The impact of the Log Export Ban reform on deforestation: evidence from Gabon

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Abstract

The Log Export Ban (LEB) reform aims to ban unprocessed wood export. In 2010, Gabon adopted this reform in order to promote its wood industry while not taking account potential effects on deforestation. From panel data at second-order administrative division (ADM2) level from 2001 to 2018, this study investigates the impact of the LEB reform on deforestation in Gabon. The estimation strategy relies on a difference in difference (DiD) method in which the ADM2 in Cameroon and the Republic of the Congo are used as control group. The parallel trend test shows that there is no significant difference in deforestation level between Gabon and the control group before 2010. In addition, our results reveal that while deforestation increases in all three countries after 2010, compared to its neighbors, Gabon benefited from avoided deforestation estimated at nearly 2,100 km^2 from 2010 to 2018.

Keywords: Deforestation, Log Export Ban, Difference-in-Differences, Gabon

JEL Classification: C23; F13; Q51

1 Introduction

Since the end of World War II, many developing countries have implemented a high level of protection for newly established industries. The infant industry argument is based on the idea that a developing country with a potential comparative advantage in a manufacturing sector may not be

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able to compete with older, well-established industries in developed countries. Thus, the states put in place restrictions on imports through taxes or import quotas. This is the import substitution industrialization strategy which consists to create a significant domestic demand for local industries. This demand allows an increase of industry's needs in equipments. These needs led to the etablishment of "industrializing" industry. In contrast, there are another industrialization strategy focused on the export. This is the strategy consist to replace gradually exports by domestic processing of raw material. Export substitution strategy had been adopted by many countries to leave the level of natural ressource export to processing export and to acquire a lot of value added. The export substitution industrialization (ESI) needs some restrictions on export of raw materials. They might be the taxation on export, restrictions on quotas or export bans.

ESI in contrast with free trade has been applied in some economy sector such as forestry sector (World Ressource Initiative, 2020). The industrialization of the national wood industry in several countries has been inspired by the ESI. Indeed, the natural ressources processing is seen as a development strategy for countries exporting raw materials (Kishor et al., 2004). In the forestry sector, several restrictive measures have been adopted by countries, from the introduction of export taxes to a strict log export ban (LEB) (World Ressource Initiative, 2020). Many countries apply the LEB to achieve sustainable development goal. It pursues economic, environmental and social objectives at the same time. For example, that is a good strategy to decrease deforestation by reduction of illegal logging. Also, it allows to create a lot of jobs for logging. In addition, the LEB allows to increase the value added by log processing. Thus, the log export ban adoption motivations are globally oriented towards the mitigation of deforestation and the wood industry essor.

The Log Export Ban was firstly introduced by Canada and the United States. Two reasons can explain the LEB adoption Zhang (1996). Firstly, the export of unprocessed logs is an export of employment and investment that could be allocated to the local industry. Secondly, the measure was adopted to diversify the economy. For Van Kooten (2014) British Columbia in Canada adopts restrictions on the export of logs to promote local processing and associated employment benefits. However, from the end of the 1990s, the justifications of the LEB shifted towards solving the problems of deforestation (Tumaneng-Diete et al., 2005). In more cases, the reasons are combined both for the protection of endangered species and the development of the local processing industry (Kishor et al., 2004). For example, in the Philippines, Malaysia and Indonesia, the LEB had been introduced for forest degradation mitigation, deforestation and for economic development reasons (Tachibana, 2000).

In central Africa, only Gabon apply the LEB. Gabon has a rich and diversified forestry potential since colonial times. It was a period when the practices where oriented toward wood extraction without local wood processing. All forestry activity was oriented towards the exploitation and export of raw timber to France. It was in 1904 that the first sawmill for wood processing was created. After World War II, Gabon began to develop its wood processing industry (Kombila-Mouloungui, 2019). To front of the need increased in wood to rebuild Europe, many processing industries were established in Gabon between 1940 and 1960. However, the development of the local industry had only slightly changed the export rates of log production. After 1960, the colonial legacy was characterised by a forestry activity dependent on the export of raw timber. However, initiatives were undertaken by the government such as the creation of the Industrial Permit in 1968 whose holders had to process part of their production. These initiatives were reinforced by the law 1/82 of July 22, 1982 stipulating an obligatory local processing of 75% of the production. However, this 75% target was never reached, prompting the Gabonese government to lower the local processing rate to 50% in 2000, while maintaining the initial target of 75% by 2012 (Kombila-Mouloungui, 2019). In 2000, the process rate was around 15% that means 450,000 m^3 of log processed. Far from reaching the objectives set for 2012, the government has decided to put in place the LEB in 2010.

Since colonial time, the government has promoted local wood process rather than sustainable forest management. Gabon has a forest potential about 22 million hectares. The deforestation level was 810 Km^2 between 1990 and 2000, and 235 Km^2 between 2000 and 2010 (De Wasseige et al., 2014). This level of national deforestation may hide local disparities. The Gabonese industrial policy of the wood sector is compatible with Southeast Asian countries's in the 1970s and 1980s where the industrial policy has not remained without consequences on the environment, more specifically on deforestation.

Despite the multiple causes of deforestation in the Congo Basin, this study aims to assess the effect of the log export ban on tree cover loss in Gabon. While there are several studies on the impacts of LEB, many of them focus on economical performances rather than environmental performances. These include the impact of LEB on productivity and wood industry growth (Amoah et al., 2009), trade policy (Van Kooten, 2014), industry performance and wood market (Tachibana, 2000).

Our contribution to existing literature is twofold. First, we implement a difference in difference (DiD) method to estimate the impact of LEB on deforestation in second-order administrative division (ADM2) of Gabon. The DiD method is made by comparing Gabon ADM2 to Cameroon and Congo ADM2 (control group). Second, we support the limited literature on the effect of LEB on deforestation (Karsenty and Piketty, 2001).

The study proceeds as follows. Section 2 discusses the effectiveness of the log export ban policy in achieving the twofold goal of conservation and economic development. Section 3 presents the estimation strategy and data used. Section 4 and Section 5 show the results and robustness checks. The last Section concludes and discusses the policy implications.

2 Log export ban policy: conservation or economic development

The restrictive measures on timber exports have been adopted by several developing countries and some developed countries. These government measures include export restrictions through quotas and export licenses for some cases and strict export bans for others.

The LEB is considered by some authors as a second-best policy instrument for the management of environmental externalities, even it is easy to implement (Resosudarmo and Yusuf, 2006). It has been set up in several countries to combat abusive exploitation of forests. The literature on the LEB is oriented towards the assessment of its effects on the economic development and the conservation. In most countries, the aims of the reform is to substitute the export of logs by processed wood in order to have a higher value-added.

The literature on the environmental effect of LEB opposes two opposite trends. One line of research has focused on the positive impact of LEB on the forest. Thus, the environmental argument in favour of LEB is that it reduces the pressure on the forest due to the constraints of international markets outlets. It promotes a reduction in deforestation and the protection of endangered species. Log export restrictions in the Philippines lead to forest conservation (Tumaneng-Diete et al., 2005). However, the authors note that it is difficult to pursue forest conservation objectives and to maximize the economic and social benefits of the reform. Indeed, restrictive policies related to the timber industry have favoured the deforestation decreasing. But, this decrease has been to the detriment of production, trade and overall welfare, which have been penalized. On the other hand, the LEB should lead to a decrease of illegal logging. In fact, the adoption of the measure lowers local timber prices, thus eliminating incentives to take unnecessary risks (Resosudarmo and Yusuf, 2006). Indeed, in the case of a country endowed with forest resources, the LEB lowers log price from a high world market prices (the prices of external demand) to a much lower local price. This low price has a negative effect on illegal logging. In fact, the risks involved are much greater in relation to the profits made. Also, this lower price makes the wood extraction less profitable and a drop in international demand for local wood because the borders are closed. The direct aim of LEB is the local log price decreasing and a crowding out of external demand by local demand for industries in order to galvanize the industrialization of the wood sector with a much lower raw material cost (Fooks et al., 2013).

Another literature on the LEB is in favour of its removal or at least admits that the objective of forest conservation is not being achieved (Kishor et al., 2004). For Barbier and Rauscher (1994), trade-restrictive measures in general and the ban on timber exports in particular do not encourage the adoption of sustainable management practices in tropical timber harvesting. Indeed, the purpose of log prices lower favours the supply of raw material at lower cost to local industries. In doing so, industries tend to make a trade-off between the factors of production and the raw material (logs). Indeed, when the log price declines relative to the capital and labour price, the firms replace these inputs with an increased supply of logs as the relative price of wood relative to primary inputs declines. Thus, the fall in price leads to a substitution between the production factors and the raw material. This leads to an increase in the demand for wood to satisfy the new demand of local firms following the drop in price. The rise of demand generates increased pressure on the forest (Kishor et al., 2004). Also, this low log cost available leads to inefficiencies in log processing, pushing industries to use much more wood than usual (Resosudarmo and Yusuf, 2006).

In addition, there is a controversial debate about the effect of LEB or other trade restrictive on deforestation leading to lower timber prices (Amsberg, 1998). Indeed, the decreasing log prices reducing profits in the forestry sector could accelerate deforestation through the reconversion of forests for agricultural purposes (Amsberg, 1998; Mæstad, 2001). However, the relationship between the LEB and agriculture is complex. The LEB adoption having a direct effect on log price acts on the incentives to convert or not the forest for agricultural use. These incentives are highly dependent on the way the forest and agriculture are managed (Mæstad, 2001). Indeed, according to Amsberg's results, the rise in log prices is leading to an increase in the exploitation of unmanaged forests because remote and unmanaged forests with very high extraction costs are becoming profitable. At the same time, this price increase leads to an increase in the profitability of forests for log production in managed forests leading to an raise in land allocated for log production. The opposite effect is seen in the case of lower log prices, i.e. a fall in the area of managed and unmanaged forests.

Moreover, the LEB will have an effect on incentives to convert forest to agricultural uses only if it allows conversion costs reduction. Indeed, when very few trees are felled, clearing forest for agriculture becomes difficult and very costly. Thus, reform, by trying to discourage the exploitation of wood, leads at the same time to increase the conversion cost and discourages reconversion for agricultural purposes.

Finally, the LEB does not encourage industries to use sophisticated technology. They compensate their technological backwardness by using more wood. Thus, the pressure on the forest increases. In Indonesia, the restrictives trade measures in 1975 led to the LEB adoption in 1985. This measure allowed the country to increase from 41% of world tropical timber exports in 1979 to about 50% of world plywood exports in 1989 (Karsenty and Piketty, 1996). The LEB has galvanized the local wood industry with an increase in wood processing capacity. Indeed, between 1980 and 1989, the plywood production capacities were multiplied by 4. However, the material yield rate[1] in the same period is

[1] Material yield rate is the ratio between the volume of wood produced after processing and the volume of raw wood entering the plant.

50% and lower than other Asian countries. Indeed, 26.7 million m^3 of processed wood production capacity in Indonesia, the log supply need would be about 54.5 million m^3 (Karsenty and Piketty, 1996). In the same time, plywood estimates show a processing capacity of 43.2 million m^3 of logs, more than the entire official national log production. Thus, the LEB has provided an incentive for the plywood industries without pushing to advanced stages or levels of processing. The wood industries have a need that goes beyond the permitted annual quantities. Furthermore, Brann (2002) has shown that the development of the wood processing industry in Indonesia is increasing the pressure on forest resources.

For several authors, restrictive measures on timber trade are not solutions for biodiversity conservation and economic growth. In contrast, they act negatively on environment and economy. Thus, the best strategy to deal with deforestation issues must be dosmestic, to the detriment of trade measures (Pearson et al., 2000). Actions should focus on consumption and production behaviour, property rights and the creation of the wood market.

According to Mæstad (2001), although trade measures have some desirable effects, they are clearly an ineffective means of environmental protection. In fact, environmental problems are caused by timber extraction and not by the timber trade. As a result, some authors support LEB removing. Kishor et al. (2004) show the removal of LEB in Costa Rica would be beneficial for both the economy and the environment. The growth in demand for wood resulting from the removal of the barriers will require about 47500 hectares, less than 4% of the natural forest cover.

In Gabon case, a World Bank study evaluated the effect of LEB on forest resources. This study deals with economic issues and CO_2 emissions. The results show that the log production curve was in continuous decline from 2007 to 2012. As for CO_2 emissions, there was an emission avoidance about 11.53 million tCO_2/year for 6 years after the reform (World Bank report, 2016).

3 Estimation strategy and Data

3.1 Estimation strategy

We estimate the contribution of the LEB on forest cover loss in Gabon using Difference in Differences (DiD) estimation. The DiD methodology in impact analysis requires two conditions.

First, there must have a treated individual and a non-treated individual called counterfactual or control group . Our control group are Cameroon and the Republic of Congo for several reasons. First, these two countries share a common border with Gabon. Also, these tropical countries of Central Africa have significant forest potential with a regional climate favourable to Gabon's image. In addition, these three countries are members of CEMAC so that they share several common economic and political characteristics that are subject to community harmonization. Furthermore, these countries are members of the Central African Forest Commission (COMIFAC), the regional body committed to the conservation, sustainable and management of Central African forest ecosystems. The COMIFAC strengthens the harmonisation and convergence of countries in the field of forestry and environmental policy.

In addition, our analysis focuses on the second administrative division in each country. This is the departments in Gabon and Cameroon and the districts in the Republic of Congo. This study level is justified by the fact that the departments in Gabon are considered to be geographical entities that have undergone reform. Thus, the policy is specific to Gabon. The districts and departments in Cameroon and the Republic of Congo are outside the treatment area. The latter are our control groups. Also, it should be noted that throughout the study period, the countries in the control group did not apply strictly a reform concerning the log export restrictions.

Second, the DiD methodology requires before and after reform situation. While the LEB was introduced in 2010, we conside the period before 2010 as pre-reform and from 2010 as post-reform. We also take into account the other factors likely to affect deforestation. Also, the DiD allows to control for permanent differences between groups in unobservable factors that affect outcomes. Thus, changes in the deforestation gap between intervention and control group from LEB adoption are attributed to the reform.

We thus estimate the following equation to evaluate the impact of the LEB on deforestation in Gabon :

$$TCL_{i,t} = \beta_0 + \beta_1 TIME_{i,t} + \beta_2 TREAT_i + \beta_3 TIME_{i,t} \times TREAT_i + \gamma log(X_{i,t}) + \epsilon_{i,t} \tag{1}$$

where Tree Cover Loss ($TCL_{i,t}$) is the area of forest cover lost at the 30% threshold[2]. $TREAT_i$ is a dummy variable taking the value 1 if the department has undergone reform and 0 otherwise. $TIME_{i,t}$ is also a dummy variable taking the value 0 before the year of reform and 1 from the year of intervention. $X_{i,t}$ is a vector of covariates composed of *Density*, *Grasslands*, *Croplands*, *Urbanbuiltup*, *Rainfall* and *Temp*. Finally, $\epsilon_{i,t}$ is the regression error term.

[2]The 30% threshold is the default threshold used by Global Forest Watch. This threshold means that a loss of forest cover is only considered to occur if there is a 30% loss of canopy cover compared to the satellite pixel image.

3.2 Data

This work allows to measure the impact of LEB on forest cover loss in Gabon. For this purpose, data are collected for 143 ADM2, with 37, 58 and 48 ADM2 respectively in Gabon, Cameroon and the Republic of the Congo[3]. The deforestation data are collected on the Hansen et al. database, with a canopy coverage threshold of 30%, the default value used in the Global Forest Watch (GFW) studies. The covariates *Density, Rainfall* and *Temp* data are downloaded on aiddata and their raw source are shown in Table 1 . The covariates *Grasslands*, *Croplands* and *Urbanbuiltup* data are in pixel format and reprocessed to be consistent with deforestation data (Table 1). Land use data are available for 2001, 2005, 2009, 2013 et 2017. So, we are proceeding by imputing missing data in order to increase the number of observations. All data are available from 2001 to 2018 except *Rainfall* and *Temp* data that are avalaible from 2001 to 2017.

Table 1: Definition and data source

Variable	Definition	Unit	Source
TCL	Tree cover loss (30%)	Km^2	Hansen et al. (2013)
TIME	Treatment period dummy		
TREAT	Treatment dummy		
Density	Population density	Pop/Km^2	Columbia University (2016)
Grasslands	Grassland area	Km^2	Friedl and Sulla-Menashe (2019)
Croplands	Agricultural land areas	Km^2	Friedl and Sulla-Menashe (2019)
Urbanbuiltup	urbanisation and building area	Km^2	Friedl and Sulla-Menashe (2019)
Rainfall	Total precipitation per year	mm	Matsuura and Willmott (2018)
Temp	Yearly land surface temperature	°C	Wan et al. (2015)

3.3 Descriptive statistics

In Table 2, we distinguish our two study groups in order to measure differences in our samples. For our variable of deforestation, the mean level over the entire study period is about 6.1 Km^2 for the treated group and about 10 Km^2 for the control group. However, this difference does not allow us to capture the impact of the reform. To understand this impact, we need to study our two groups in a before and after situation. Thus, Figure 1 shows the deforestation levels between the treatment and control groups. To consolidate our choice of counterfactuals, we show the evolution of the average deforestation levels in the ADM2 of each country (Figure 1). Thus, these graphs provide an overview of the effect of the reform on the level of deforestation between the two study groups. Also, an unbiased estimate of the DiD method is based on parallel trend assumption. Based on this hypothesis, in the absence of the government reform, the trend in forest cover loss should be the same in the ADM2 affected by the reform as in the non-affected ADM2. Our first two graphs make it possible to

[3]The data available for the Republic of the Congo is not exhaustive(only 48 ADM2)

highlight this fact, which is not subsequently rejected by the econometric estimation.

To support our control group choice, the Table 3 shows that the average mean of TCL before the LEB adoption is only significant at 10% with a coefficient of 0.74. This shows that both groups had very similar levels of deforestation before the LEB implementation.

According to Figure 1, the decline in the level of deforestation in Gabon in 2010 can be explained by the announcement of LEB adoption. This announcement probably had an impact on incentives for logging because priority had to be given to the export of wood already cut before the introduction of the reform. Thus, the efforts of logging companies in 2010 were directed towards the quick evacuation of log production to the outside before may 2010 rather than exploiting more wood (Terheggen, 2011). By August 2010, the immediate consequence of LEB adoption was an increase of log production and exportation in Cameroon.

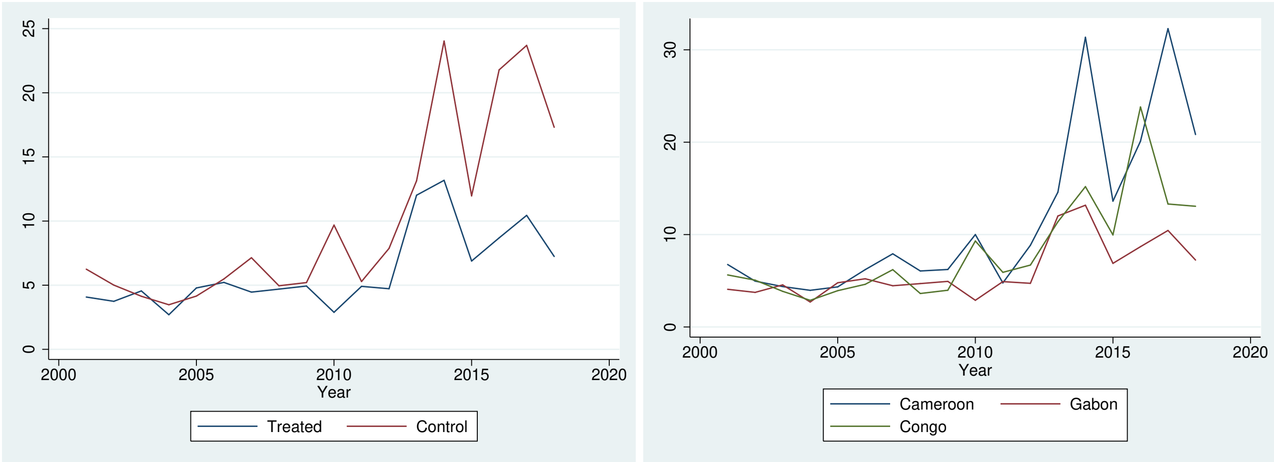
However, the TCL country average hides some disparities between the ADM2. To overcome this problem, we analyse the deforestation in all ADM2 before and after intervention (Figures 2 for Gabon, 3 for Cameroon and 4 for Congo). We can see that the deforestation increase in all countries and almost all ADM2 after 2010. However, this increase is more important in Cameroon than Gabon and Congo. In Cameroon, we have around quarter of ADM2 where the tree cover loss achieves more than 45 Km^2 (Figure 3). In Congo, just 2 ADM2 achieve 45Km^2 with a considerable gap compared to others ADM2 (Figure 4). In Gabon, the hight deforestation level is less than 30 Km^2 (Figure 2). This show that the deforestation increase in all countries. But, this increase is less in Gabon compared to Cameroon and Congo. Thus, the Table 4 presents that difference between intervention and non-intervention group increase after LEB adoption. So, there are an average gap of TCL around 7 Km^2 between the two groups.

Table 2: Descriptive statistics

VARIABLES	Full sample		Treatment group		Control group	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
TCL	9.0	17.0	6.1	7.6	10.0	19.2
Density	151.4	701.5	7.5	17.6	201.6	808.7
Grasslands	168.7	629.16	103.4	427.3	191.5	684.4
Croplands	161.3	755.3	9.8	18.5	214.2	871.0
Urbanbuiltup	9.7	17.6	7.5	15.2	10.4	18.3
Rainfall	1620.2	441.4	1786.6	422.9	1561.6	432.9
Temp	27.1	2.9	25.8	1.3	27.6	3.1

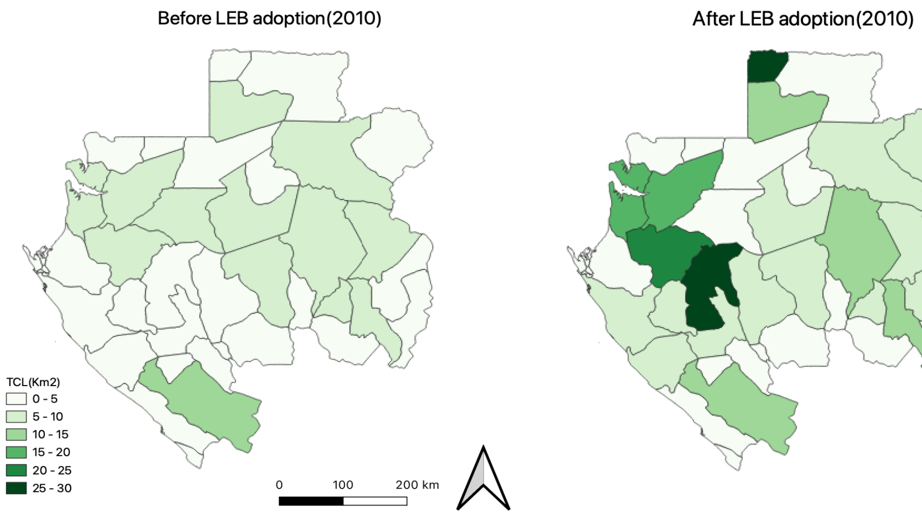
Source: Authors

Figure 1: Tree Cover Loss Trend



Source: Authors

Figure 2: Gabon deforestation

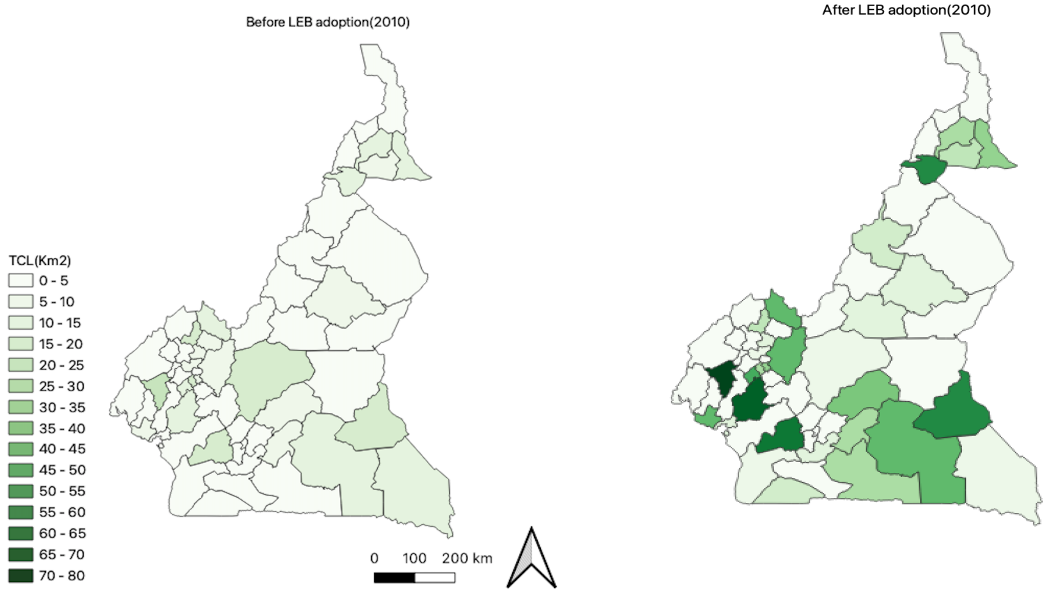


Source: Authors

Fuhtermore, to consolidate this choice we must analyse our covariates before intervention. Table 3 shows the sample means of all covariates between our two groups before treatment. There are treatment group mean in colomn (1) and the potential control group in colomn (2). The difference between the two groups are shown in column (3) with statistics significance.

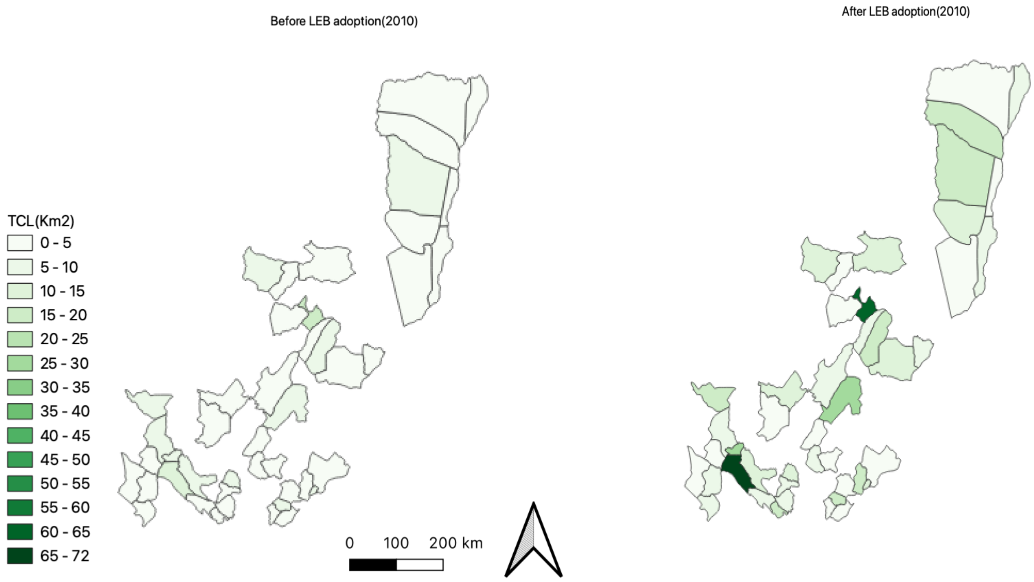
Table 3 shows that prior to LEB adoption, there was a significant difference between all covariates. So, to take account this difference between all covariates allows to capture the intervention effect. There are good reasons to choose these variables to estimate LEB effect on deforestation.

Figure 3: Cameroon deforestation



Source: Authors

Figure 4: Congo deforestation



Source: Authors

Table 3: Before LEB adoption

	(1)	(2)	(3)=(2)-(1)
	Treated	Control	Diff
TCL	4.35	5.09	0.74*
			(1.84)
Density	6.74	178.23	171.5***
			(4.54)
Grasslands	63.44	118.88	55.44*
			(1.96)
Croplands	13.44	128.96	115.5***
			(7.3)
Urbanbuilt	7.06	9.44	2.378**
			(2.58)
Rainfall	1583.86	1505.62	-78.24**
			(-3.22)
Temp	25.77	27.57	1.80***
			(10.17)
N			1287

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 4: After LEB adoption

	(1)	(2)	(3)=(2)-(1)
	Treated	Control	Diff
TCL	7.88	14.97	7.09***
			(4.99)
Density	8.35	224.91	216.55***
			(4.32)
Grasslands	143.40	264.12	120.72**
			(2.48)
Croplands	6.24	299.50	293.26***
			(4.48)
Urbanbuilt	7.86	11.39	3.53***
			(2.75)
Rainfall	2014.59	1624.5	-390.07***
			(-12.94)
Temp	25.82	27.67	1.85***
			(9.93)
N			1287

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

4 Results

4.1 Panel analysis

To better specify our study design, we use the panel data to take account for both dimension our data (Table 5). The Hausman test shows that random effects are preferred to fixed effects for all specifications[4].

Column (1) shows the DiD estimate without covariates. The coefficient of our interest variable

[4]The results with FE are very close and available on request.

(*TIME*×*TREAT*) is -6.35 and significant at 1%. So the LEB adoption allows the Gabon ADM2 to avoid deforestation compared to ADM2 of Cameroon and Congo. This deforestation avoided should be commented with some restraint. Indeed, the deforestation evolution trend of Gabon is similar to counterfactual group along this study (Figure 1). Thus, in the pre-reform period, deforestation curves are almost confused with some overlaps. However, the deforestation level growth in both groups after the reform shows that deforestation levels increase significantly. Overall, the reform allows Gabon ADM2 to avoid an average of 6.35 Km^2 of forest cover loss by ADM2 and by year from 2010. So, this avoided deforestation is estimated around 2,100 km^2 from 2010 to 2018. It is around Istanbul surface.

From Columns (2) to (7), we add covariates to control for potential deforestation factors. In Column (2), the population density variable is used to measure population pressure on the forest. Anthropogenic actions are the major cause of deforestation (Geist and Lambin, 2002). People density allows us to show how demographic pressure can affect the reconversion of land for agricultural purposes in order to meet food needs in communities. This demographic pressure also acts on the level of firewood cutting, which is considered as a one major cause of deforestation. Until 2014, fuelwood accounted for about 95% of the total energy used in Sahelian countries (Gillet et al., 2016). Thus, the population density variable allows to evaluate the pressure of populations (fuelwood, timber extraction). Also, people density is used to measure the possible reconversion of the forest for other purposes (agricultural, economic). In fact, the people needs increase with population growth, such as land for subsistence agriculture. To this effect, the coefficient of our variable of interest (*TIME*×*TREAT*) is -6.356 with a significance of 1%. Thus, taking into account the density allows to increase the average forest lost avoided by year to 6.356 km^2 in Gabon compared to control group. Indeed, the descriptive statistic shows us that the average population density is very low in Gabon (7.5) compared to our control group (201.6). Thus, the Gabonese forest is not subject to strong demographic pressure compared to forests in neighbouring countries. But, coefficient of *density* is negative and non-significant. Indeed, the large cities are located outside the forest areas. It is the less populated rural areas that are closed to the forests. DeFries et al. (2010) show that the forest loss is positively correlated with urban population growth and rural population growth is not associated with forest loss.

In the Columns (3), (4) and (5) of our model, we add respectively *Grasslands*, *Croplands* and *Urbanbuiltup* that are land use variables. Indeed, the land reconversion for agricultural purposes is considered as the first source of deforestation (Geist and Lambin, 2002). However, we do not have access to data allowing to directly identify this reconversion of forest land for agricultural purpose. However, we use variables showing the evolution of cultivated land (*Croplands*). In addition, we use a variable highlighting the areas of grassland (*Grasslands*) that can be used for grazing. Indeed, the conversion of forests in developing countries is intended for agriculture and grazing (Hosonuma et al., 2012). Also, we use an urbanization and infrastructure construction variable to isolate the impact of urbanization on deforestation. In fact, urbanization is a one major cause of deforestation in tropical countries (Geist and Lambin, 2002; Hosonuma et al., 2012). Moreover, the expansion of cities favours peri-urban deforestation and it pressures the forest for fuelwood collection (Mertens and Lambin, 1997). Also, the development of road infrastructures makes it possible to open up inaccessible and very remote forest areas, thus making forestry exploitation more profitable through lower transport costs (Gillet et al., 2016). Thus, we use these variables concerning the land use in our estimation. In Column 4, the coefficient of DiD variable (*TIME*×*TREAT*) is -5.911 and still significant at 1%. Thus, Add *Croplands* in our first column allows to avoid deforestation around 5.9 Km^2 each year after LEB adoption. Also, the covariate *Croplands* is found to be negative and significant at 1%. This negative effect of *Croplands* might be explain by the localization of croplands in relation to forested areas.In the three countries of this study, agricultural land are located far away from forested land so that an expansion of cropland should not impact deforestation. Also, for agricultural land close to forest, the reconversion cost may be hight if there are not many trees already cut. Thus, the croplands expansion will not be directed towards the forest.

In the Columns (3) and (5), *TIME*×*TREAT* is respectively -5.461 and -5.911 and significant at 1%. There are an avoided deforestation in Gabon after LEB adoption. Also, *Grasslands* and *Urbanbuiltup* are significant and positive. Thus, a 1% increase in the area of *Grasslands* leads to a raise in TCL of 0.016 Km^2. Also, a 1% growth in the area of Urbanbuiltup leds to an increase of deforestation around 0.026 Km^2.

In Columns (6) and (7) we introduce climatic variables. We use total annual rainfall and soil surface temperature data to capture the impact of flood, forest fires or droughts considered as proximates causes of deforestation in the literature (Geist and Lambin, 2002). In both Column, our interest variable is still negative and significant. The rainfall variable is positive and significative to 1%. So, a one percent increase of *Rainfall* rises tree cover loss of 0.05 Km^2. Indeed, the Congo Basin has an climate condition favorable with high humidity. Thus, an increase of rainfall rises the risk of flood that affect negatively deforestation.

In contrast, the land surface temperature variable is negative and significant at 1%. There are 27.14°C in average. In the Congo Basin, the climate is hot and humid with a temperature that varies between 22 and 32°C (De Wasseige et al., 2015). The diurnal limit temperature that the forests in this region can withstand is 32°C(CIRAD (2019)). There are not a linear relationship between deforestation and soil temperature in tropical forest [5]. The negative impact in our case shows that deforestation decrease with temperature increase.

Table 5: DiD regression for each covariate

TCL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TIME	9.885***	9.970***	8.991***	8.767***	9.386***	9.312***	9.669***
	(1.373)	(1.368)	(1.254)	(1.245)	(1.305)	(1.323)	(1.362)
TREAT	-0.738	-1.718*	0.0641	-3.452***	0.0203	-1.162	-1.949**
	(0.690)	(1.043)	(0.854)	(1.170)	(0.706)	(0.745)	(0.892)
TIME $\times$ TREAT	-6.350***	-6.356***	-5.461***	-5.911***	-5.846***	-6.851***	-6.015***
	(1.672)	(1.674)	(1.630)	(1.675)	(1.657)	(1.744)	(1.692)
LDensity		-0.469					
		(0.390)					
LGrasslands			1.673***				
			(0.397)				
LCroplands				-1.640***			
				(0.359)			
LUrbanbuiltup					2.659**		
					(1.059)		
LRainfall						5.012***	
						(1.407)	
LTemp							-19.28***
							(5.952)
_cons	5.089***	6.548***	1.116	10.44***	0.530	-31.35***	68.93***
	(0.512)	(1.263)	(0.798)	(1.468)	(1.627)	(10.03)	(19.96)
N	2,574	2,574	2,431	2,431	2,431	2,414	2,431
R^2	0.102	0.101	0.126	0.104	0.104	0.098	0.092

Estimation method: Random effect estimator with robust standard errors given in parentheses. Dependent variable: Tree Cover Loss (TCL).
***** significance level at 1%, ** significance level at 5%, * significance level at 10%.**

After taking account each covariate individually, we introduce covariates together in Table 6. We first introduce anthropic actions followed by natural factors.

[5]There is a non-linear quadratic relationship between deforestation and temperature in our sample where the threshold is estimated at 28 C°C

Table 6: DiD regression for overall covariates

TCL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TIME	9.885***	9.970***	9.070***	8.013***	7.976***	7.771***	8.106***
	(1.373)	(1.368)	(1.253)	(1.109)	(1.099)	(1.079)	(1.154)
TREAT	-0.738	-1.718*	-0.699	-3.669***	-4.655***	-4.671***	-5.445***
	(0.690)	(1.043)	(1.142)	(1.412)	(1.445)	(1.467)	(1.458)
TIME × TREAT	-6.350***	-6.356***	-5.481***	-5.345***	-5.275***	-5.950***	-5.713***
	(1.672)	(1.674)	(1.631)	(1.625)	(1.617)	(1.663)	(1.647)
LDensity		-0.469	-0.356	-0.278	-1.044**	-0.925*	-0.957**
		(0.390)	(0.384)	(0.383)	(0.471)	(0.474)	(0.454)
LGrasslands			1.630***	1.809***	1.633***	1.655***	1.864***
			(0.391)	(0.413)	(0.393)	(0.390)	(0.452)
LCroplands				-1.945***	-1.994***	-1.922***	-1.542***
				(0.412)	(0.413)	(0.409)	(0.442)
LUrbanbuiltup					2.725***	2.707***	2.701***
					(1.025)	(1.030)	(0.964)
LRainfall						3.884***	2.361*
						(1.254)	(1.403)
LTemp							-25.27**
							(12.19)
_cons	5.089***	6.548***	2.324*	8.004***	6.290***	-22.52**	70.56
	(0.512)	(1.263)	(1.355)	(1.786)	(1.954)	(9.397)	(44.31)
N	2,574	2,574	2,431	2,431	2,431	2,414	2,414
R^2	0.102	0.101	0.125	0.130	0.132	0.135	0.131

Estimation method: Random effect estimator with robust standard errors given in parentheses. Dependent variable: Tree Cover Loss (TCL).
***** significance level at 1%, ** significance level at 5%, * significance level at 10%.**

We still find a negative and significant effect of the LEB reform on deforestation in the departments of Gabon. In Column (7) (with all covariates), we find that about 5.713 Km^2 of deforestation has been avoided by department and by year in Gabon.

4.2 Parallel trend test

The success of difference-in-difference is based on the assumption of parallel trend between the control and treatment groups. Thus, if the change in trend between the two study groups does not show a significant difference, then the parallel trend hypothesis can be established and the results of the difference-in-difference model are unbiased. We set up an equation to test this hypothesis during the five years preceding LEB adoption to minimize collinearity issues between the different years through the following equation :

$$TCL_{i,t} = \alpha + \sum_{j=1}^{5} \beta_j TIME_{-j} \times TREAT_i + \gamma log(X_{i,t}) + \epsilon_{i,t} \tag{2}$$

with $TIME_{-1}$, $TIME_{-2}$, $TIME_{-3}$, $TIME_{-4}$ and $TIME_{-5}$ are dummy variables representing respectively one, two, three, four and five years prior the LEB implementation. Also, if the department is located in Gabon $TREAT_i$=1, and 0 otherwise. The coefficients β_j of $TIME_{-j} \times TREAT_i$ can be used to evaluate whether the growth trend before LEB adoption is the same between treatment and control groups. The non-significant of these coefficient shows that there are not significant difference between the treatment and control group in deforestation level before policy adoption. The Table 7 shows that the coefficient are not significant for all specification and years. So, the parallel trend assumption is fulfilled.

Table 7: Parallel trend test

TCL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TIME$_{-5}$ × TREAT	-2.198	-1.977	-0.353	-0.533	-0.779	1.602	1.375
	(2.386)	(2.390)	(0.796)	(0.831)	(0.831)	(0.877)	(0.855)
TIME$_{-4}$ × TREAT	-1.764	-1.557	0.182	0.0241	-0.213	1.175	0.980
	(2.386)	(2.390)	(1.008)	(1.077)	(1.089)	(1.103)	(1.084)
TIME$_{-3}$ × TREAT	-2.520	-2.327	-0.441	-0.591	-0.822	-0.786	-0.937
	(2.386)	(2.390)	(0.773)	(0.811)	(0.803)	(0.798)	(0.816)
TIME$_{-2}$ × TREAT	-2.286	-2.107	-0.0258	-0.175	-0.404	1.034	0.834
	(2.386)	(2.389)	(0.810)	(0.872)	(0.872)	(0.890)	(0.867)
TIME$_{-1}$ × TREAT	-2.047	-1.882	0.506	0.354	0.119	0.407	0.240
	(2.386)	(2.389)	(0.977)	(0.952)	(0.947)	(0.931)	(0.958)
LDensity		0.700*	0.618	1.007**	0.337	0.558	0.480
		(0.410)	(0.434)	(0.466)	(0.480)	(0.479)	(0.471)
LGrasslands			2.056***	2.313***	2.144***	2.216***	2.175***
			(0.451)	(0.477)	(0.453)	(0.448)	(0.501)
LCroplands				-2.747***	-2.745***	-2.450***	-2.450***
				(0.479)	(0.481)	(0.475)	(0.521)
LUrbanbuiltup					2.570**	2.430**	2.361**
					(1.031)	(1.051)	(0.992)
LRainfall						7.638***	7.379***
						(1.454)	(1.584)
LTemp							0.157
							(12.22)
_cons	9.174***	7.301***	2.151*	7.672***	5.567***	-51.84***	-50.02
	(0.852)	(1.385)	(1.274)	(1.298)	(1.709)	(11.13)	(44.42)
N	2574	2574	2431	2431	2431	2414	2414
R^2	0.001	0.007	0.058	0.077	0.081	0.092	0.092

Estimation method: Random effect estimator with robust standard errors given in parentheses. Dependent variable: Tree Cover Loss (TCL).
***** significance level at 1%, ** significance level at 5%, * significance level at 10%.**

5 Robustness

5.1 Entropy balancing

The descriptive statistics analysis shows that there are significant differences between the different covariates in the two groups. In order to reduce these differences and to better capture the effect of the reform, we calculate a set of synthetic variables. We use entropy balancing strategy to select matches of units exposed to treatment to get the best counterfactuel for all covariates (Hainmueller, 2012). Entropy balancing is implemented in two steps. Firstly, we compute the weights that are assigned to unit not exposed to treatement. These weights are selected to satisfy a series of balancing constraints based on the distribution of the observables in treatment and control group. Thus, there are no statistically significant differences between our two groups. Indeed, a better comparison relies on individuals with similar characteristics to measure the impact of the policy. Thus, we obtain covariates mean in the control group very close to the treatment group. So, we use this reweighting in our regression (Table 11) to estimate the effect of LEB adoption on tree cover loss. The Table 8 shows the results.

Table 8: Reweighted regression

TCL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TIME	17.83***	18.87***	18.61***	14.39**	14.19**	16.95***	15.43**
	(4.443)	(3.704)	(3.770)	(5.665)	(5.781)	(5.225)	(6.073)
TREAT	3.435	3.111	5.450	-2.652	-1.610	-1.052	10.91
	(2.509)	(3.043)	(4.517)	(6.851)	(6.274)	(6.070)	(7.593)
TIME $\times$TREAT	-12.08***	-12.49***	-12.29***	-11.73***	-11.32***	-10.13***	-9.227***
	(4.669)	(3.808)	(3.693)	(3.250)	(3.006)	(2.742)	(2.479)
LDensity		-1.384	-2.866	-2.465	-2.533	-3.088	-3.204
		(4.790)	(4.270)	(4.512)	(4.499)	(4.324)	(4.300)
LGrasslands			1.634	1.801	1.928	2.027	2.228
			(1.503)	(1.606)	(1.703)	(1.697)	(1.828)
LCroplands				-2.026	-2.302	-2.006	-2.379
				(2.201)	(2.416)	(2.307)	(2.579)
LUrbanbuiltup					-16.74	-17.44	-17.24
					(15.01)	(15.25)	(15.13)
LRainfall						-12.13*	-12.77*
						(6.939)	(7.340)
LTemp							153.4
							(123.3)
_cons	2.124	4.979	3.170	12.58	59.21	149.4*	-350.1
	(2.836)	(11.48)	(13.01)	(8.426)	(41.54)	(85.30)	(343.6)
N	2365	2365	2365	2365	2365	2365	2365
R^2	0.363	0.363	0.365	0.366	0.368	0.370	0.373
AMD2	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Estimation method: OLS estimator with ADM2 effect, Year effect and robust standard errors given in parentheses.
***** significance level at 1%, ** significance level at 5%, * significance level at 10%. Dependent variable: Tree Cover Loss (TCL).**

The results show that in all our specifications, the variable measuring the impact of the reform is negative and significant. Howver, the effet of LEB reform is stronger than in Tables 5 and 6 (without the entropy balancing strategy). Thus, these results confirm that the Gabon ADM2 benefit from an avoided deforestation compared to ADM2 of Cameroon and Congo even if they had the same covariate mean.

5.2 Spatial auto-correlation

In this study we deal with land-use data to estimate our model. Thus, we are likely to be exposed to spatial autocorrelation. Indeed, it is possible that the deforestation of one locality may influence the deforestation level of a neighboring locality. Spatial autocorrelation reduces model precision and predictive power in deforestation analyses (Mets et al., 2017). Consequently, a clustering approach is adopted and considers that all ADM2 in the same ADM1 (Table 9) or the same country (Table 10) are spatially correlated.

Table 9: DiD regression with cluster by ADM1

TCL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TIME	9.885***	9.970***	9.070***	8.013***	7.976***	7.771***	8.106***
	(2.531)	(2.523)	(2.240)	(2.048)	(2.054)	(2.053)	(2.205)
TREAT	-0.738	-1.718	-0.699	-3.669**	-4.655**	-4.671**	-5.445***
	(0.966)	(1.284)	(1.500)	(1.864)	(2.055)	(2.111)	(2.082)
TIME × TREAT	-6.350**	-6.356**	-5.481**	-5.345**	-5.275**	-5.950**	-5.713**
	(2.653)	(2.658)	(2.456)	(2.486)	(2.475)	(2.517)	(2.470)
LDensity		-0.469	-0.356	-0.278	-1.044*	-0.925*	-0.957*
		(0.484)	(0.507)	(0.426)	(0.553)	(0.555)	(0.533)
LGrasslands			1.630***	1.809***	1.633**	1.655**	1.864**
			(0.622)	(0.688)	(0.675)	(0.665)	(0.782)
LCroplands				-1.945***	-1.994***	-1.922***	-1.542***
				(0.564)	(0.558)	(0.534)	(0.454)
LUrbanbuiltup					2.725**	2.707**	2.701***
					(1.061)	(1.057)	(0.973)
LRainfall						3.884**	2.361
						(1.936)	(2.235)
LTemp							-25.27
							(17.53)
_cons	5.089***	6.548***	2.324	8.004***	6.290***	-22.52	70.56
	(0.862)	(1.596)	(1.628)	(2.278)	(1.894)	(13.96)	(67.38)
N	2574	2574	2431	2431	2431	2414	2414
R2	0.102	0.101	0.125	0.130	0.132	0.135	0.131

Estimation method: Random effect estimator with robust standard errors given in parentheses. Errors are clustered by ADM1.
***** significance level at 1%, ** significance level at 5%, * significance level at 10%. Dependent variable: Tree Cover Loss (TCL).**

Table 10: DiD regression with cluster by country

TCL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TIME	9.885***	9.970***	9.070***	8.013***	7.976***	7.771***	8.106***
	(1.753)	(1.921)	(1.902)	(1.540)	(1.490)	(1.523)	(1.748)
TREAT	-0.738	-1.718	-0.699	-3.669	-4.655	-4.671	-5.445
	(0.526)	(2.986)	(3.182)	(4.710)	(5.307)	(5.158)	(5.044)
TIME × TREAT	-6.350***	-6.356***	-5.481***	-5.345***	-5.275***	-5.950***	-5.713***
	(1.753)	(1.756)	(1.772)	(1.932)	(1.874)	(1.706)	(1.523)
LDensity		-0.469	-0.356	-0.278	-1.044	-0.925	-0.957
		(1.003)	(1.008)	(0.821)	(1.250)	(1.410)	(1.345)
LGrasslands			1.630**	1.809*	1.633	1.655	1.864
			(0.735)	(1.076)	(0.996)	(1.035)	(1.195)
LCroplands				-1.945*	-1.994*	-1.922*	-1.542*
				(1.098)	(1.163)	(1.088)	(0.803)
LUrbanbuiltup					2.725*	2.707*	2.701*
					(1.532)	(1.533)	(1.491)
LRainfall						3.884***	2.361
						(0.687)	(2.276)
LTemp							-25.27*
							(14.96)
_cons	5.089***	6.548	2.324	8.004	6.290	-22.52**	70.56
	(0.526)	(4.008)	(3.038)	(5.293)	(4.421)	(9.148)	(68.20)
N	2574	2574	2431	2431	2431	2414	2414
R^2	0.102	0.101	0.125	0.130	0.132	0.135	0.131

Estimation method: Random effect estimator with robust standard errors given in parentheses. Errors are clustered by country.
***** significance level at 1%, ** significance level at 5%, * significance level at 10%. Dependent variable: Tree Cover Loss (TCL).**

Altogether, our results confirm the negative and significant effect of LEB reform on deforestation.

6 Conclusion

This work aims to study the impact of the 2010 LEB reform on deforestation in ADM2 of Gabon. With a DiD analysis, we find that the measure allows Gabon to benefit to avoided deforestation compared to Cameroon and Congo. Our results are robust to several specifications (panel data, control of important factors of deforestation, entropy balancing strategy and cluster approach). Also, the parallel trend assumption is confirmed. In other terms, Gabon, Cameroon and Congo experienced the same level deforestation before 2010. After 2010, while the deforestation increased in all countries, Gabon experienced lower deforestation than its two neighbors. We attribute this "avoided" deforestation to the LEB reform.

In a Central African community context, such a trade measure is likely to have leakage effects if it is not applied in a community setting. Indeed, Gabon shares 2,551 km of borders with its neighboring countries. These forest borders can constitute leakage channels for illegal logging for export from the port areas of neighboring countries. Also, the lower price in Gabon compared to other countries may encourage this leakage behavior through porous borders. Thus, the effectiveness of the export ban on reducing deforestation in Gabon would be enhanced if all neighboring countries and more broadly the countries of the Congo Basin adopted the same approach. These results support the CEMAC zone's initiative to ban log exports from 2022 for all member countries.

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Appendix

Entropy balancing

Entropy balancing consists to minimise the metric distance:

$$\min_{w_i} H(w) = \sum_{\{i|D=0\}} w_i \, log(w_i/q_i) \tag{3}$$

where w_i is the weight chosen for each control unit.

$D_i \in \{0,1\}$ is a dummy indicator that is 1 for intervention group and 0 otherwise. $q_i = 1/n_0$ is a base weight

The weights are selected on some balance and normalizing constraint that are presented in following equation:

$$\sum_{\{i|D=0\}} w_i \, c_{ri}(X_i) = m_r \quad with \;\; r \in 1, ..., R \quad and \tag{4}$$

$$\sum_{\{i|D=0\}} w_i = 1 \quad and \tag{5}$$

$$w_i \geq 0 \quad for\; all\; i\; such\; that\; D = 0 \tag{6}$$

$c_{ri}(X_i) = m_r$ describes a set of R balance constraints imposed on the covariates moments of reweighted control group. For each covariates, the balance constraints are imposed to equate the moments of the covariate distribution between intervention group and the reweighted control group. In the moment constraints, they may include the mean, the variance and the skewness. A balance constraint is formulated such that m_r contains the moment of order r of a specific covariate X_j for the treatment group and the moment function is specified for the control group as $C_{ri}(X_{ij}) = X_{ij}^r$ or $c_{ri}(X_i j) = (X_{ij} - \mu_j)^r$ with mean μ_j.

In entropy balancing, we need to assign one weight for each control unit. The weight allow to solve the entropy balancing scheme are computed from dual problem thet is unconstrained and reduced to a system of non-linear equations in R Lagrange multipliers Hainmueller and Xu (2013). The dual problem is given by:

$$\min_{Z} L^d = \log(Q^T \exp(-C^T Z)) + M^T Z \tag{7}$$

Where $Z = \{\lambda_1, ..., \lambda_R\}$ is a vector (Z*) of Lagrange multipliers for the balance constraints, rewritten in matrix form as CW= M with the (R $\times$ n_0) constriant matrix, C= $[c_1(X_i), ..., c_R(X_i)]^T$, and the moment vector, $M = [m_1, ..., m_R]$. The vector Z* that solves the dual problem also solves the primal problem. The solution weights are recovered using:

$$W^* = \frac{Q \cdot \exp(-C^T Z^*)}{Q^T \exp(-C^T Z^*) \cdot} \tag{8}$$

To solve the dual problem we use a Levenberg-Marquardt scheme that makes use of second order information by iterating

$$Z^{new} = Z^{old} - l\nabla_Z^2(L^d)^{-1}\nabla Z(L^d) \tag{9}$$

where l is a scalar denoting the step lenght. The optimal step length is selected for each iteration.

Table 11: Covariates balancing

Before reweighting
Mean estimate

	(1)	(2)	(3) = (2) - (1)
	Treated	Control	Diff
Density	7.45	179.97	172.52
Grasslands	92.25	170.02	77.77
Croplands	10.56	190.49	179.93
Urbanbuiltup	7.34	9.79	2.45
Temp	25.79	27.59	1.80
Rainfall	1786.56	1561.57	-224.99

After reweighting
Mean estimate

	(1)	(4)	(5) = (4) - (1)
	Treated	Control	Diff
Density	7.45	7.45	0.00
Grasslands	92.25	92.31	0.06
Croplands	10.56	10.65	0.09
Urbanbuiltup	7.34	7.34	0.00
Temp	25.79	25.79	0.00
Rainfall	1786.56	1786.56	0.00