.00287)	
Maize Productivity		-0.00545***		-0.00545***	
		(0.000282)		(0.000282)	
Distance to Dirt Road (km)		0.0407***		0.0407***	
		(0.0106)		(0.0106)	
Distance to Kampala (km)		-0.193***		-0.193***	
		(0.00909)		(0.00909)	
Distance to Closest City (km)		0.250***		0.250***	
		(0.0257)		(0.0257)	
Population		-0.0430***	-0.214***	-0.0430***	-0.214***
		(0.00251)	(0.0235)	(0.00251)	(0.0235)
Years of Education		2.822***	2.280	2.822***	2.280
		(0.824)	(2.063)	(0.824)	(2.063)
Agricultural Employment (%)		70.84***	21.35	70.84***	21.35
		(9.052)	(13.24)	(9.052)	(13.24)
Poverty (%)		-119.6***		-119.6***	
		(8.539)		(8.539)	
Constant	91.08***	123.1***	43.77***	81.34***	11.58
	(5.471)	(10.00)	(16.98)	(9.551)	(18.84)
N	1420930	1412770	1412770	1412770	1412770
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.7: Uganda Event Study (Log Specification) Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1)	Year			
	Loss (m^2)	t = 2016	t = 2015	t = 2014	t = 2013
log(Distance to Kenya Crossing)					
log(Distance to Kenya Crossing) x t Year Dummy		12.66***	8.338***	10.10***	23.07***
		(2.579)	(2.413)	(2.195)	(3.139)
t Year Dummy		-22.74	-89.15***	-107.2***	-97.64**
		(30.07)	(27.63)	(25.30)	(42.24)
Ruggedness x t		14.89**	26.88***	30.30***	115.1***
		(6.283)	(5.800)	(5.491)	(9.613)
Slope (%) x t Year Dummy		0.00423*	-0.00453**	-0.00828***	0.0507***
		(0.00218)	(0.00206)	(0.00201)	(0.0141)
Maize Productivity x t Year Dummy		0.00391***	0.00790***	0.0102***	0.00512***
		(0.000876)	(0.000787)	(0.000752)	(0.00115)
Distance to Dirt Road (km) x t Year Dummy		-0.207***	-0.146***	-0.196***	-0.00165
		(0.0399)	(0.0364)	(0.0352)	(0.0527)
Distance to Kampala (km) x t Year Dummy		-0.141***	-0.0164	0.0238	-0.261***
		(0.0350)	(0.0315)	(0.0305)	(0.0469)
Distance to Closest City (km) x t Year Dummy		-0.265***	-0.274***	-0.412***	-0.0614
		(0.0753)	(0.0696)	(0.0668)	(0.0999)
Population x t Year Dummy		0.0205***	0.0412***	0.0527***	0.0192**
		(0.00620)	(0.00461)	(0.00465)	(0.00966)
Years of Education x t Year Dummy		0.445	3.406	3.947	7.027*
		(2.853)	(2.606)	(2.421)	(3.969)
Agricultural Employment (%) x t Year Dummy		-99.15***	-89.99***	-109.1***	174.5***
		(28.16)	(26.39)	(25.09)	(38.11)
Poverty (%) x t Year Dummy		89.65***	136.7***	132.1***	-142.5***
		(24.96)	(23.62)	(20.88)	(33.96)
Constant	34.62***				
	(0.855)				
N	1412770				
Grid Cell Fixed Effect	Yes				

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.8: Uganda Event Study (Inverse Specification) Incorporating Controls and Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$	-76.42***	82.76***		82.76***	
	(24.62)	(26.30)		(26.30)	
2013 Year Dummy	69.32***	69.92***	64.61***		
	(1.711)	(1.840)	(1.970)		
2014 Year Dummy	-28.21***	-27.43***	-32.74***		
	(1.128)	(1.248)	(1.440)		
2015 Year Dummy	-21.27***	-19.68***	-21.33***		
	(1.203)	(1.311)	(1.331)		
2016 Year Dummy	-7.608***	-7.745***	-7.745***		
	(1.301)	(1.301)	(1.301)		
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x 2013 Year Dummy	-484.0***	-541.9***	-510.5***	-541.9***	-510.5***
	(62.02)	(69.00)	(65.74)	(69.00)	(65.74)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x 2014 Year Dummy	82.16***	25.00	56.38*	25.00	56.38*
	(28.74)	(29.22)	(30.31)	(29.22)	(30.31)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x 2015 Year Dummy	122.2***	70.57*	122.6***	70.57*	122.6***
	(38.01)	(37.72)	(39.84)	(37.72)	(39.84)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x 2016 Year Dummy	-12.75	-14.57	-14.57	-14.57	-14.57
	(33.43)	(33.52)	(33.52)	(33.52)	(33.52)
Ruggedness		7.767***		7.767***	
		(2.102)		(2.102)	
Slope (%)		0.0223***		0.0223***	
		(0.00286)		(0.00286)	
Maize Productivity		-0.00551***		-0.00551***	
		(0.000283)		(0.000283)	
Distance to Dirt Road (km)		0.0194**		0.0194**	
		(0.00886)		(0.00886)	
Distance to Kampala (km)		-0.220***		-0.220***	
		(0.00677)		(0.00677)	
Distance to Closest City (km)		0.247***		0.247***	
		(0.0257)		(0.0257)	
Population		-0.0424***	-0.211***	-0.0424***	-0.211***
		(0.00246)	(0.0234)	(0.00246)	(0.0234)
Years of Education		1.531*	0.478	1.531*	0.478
		(0.826)	(1.998)	(0.826)	(1.998)
Agricultural Employment (%)		46.35***	-0.980	46.35***	-0.980
		(8.139)	(11.56)	(8.139)	(11.56)
Poverty (%)		-110.4***		-110.4***	
		(6.967)		(6.967)	
Constant	35.24***	85.60***	61.26***	88.62***	61.81***
	(1.036)	(8.610)	(16.13)	(8.253)	(15.85)
N	1420930	1412770	1412770	1412770	1412770
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.9: Uganda Event Study (Inverse Specification) Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1) Loss (m^2)	Year t = 2016	t = 2015	t = 2014	t = 2013
$\frac{1}{\text{Distance to Kenya Border Crossing}}$					
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x t Year Dummy		-112.3***	8.571	-44.34	-333.1***
		(42.14)	(38.82)	(31.69)	(60.52)
t Year Dummy		34.85	-49.54*	-60.31**	4.662
		(28.25)	(25.82)	(23.71)	(39.85)
Ruggedness x t		6.504	20.26***	23.02***	101.5***
		(5.655)	(5.271)	(5.010)	(9.171)
Slope (%) x t Year Dummy		0.00131	-0.00674***	-0.0108***	0.0458***
		(0.00210)	(0.00200)	(0.00195)	(0.0141)
Maize Productivity x t Year Dummy		0.00406***	0.00803***	0.0103***	0.00535***
		(0.000882)	(0.000793)	(0.000758)	(0.00115)
Distance to Dirt Road (km) x t Year Dummy		-0.160***	-0.111***	-0.156***	0.0764
		(0.0346)	(0.0319)	(0.0304)	(0.0474)
Distance to Kampala (km) x t Year Dummy		-0.0701**	0.0349	0.0827***	-0.139***
		(0.0283)	(0.0256)	(0.0248)	(0.0400)
Distance to Closest City (km) x t Year Dummy		-0.261***	-0.269***	-0.408***	-0.0548
		(0.0752)	(0.0696)	(0.0667)	(0.0997)
Population x t Year Dummy		0.0179***	0.0390***	0.0504***	0.0153
		(0.00612)	(0.00454)	(0.00457)	(0.00956)
Years of Education x t Year Dummy		1.592	3.896	4.716*	9.530**
		(2.895)	(2.632)	(2.458)	(4.020)
Agricultural Employment (%) x t Year Dummy		-104.7***	-95.46***	-114.5***	167.3***
		(28.33)	(26.53)	(25.25)	(38.22)
Poverty (%) x t Year Dummy		33.76	92.99***	83.74***	-233.6***
		(20.74)	(19.84)	(17.38)	(28.58)
Constant	34.62***				
	(0.855)				
N	1412770				
Grid Cell Fixed Effect	Yes				

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix E

Uganda Robustness Checks

Table E.1: Uganda Difference in Differences (Log Specification Using Distance to Kenyan Border) Incorporating Controls and Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
log(Distance to Kenya Border)	-2.965***	-0.703		-0.0957	
	(0.311)	(0.553)		(0.558)	
Logging Ban (t = 2018)	-12.91***	-6.428*	-1.708		
	(3.314)	(3.330)	(3.458)		
log(Distance to Kenya Border) x Logging Ban	-1.072*	-2.265***	-2.305***	-2.856***	-1.999***
	(0.553)	(0.574)	(0.595)	(0.587)	(0.600)
Ruggedness		5.042**		5.299***	
		(1.996)		(1.998)	
Slope (%)		0.0208***		0.0200***	
		(0.00241)		(0.00241)	
Maize Productivity		-0.00512***		-0.00528***	
		(0.000258)		(0.000256)	
Distance to Dirt Road (km)		0.00992		0.0163*	
		(0.00859)		(0.00864)	
Distance to Kampala (km)		-0.209***		-0.205***	
		(0.00697)		(0.00703)	
Distance to Closest City (km)		0.220***		0.237***	
		(0.0230)		(0.0230)	
Population		-0.0471***	-0.509***	-0.0406***	-0.182***
		(0.00244)	(0.0214)	(0.00230)	(0.0234)
Years of Education		2.090***	1.763	1.203*	1.191
		(0.674)	(1.858)	(0.661)	(1.726)
Agricultural Employment (%)		32.11***	11.56	45.34***	17.60*
		(6.696)	(9.980)	(7.355)	(9.954)
Poverty (%)		-109.1***		-106.4***	
		(7.005)		(7.024)	
Constant	53.00***	92.66***	88.22***	87.31***	46.73***
	(1.796)	(7.331)	(14.45)	(7.315)	(13.68)
N	1705116	1695324	1695324	1695324	1695324
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Uganda Difference in Differences (Inverse Specification Using Distance to Kenyan Border) Incorporating Controls and Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
$\frac{1}{\text{Distance to Kenya Border}}$	-22.65***	-12.32***		-13.00***	
	(2.099)	(1.514)		(1.561)	
Logging Ban (t = 2018)	-18.88***	-18.94***	-14.41***		
	(0.820)	(0.847)	(0.857)		
$\frac{1}{\text{Distance to Kenya Border}}$ x Logging Ban	10.37***	11.97***	11.89***	12.60***	11.51***
	(1.518)	(1.658)	(1.714)	(1.697)	(1.675)
Ruggedness		6.658***		6.381***	
		(1.841)		(1.839)	
Slope (%)		0.0212***		0.0203***	
		(0.00241)		(0.00241)	
Maize Productivity		-0.00520***		-0.00535***	
		(0.000259)		(0.000257)	
Distance to Dirt Road (km)		0.00198		0.0107	
		(0.00730)		(0.00739)	
Distance to Kampala (km)		-0.219***		-0.212***	
		(0.00546)		(0.00562)	
Distance to Closest City (km)		0.218***		0.235***	
		(0.0230)		(0.0230)	
Population		-0.0467***	-0.507***	-0.0403***	-0.181***
		(0.00241)	(0.0214)	(0.00226)	(0.0234)
Years of Education		1.842***	1.520	1.018	1.003
		(0.677)	(1.837)	(0.665)	(1.710)
Agricultural Employment (%)		30.95***	8.777	43.44***	15.23
		(6.551)	(9.705)	(7.161)	(9.666)
Poverty (%)		-101.2***		-101.3***	
		(6.003)		(6.002)	
Constant	37.10***	92.15***	90.39***	86.99***	46.63***
	(0.418)	(6.671)	(14.27)	(6.763)	(13.67)
N	1705116	1695324	1695324	1695324	1695324
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure E.1: Uganda Difference in Differences (Interval Specification) Excluding 10th Percentile of Observations By Distance to Border

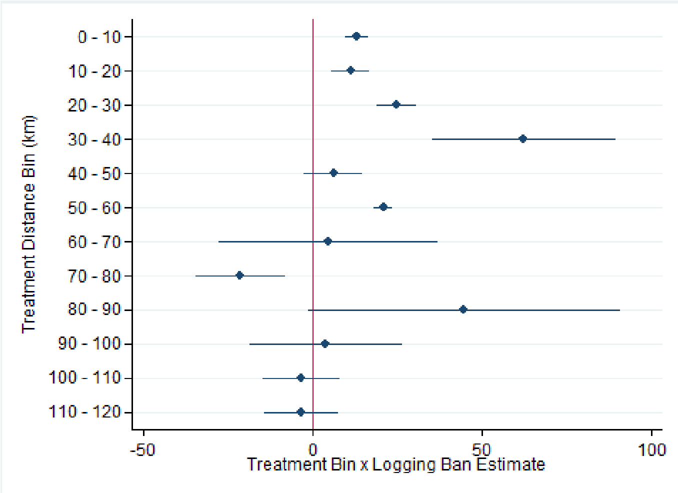


Figure E.2: Uganda Difference in Differences (Interval Specification) Including Full Sample

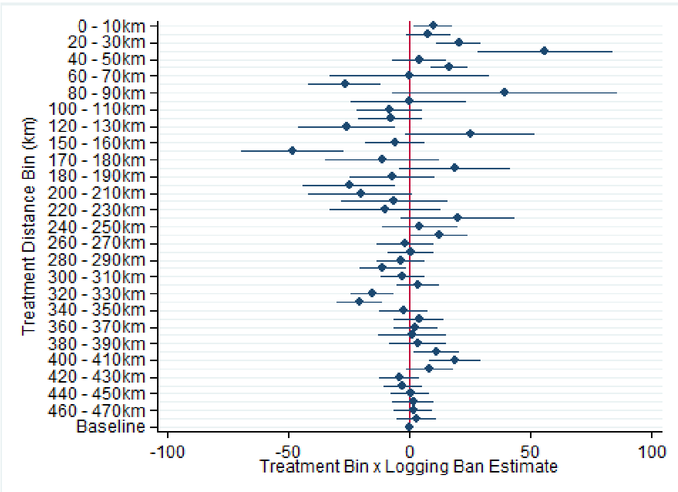


Figure E.3: Uganda Difference in Differences (Interval Specification) Excluding Furthest 10% of Observations by Distance to Border

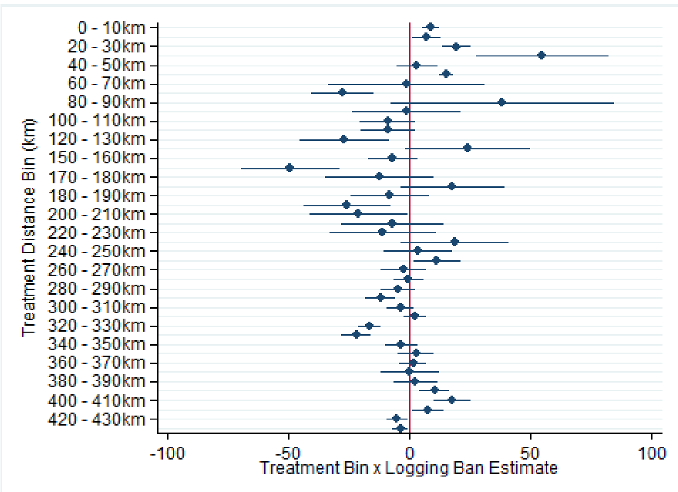


Figure E.4: Uganda Difference in Differences (Interval Specification) Excluding Furthest 25% of Observations by Distance to Border

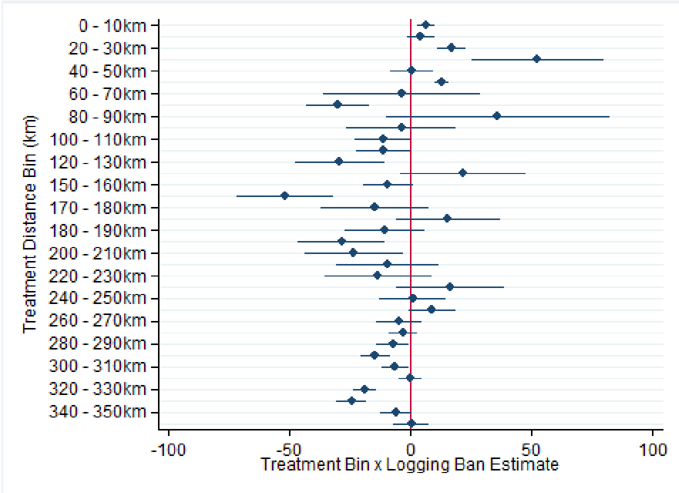


Figure E.5: Uganda Difference in Differences (Interval Specification) Excluding Furthest 50% of Observations by Distance to Border

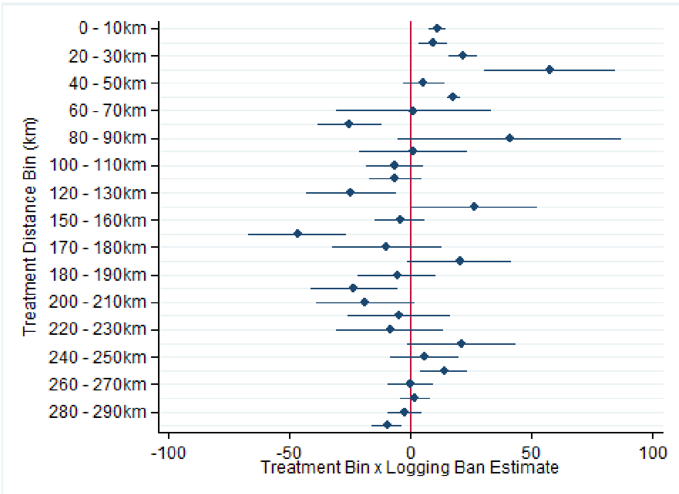


Figure E.6: Uganda Difference in Differences (Interval Specification) Excluding Furthest 75% of Observations by Distance to Border

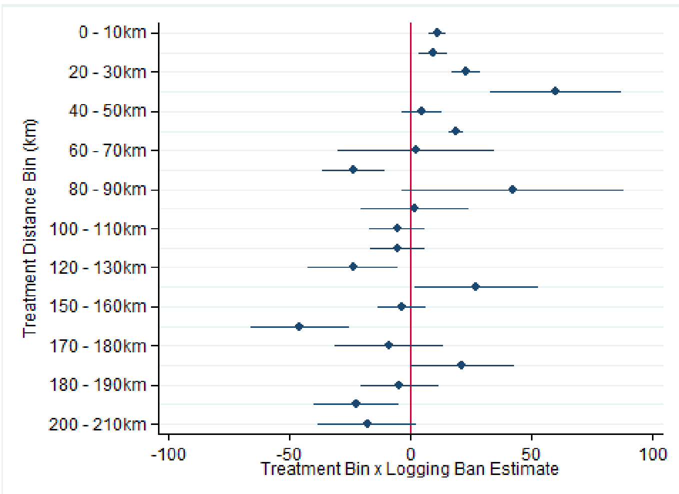


Table E.3: Uganda Difference in Differences (Log Specification) Incorporating Controls and Fixed Effects Using Deforested Sample

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
log(Distance to Kenya Border Crossing)	-64.11***	-92.52***		-88.74***	
	(7.900)	(12.98)		(12.93)	
Logging Ban (t = 2018)	38.70	-54.29	29.97		
	(96.94)	(100.8)	(102.2)		
log(Distance to Kenya Border Crossing) x Logging Ban	-60.00***	-42.51**	-49.29***	-33.32*	-33.10*
	(16.98)	(17.71)	(17.90)	(17.65)	(17.84)
Ruggedness		-445.3***		-446.8***	
		(34.75)		(34.78)	
Slope (%)		0.0288		0.0180	
		(0.0363)		(0.0363)	
Maize Productivity		-0.0577***		-0.0607***	
		(0.00384)		(0.00374)	
Distance to Dirt Road (km)		0.458***		0.485***	
		(0.103)		(0.103)	
Distance to Kampala (km)		-0.108		-0.148	
		(0.113)		(0.112)	
Distance to Closest City (km)		2.077***		2.225***	
		(0.299)		(0.297)	
Population		-0.347***	-5.035***	-0.271***	-1.258***
		(0.0357)	(0.450)	(0.0284)	(0.216)
Years of Education		44.87***	85.66**	18.89*	7.684
		(10.85)	(34.16)	(10.73)	(34.57)
Agricultural Employment (%)		-149.2	-138.3	-333.6***	-398.9***
		(91.58)	(129.2)	(88.41)	(126.3)
Poverty (%)		-976.0***		-988.3***	
		(111.9)		(111.4)	
Constant	920.7***	1130.8***	748.0***	1308.6***	793.9***
	(44.03)	(111.9)	(263.9)	(104.0)	(247.9)
N	110298	109560	109560	109560	109560
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.4: Uganda Difference in Differences (Inverse Specification) Incorporating Controls and Fixed Effects Using Deforested Sample

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)	(5) Loss (m^2)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$	-1359.0***	1533.5***		1469.1***	
	(425.3)	(528.4)		(527.4)	
Logging Ban (t = 2018)	-299.1***	-296.0***	-250.2***		
	(13.29)	(13.22)	(13.74)		
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x Logging Ban	1665.0**	1394.8*	1764.5**	1237.2	1265.4
	(789.9)	(790.1)	(803.0)	(786.3)	(786.8)
Ruggedness		-397.3***		-401.3***	
		(34.00)		(34.00)	
Slope (%)		0.0391		0.0277	
		(0.0362)		(0.0362)	
Maize Productivity		-0.0592***		-0.0621***	
		(0.00383)		(0.00374)	
Distance to Dirt Road (km)		0.178*		0.221**	
		(0.0926)		(0.0924)	
Distance to Kampala (km)		-0.660***		-0.669***	
		(0.0827)		(0.0824)	
Distance to Closest City (km)		2.181***		2.325***	
		(0.299)		(0.298)	
Population		-0.344***	-5.032***	-0.268***	-1.253***
		(0.0349)	(0.449)	(0.0277)	(0.216)
Years of Education		29.40***	84.56**	4.118	6.430
		(10.64)	(34.14)	(10.52)	(34.53)
Agricultural Employment (%)		-183.3**	-171.1	-363.1***	-422.3***
		(89.11)	(126.2)	(86.08)	(123.2)
Poverty (%)		-637.9***		-667.9***	
		(98.66)		(98.36)	
Constant	576.9***	780.5***	764.6***	938.2***	776.8***
	(5.580)	(91.87)	(263.4)	(89.15)	(249.2)
N	110298	109560	109560	109560	109560
Controls	No	Yes	Yes	Yes	Yes
Grid Cell Fixed Effect	No	No	Yes	No	Yes
Year Fixed Effect	No	No	No	Yes	Yes

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.5: Uganda Difference in Differences (Log Specification) Tobit Incorporating Controls and Year Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
ln(Distance to Kenya Border Crossing)	-294.4***	177.1**	-429.2***	142.8**
	(33.03)	(69.20)	(34.75)	(71.47)
Logging Ban (t = 2018)	542.6	4051.6***	1857.2***	5050.9***
	(575.6)	(696.4)	(563.3)	(700.7)
ln(Distance to Kenya Border Crossing) x Logging Ban	-830.7***	-1459.7***	-657.9***	-1251.6***
	(106.5)	(129.6)	(103.6)	(130.0)
Ruggedness		3223.0***		3106.2***
		(199.5)		(211.9)
Slope (%)		2.231***		2.033***
		(0.314)		(0.344)
Maize Productivity		-0.341***		-0.470***
		(0.0199)		(0.0211)
Distance to Dirt Road (km)		3.170***		4.851***
		(0.520)		(0.559)
Distance to Kampala (km)		-20.96***		-22.54***
		(0.616)		(0.652)
Distance to Closest City (km)		3.657**		10.48***
		(1.586)		(1.676)
Population		-4.587***		-2.863***
		(0.236)		(0.227)
Years of Education		1007.4***		492.6***
		(59.09)		(67.38)
Agricultural Employment (%)		2144.4***		680.5
		(377.9)		(416.6)
Poverty (%)		-4685.0***		-4568.6***
		(566.7)		(591.7)
2013 Year Dummy			6593.9***	6446.2***
			(84.42)	(84.12)
2014 Year Dummy			-3671.0***	-3729.5***
			(132.5)	(131.7)
2015 Year Dummy			-2084.8***	-2104.1***
			(110.7)	(110.3)
2016 Year Dummy			-589.7***	-614.6***
			(97.01)	(96.62)
Constant	-16857.9***	-20720.9***	-17608.1***	-18407.4***
	(212.7)	(540.4)	(230.4)	(610.7)
Variance	70089480.6***	64828712.4***	65466887.5***	60176519.8***
	(878797.0)	(811103.6)	(816663.2)	(748544.5)
N	1705116	1695324	1705116	1695324
Controls	No	Yes	No	Yes
Year Fixed Effect	No	No	Yes	Yes

Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.6: Uganda Difference in Differences (Inverse Specification) Tobit Incorporating Controls and Year Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)	(4) Loss (m^2)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$	-21640.3***	-559.2	-15377.4***	1741.8
	(2368.3)	(2406.4)	(2339.5)	(2000.1)
Logging Ban (t = 2018)	-4082.2***	-3893.4***	-1799.9***	-1731.8***
	(97.30)	(95.09)	(110.0)	(108.0)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x Logging Ban (t = 2018)	25004.0***	10221.4***	18594.2***	7321.3**
	(4403.3)	(3434.9)	(4289.7)	(3140.7)
Ruggedness		3237.9***		3116.1***
		(196.1)		(208.0)
Slope (%)		2.214***		2.020***
		(0.313)		(0.343)
Maize Productivity		-0.340***		-0.468***
		(0.0198)		(0.0210)
Distance to Dirt Road (km)		3.256***		4.850***
		(0.463)		(0.495)
Distance to Kampala (km)		-20.70***		-22.48***
		(0.468)		(0.507)
Distance to Closest City (km)		3.778**		10.60***
		(1.584)		(1.675)
Population		-4.599***		-2.879***
		(0.236)		(0.227)
Years of Education		1004.2***		480.8***
		(57.51)		(66.18)
Agricultural Employment (%)		1670.1***		86.61
		(375.0)		(411.8)
Poverty		-5014.4***		-4937.3***
		(492.4)		(509.7)
2013 Year Dummy			6576.6***	6457.6***
			(84.31)	(84.25)
2014 Year Dummy			-3663.9***	-3721.5***
			(132.3)	(131.8)
2015 Year Dummy			-2077.2***	-2096.3***
			(110.5)	(110.4)
2016 Year Dummy			-595.4***	-613.8***
			(96.95)	(96.72)
Constant	-18358.4***	-19582.6***	-19873.5***	-17339.5***
	(120.6)	(468.9)	(144.6)	(533.9)
Variance	70145721.8***	64841117.0***	65542797.4***	60186271.3***
	(879550.0)	(811260.7)	(817691.9)	(748663.2)
N	1705116	1695324	1705116	1695324
Controls	No	Yes	No	Yes
Year Fixed Effect	No	No	Yes	Yes

Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.7: Uganda Spatial Auto-Regressive Difference in Differences (Log Specification) Incorporating Controls and Year Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)
log(Distance to Kenya Border Crossing)			
Logging Ban (t = 2018)	1.220	5.101	-8.548
	(40.01)	(41.07)	(41.14)
log(Distance to Kenya Crossing) x Logging Ban	1.994	1.183	7.547
	(7.209)	(7.409)	(7.381)
Population		0.0619	-0.0811
		(0.0978)	(0.111)
Years of Education		2.465	4.651
		(11.03)	(11.31)
Agricultural Employment (%)		24.20	15.24
		(45.17)	(45.01)
2013 Year Dummy			-113.6***
			(7.673)
2014 Year Dummy			40.80***
			(7.094)
2015 Year Dummy			31.90***
			(6.570)
2016 Year Dummy			17.41***
			(6.346)
Spatial Matrix			
Loss (m^2)	1.555***	1.562***	2.707***
	(0.0457)	(0.0467)	(0.0495)
σ_e			
Constant	451.6***	451.6***	449.7***
	(1.420)	(1.420)	(1.415)
N	60702	60702	60702

Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)

Standard errors in parentheses

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

Table E.8: Uganda Spatial Auto-Regressive Difference in Differences (Log Specification) Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1) Loss (m^2)	Year t = 2018	t = 2016	t = 2015	t = 2014	t = 2013
log(Distance to Kenya Crossing)						
Logging Ban (t = 2018)	-111.1					
	(198.0)					
log(Distance to Kenya Crossing) x Logging Ban	4.005					
	(12.47)					
t Year Dummy			-139.3	-49.00	-76.83	300.2
			(188.2)	(188.2)	(188.2)	(188.2)
Ruggedness x t		-5.339	-5.479	-13.10	-21.93	-4.312
		(50.67)	(49.62)	(49.62)	(49.62)	(49.62)
Slope (%) x t Year Dummy		-0.0128	-0.00352	-0.00112	-0.00892	0.0242
		(0.0760)	(0.0760)	(0.0760)	(0.0760)	(0.0760)
Maize Productivity x t Year Dummy		0.00463	0.00380	0.00546	0.00838	-0.00163
		(0.00513)	(0.00513)	(0.00513)	(0.00513)	(0.00513)
Distance to Dirt Road (km) x t Year Dummy		0.169	0.160	0.0742	0.110	-0.785***
		(0.162)	(0.154)	(0.154)	(0.154)	(0.154)
Distance to Kampala (km) x t Year Dummy		-0.112	-0.0400	-0.188	-0.215	0.0000544
		(0.163)	(0.145)	(0.145)	(0.145)	(0.145)
Distance to Closest City (km) x t Year Dummy		-0.554	-0.390	-0.558	-0.679	-0.0878
		(0.423)	(0.423)	(0.423)	(0.423)	(0.423)
Population x t Year Dummy		0.0182	-0.00554	-0.0100	0.0144	0.0423
		(0.0484)	(0.0482)	(0.0482)	(0.0482)	(0.0482)
Years of Education x t Year Dummy		17.52	19.30	19.03	25.09	-43.13**
		(20.36)	(20.35)	(20.35)	(20.35)	(20.35)
Agricultural Employment (%) x t Year Dummy		-18.70	16.43	-90.95	-115.6	-212.4
		(148.1)	(147.8)	(147.8)	(147.8)	(147.9)
Poverty (%) x t Year Dummy		157.0	129.8	153.4	185.4	-94.23
		(146.6)	(131.5)	(131.5)	(131.5)	(131.5)
Spatial Matrix						
Loss (m^2)	3.436***					
	(0.0179)					
σ_e						
Constant	448.4***					
	(1.410)					
N	60702					
Grid Cell Fixed Effect	Yes					

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.9: Uganda Spatial Auto-Regressive Difference in Differences (Inverse Specification) Incorporating Controls and Year Fixed Effects

	(1) Loss (m^2)	(2) Loss (m^2)	(3) Loss (m^2)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$			
Logging Ban (t = 2018)	12.35**	11.70**	34.16***
	(5.349)	(5.442)	(6.661)
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x Logging Ban	-24.16	-14.52	-181.8
	(294.0)	(294.8)	(293.6)
Population		0.0613	-0.0833
		(0.0977)	(0.111)
Years of Education		2.575	5.202
		(11.01)	(11.29)
Agricultural Employment (%)		25.48	22.52
		(44.37)	(44.22)
2013 Year Dummy			-113.4***
			(7.670)
2014 Year Dummy			40.84***
			(7.094)
2015 Year Dummy			31.99***
			(6.569)
2016 Year Dummy			17.40***
			(6.346)
Spatial Matrix			
Loss (m^2)	1.555***	1.561***	2.706***
	(0.0457)	(0.0466)	(0.0495)
σ_e			
Constant	451.6***	451.6***	449.8***
	(1.420)	(1.420)	(1.415)
N	60000	60000	60000

Loss (m^2) is square metres of forest lost within a grid cell ($10,000m^2$)

Standard errors in parentheses

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

Table E.10: Uganda Spatial Auto-Regressive Difference in Differences (Inverse Specification) Incorporating Time-Invariant Controls Interacted with Year Dummies

	(1) Loss (m^2)	Year t = 2018	t = 2016	t = 2015	t = 2014	t = 2013
$\frac{1}{\text{Distance to Kenya Border Crossing}}$						
Logging Ban (t = 2018)	-92.17					
	(188.4)					
$\frac{1}{\text{Distance to Kenya Border Crossing}}$ x Logging Ban	-30.78					
t Year Dummy			-139.3	-49.00	-76.83	300.2
			(188.2)	(188.2)	(188.2)	(188.2)
Ruggedness x t		-8.210	-5.479	-13.10	-21.93	-4.311
		(49.82)	(49.62)	(49.62)	(49.62)	(49.62)
Slope (%) x t Year Dummy		-0.0133	-0.00352	-0.00112	-0.00892	0.0242
		(0.0760)	(0.0760)	(0.0760)	(0.0760)	(0.0760)
Maize Productivity x t Year Dummy		0.00466	0.00380	0.00546	0.00838	-0.00163
		(0.00513)	(0.00513)	(0.00513)	(0.00513)	(0.00513)
Distance to Dirt Road (km) x t Year Dummy		0.184	0.160	0.0742	0.110	-0.785***
		(0.155)	(0.154)	(0.154)	(0.154)	(0.154)
Distance to Kampala (km) x t Year Dummy		-0.0897	-0.0400	-0.188	-0.215	0.0000533
		(0.146)	(0.145)	(0.145)	(0.145)	(0.145)
Distance to Closest City (km) x t Year Dummy		-0.554	-0.390	-0.558	-0.679	-0.0878
		(0.423)	(0.423)	(0.423)	(0.423)	(0.423)
Population x t Year Dummy		0.0172	-0.00554	-0.0100	0.0144	0.0423
		(0.0483)	(0.0482)	(0.0482)	(0.0482)	(0.0482)
Years of Education x t Year Dummy		17.82	19.30	19.03	25.09	-43.13**
		(20.38)	(20.35)	(20.35)	(20.35)	(20.35)
Agricultural Employment (%) x t Year Dummy		-20.87	16.43	-90.95	-115.6	-212.4
		(148.1)	(147.8)	(147.8)	(147.8)	(147.9)
Poverty (%) x t Year Dummy		138.7	129.8	153.4	185.4	-94.24
		(134.2)	(131.5)	(131.5)	(131.5)	(131.5)
Spatial Matrix						
Loss (m^2)	3.436***					
	(0.0179)					
σ_e						
Constant	448.4***					
	(1.410)					
N	60000					
Grid Cell Fixed Effect	Yes					

Loss (m^2) is the square metres of forest lost within each hectare grid cell ($10,000m^2$)
Standard errors are clustered at the grid cell level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix F

Maps

Figure F.1: Sample of Grid Cells in Kenya

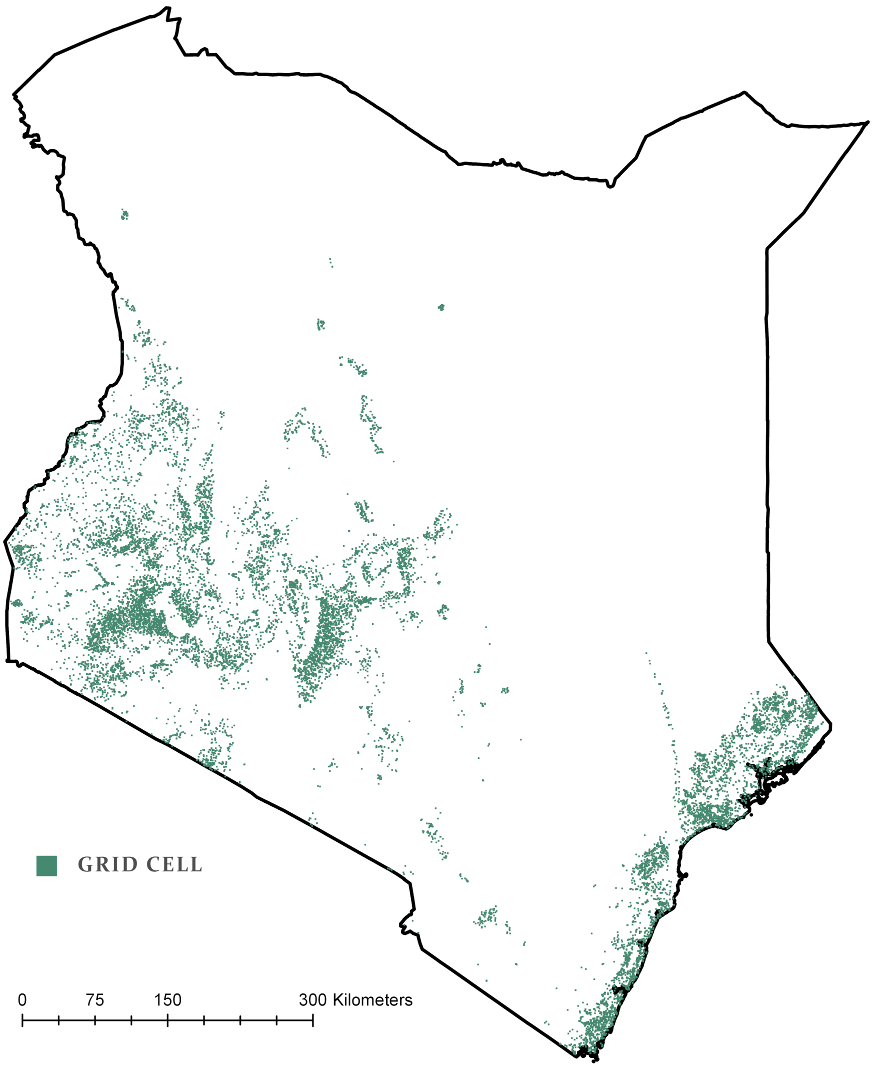


Figure F.2: Sample of Grid Cells in Uganda

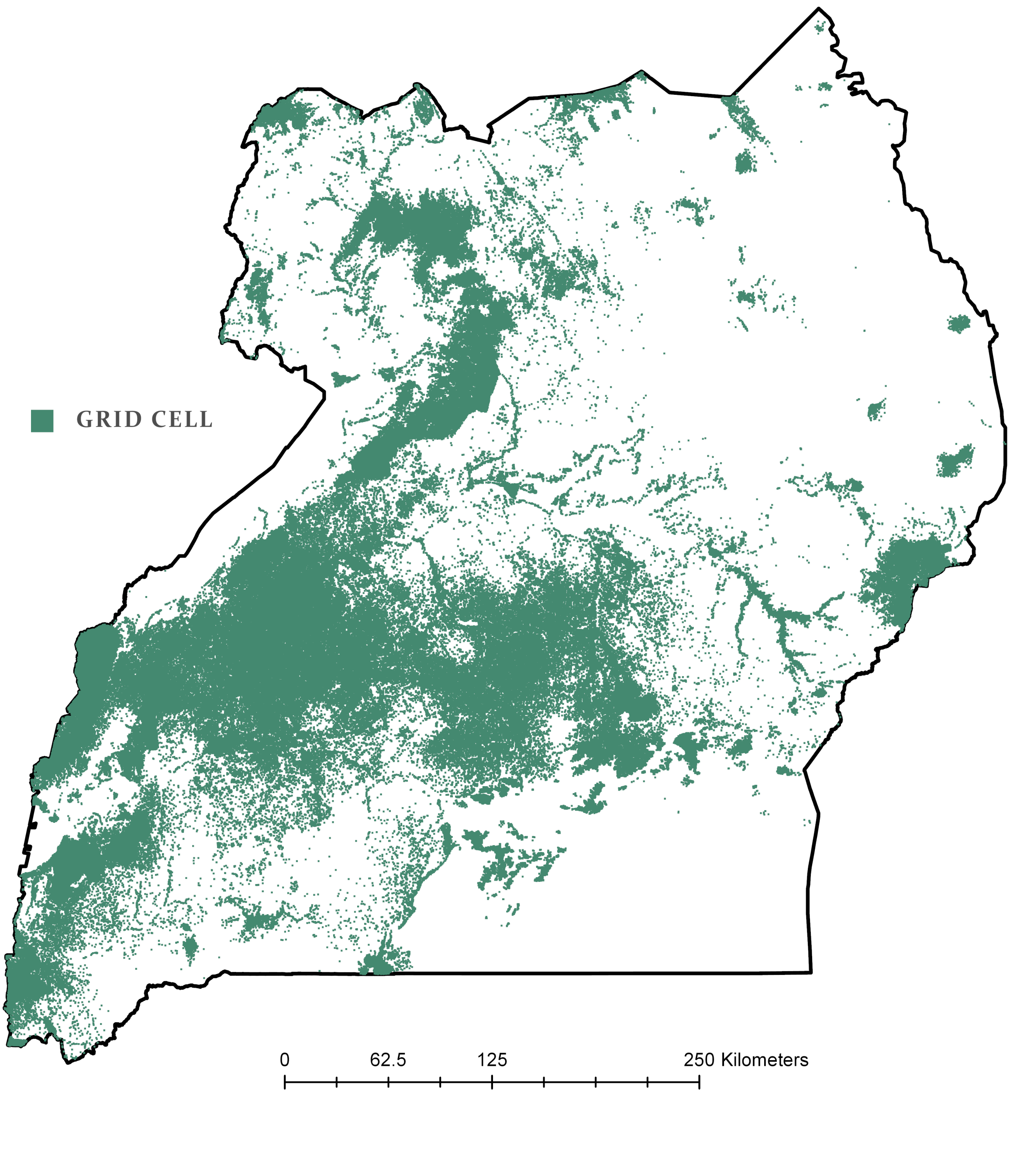


Figure F.3: Year of Most Recent Deforestation in Kenya

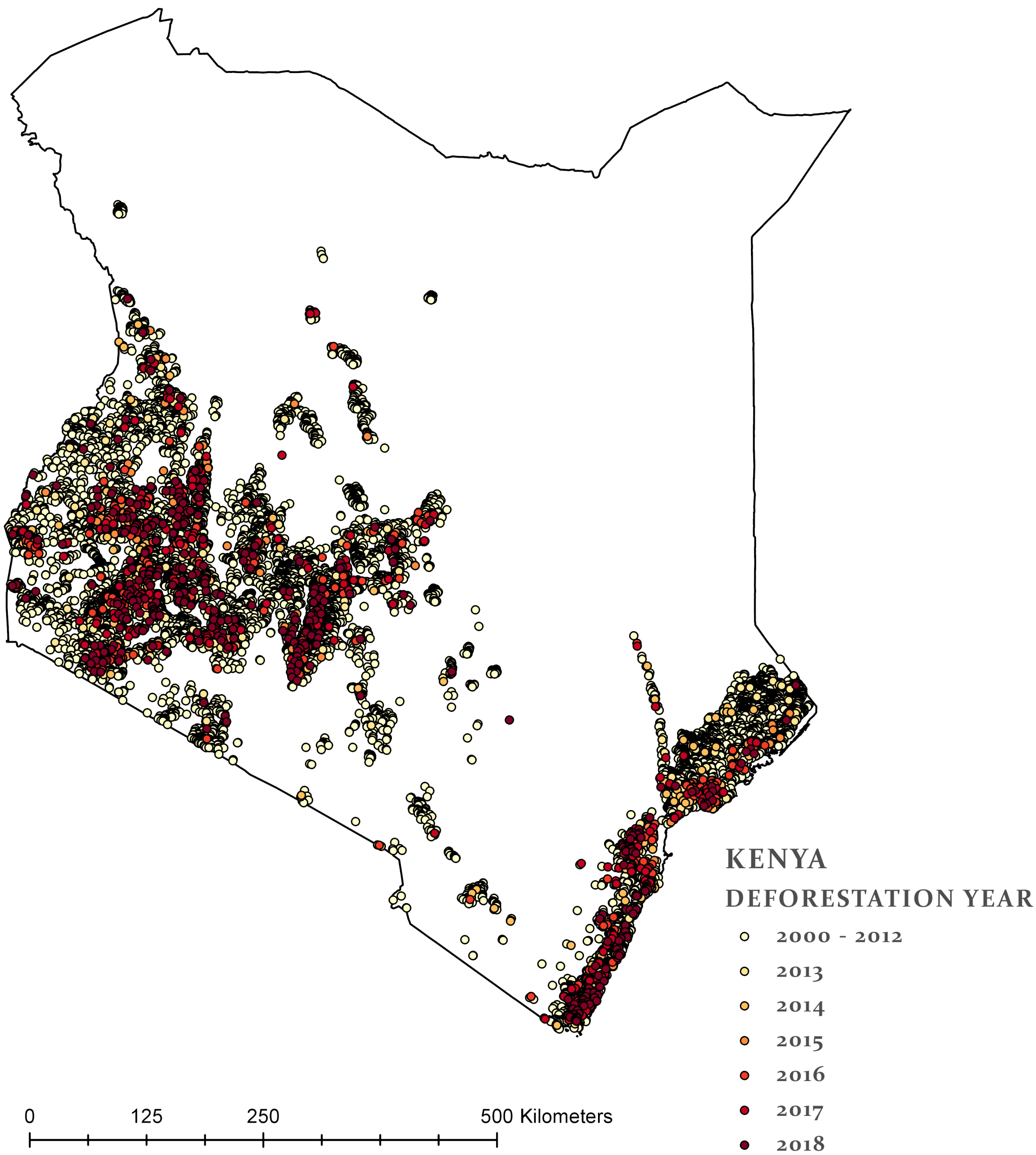


Figure F.4: Year of Most Recent Deforestation in Uganda

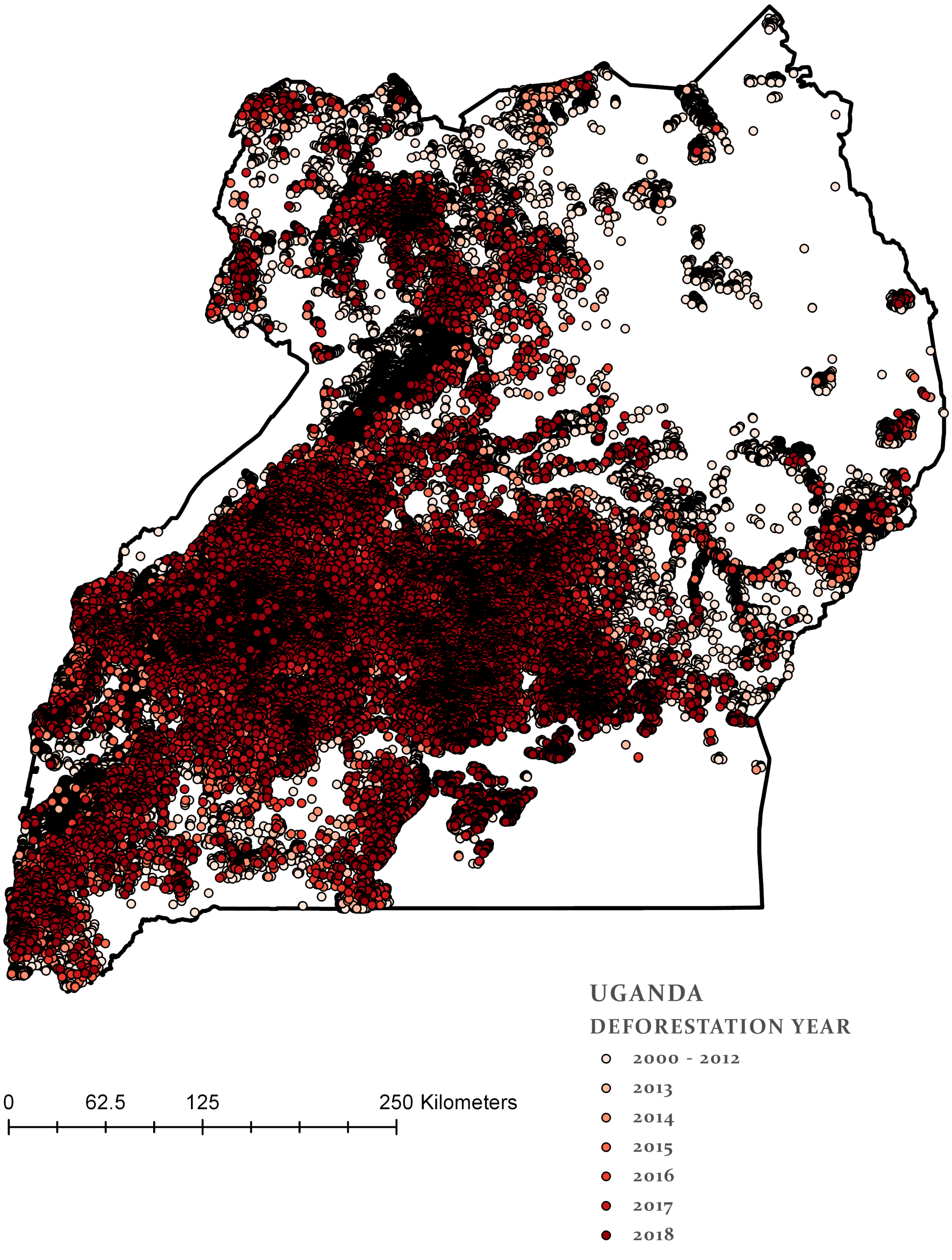


Figure F.5: Protected Areas in Kenya

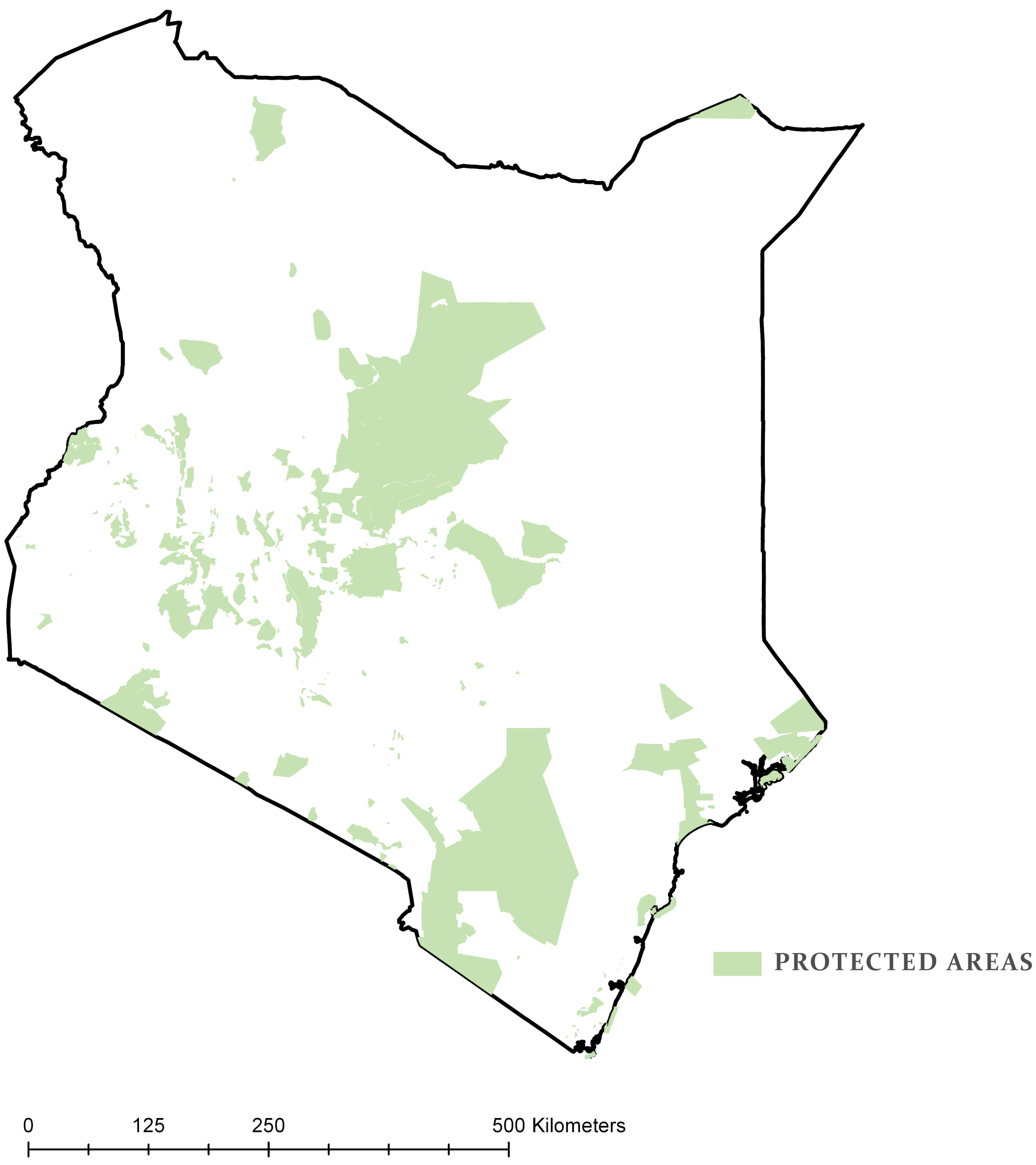


Figure F.6: Road Network in Kenya and Uganda

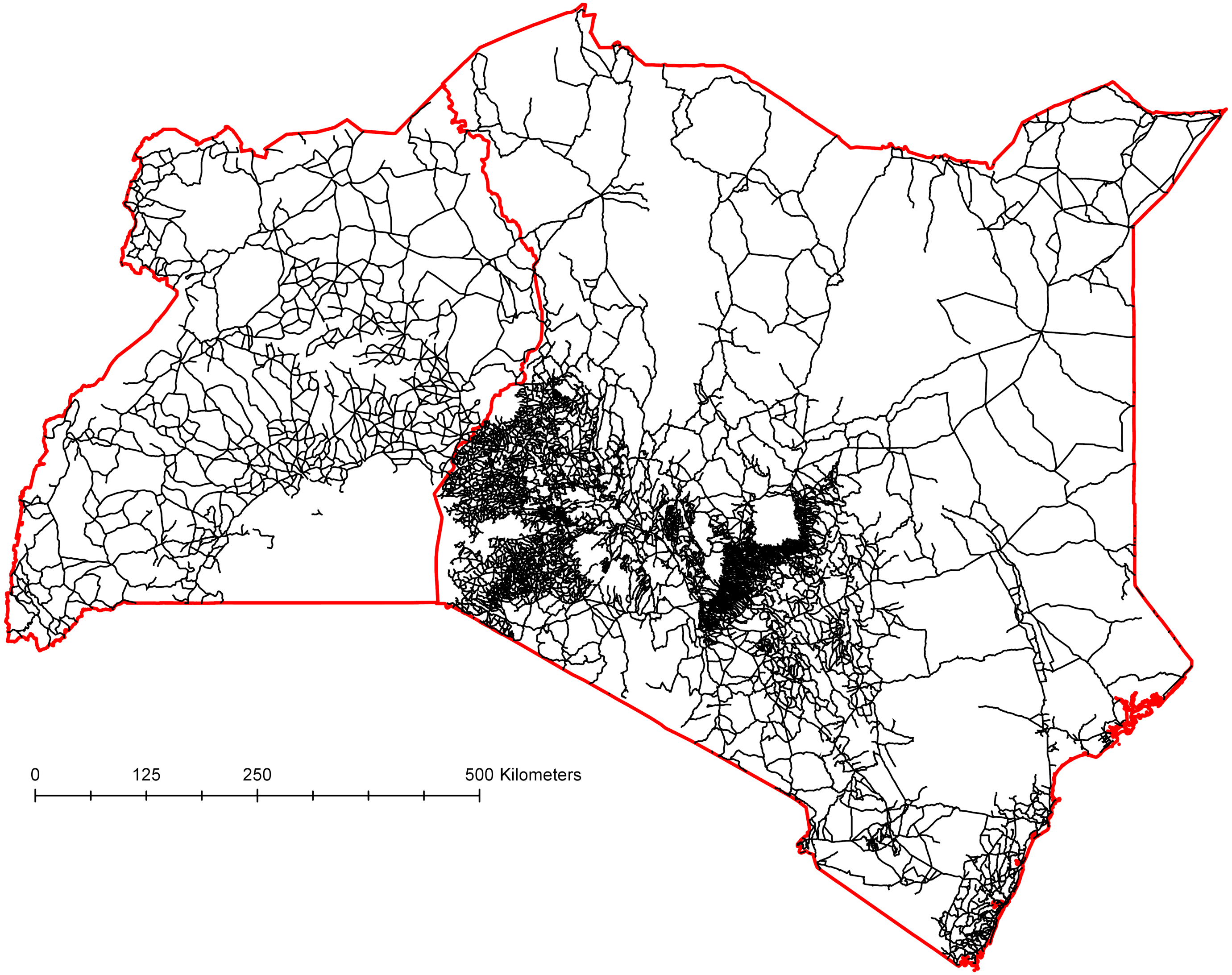


Figure F.7: Counties in Kenya

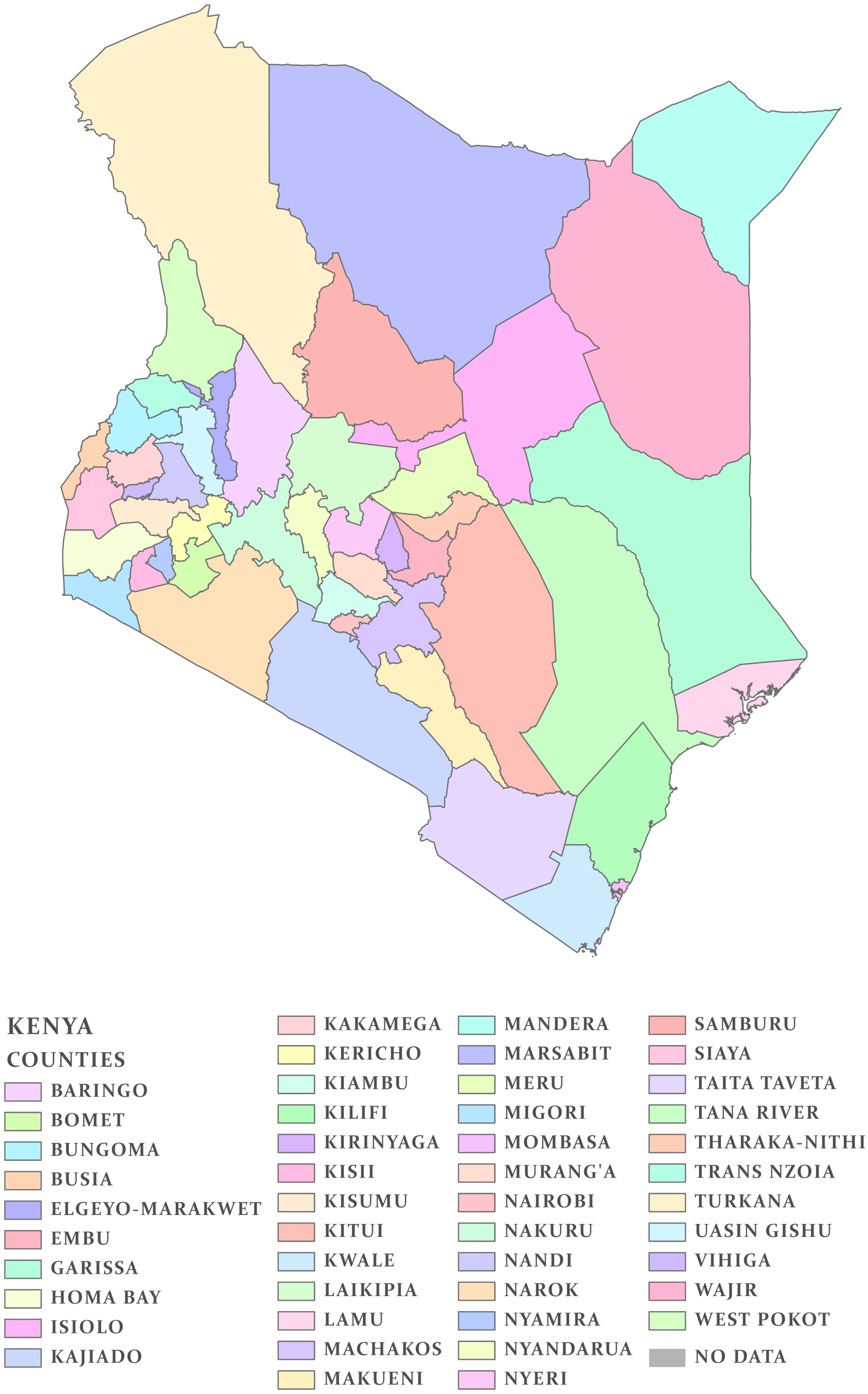


Figure F.8: Sub-Regions in Uganda