GOV51 Final Project

Effect of Democratization on Deforestation: a Macro-Level Quantitative Analysis

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Introduction

Background

Deforestation causes multiple negative effects, ranging from the loss of bio-cultural diversity, decreased water reservoir, increased risk of landslide to climate change. To address the deforestation issue in a systematic way, it is crucial to analyze the potential causes. Counterintuitively, Klopp (2012) reported that democratization could accelerate deforestation in a number of important cases, including the ones in South Nandi and Karura Forests in Kenya. While article was written in detail based on literature and interview to officials in charge, the scope of the work was limited to analyzing the particular cases in Kenya on a qualitative basis. More holistic and quantitative approach at a global scale would yield an important insight to mitigate the deforestation issues.

Objective

To examine the causal relationship of variables of concern on deforestation at country scale.

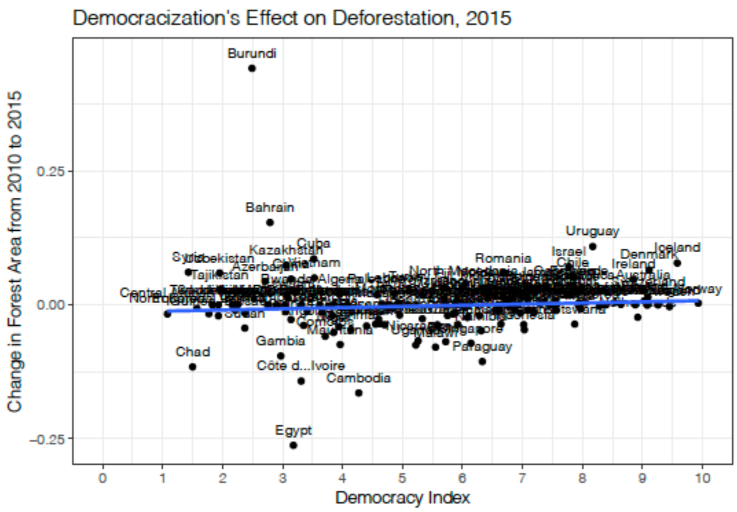
Methods

We are using a difference-in-differences model for this study, in which our primary interest is the treatment effect of democratization on deforestation. We relied on the Democracy Index developed by the Economist Intelligent Unit and have been measured annually since 2006. Our data for deforestation was taken from the Statistical Department of the United Nations. It contains the area of forest land in 1990, 2000, 2010, 2015, and 2020. Since many of our other datasets were missing the most recent data (i.e. 2019, 2020), we decided to only look at the loss of forest land from 2010 to 2015. We calculated the percent lost during those six years. As for the measure of democracy, we used The Economist Intelligence Unit's Democracy Index from 2015. The scale runs from 0 to 10, with 0 meaning least democratized and 10 meaning most democratized. We then combined the two datasets and produced graphs and linear regression models.

In addition to the Democracy Index, we also looked at other confounding variables that could have affected deforestation rates (details are discussed under "Results" chapter). We took datasets on Gini Index, GDP per capita, GDP growth per capita, agricultural land, and poverty ratio from the World Bank. For Gini, GDP, and GDP growth, we took the data from 2015 and combined them with the deforestation data, separately. For the agricultural land, we looked at the percent increase of agricultural land from 2011 to 2015. The agricultural land data only included 2011 through 2016, so we chose the year closest to 2010 to make the data comparable to the deforestation data. For the poverty ratio dataset, however, since there were lots of NA values, we had to take the average of 2011 to 2015 in order to get a number for each country. We combined all these datasets with the deforestation data and produced separate graphs and linear regressions for each.

Result and discussion

1. Effect of democratization on deforestation (all countries)

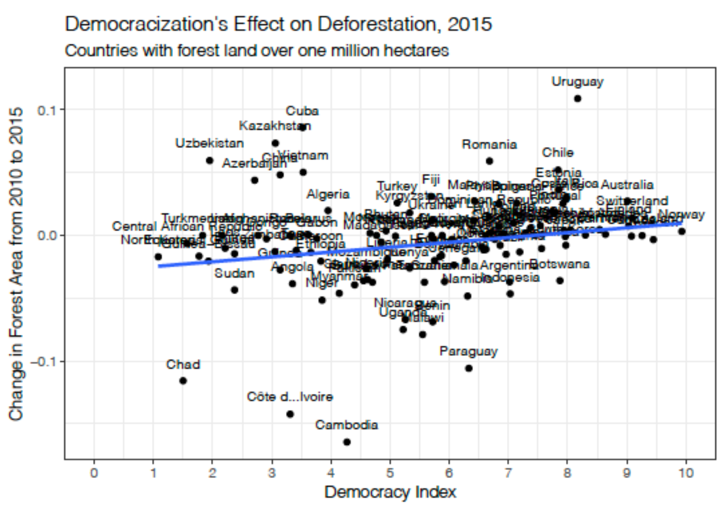


	Model 1
Intercept	-0.029***
	(0.010)
Democracy Index in 2015	0.004**
	(0.002)
Num.Obs.	115
R2	0.044
R2 Adj.	0.036

* p < 0.1, ** p < 0.05, *** p < 0.01

First, we ran a linear regression for all countries that had both data (N = 160). The result was unclear, and there seemed to be many outliers (e.g. Burundi, Bahrain, and Egypt). These countries tend to have extremely small forest coverage and a small change in absolute number could translate into a big change in terms of percentage. We therefore deselected the countries with small forest area by creating another dataset that only includes countries with forest land above 1,000,000 hectares and conducted the same process of calculating the percent loss. Hereafter, such countries are collectively referred to as the "countries with forest."

2. Effect of democratization on deforestation (countries with forest)



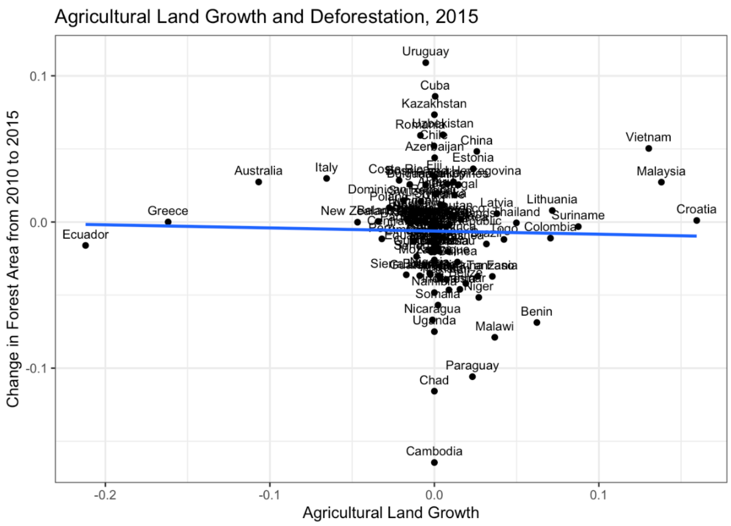
	Model 1
Intercept	-0.029***
	(0.010)
Democracy Index in 2015	0.004**
	(0.002)
Num.Obs.	115
R2	0.044
R2 Adj.	0.036

* p < 0.1, ** p < 0.05, *** p < 0.01

We now see the clearer trend. As you can see, there is a positive correlation between democracy index and change in forest area over five years. Although the R-squared values, both adjusted and unadjusted, are low, the trend is statistically significant at $p < 0.05$. We used this filtered dataset throughout the rest of our analysis as the main dependent variable.

Kenya, the country analyzed by Klopp (2012) is below the regression line among other developing countries in Africa and Latin America. Below we tried to figure out the confounding factors.

3. Agricultural land growth (countries with forest)

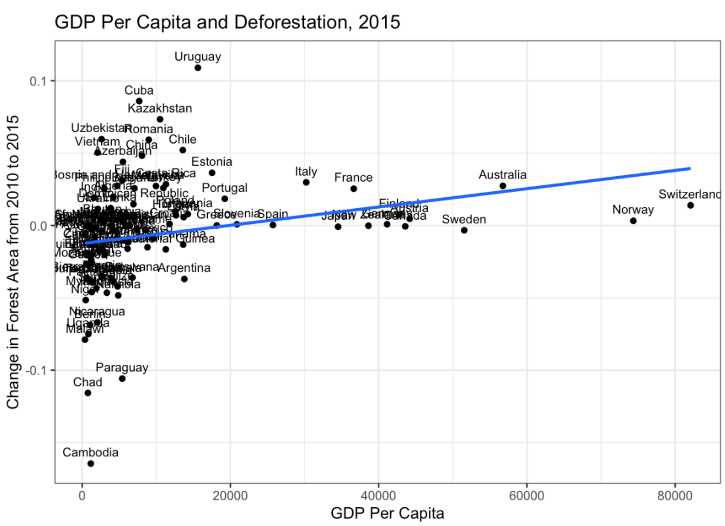


	Model 1
Intercept	-0.006*
	(0.004)
Change in agricultural land	-0.021
	(0.087)
Num.Obs.	108
R2	0.001
R2 Adj.	-0.009

* p < 0.1, ** p < 0.05, *** p < 0.01

Initially, we had hypothesized that people are clearing forest to expand the farmlands. To confirm this, we ran a regression on farmland growth and deforestation. Surprisingly, there was no clear trend again. Instead of focusing on industry, we decided to look into economic factors.

4. GDP per capita growth (countries with forest)

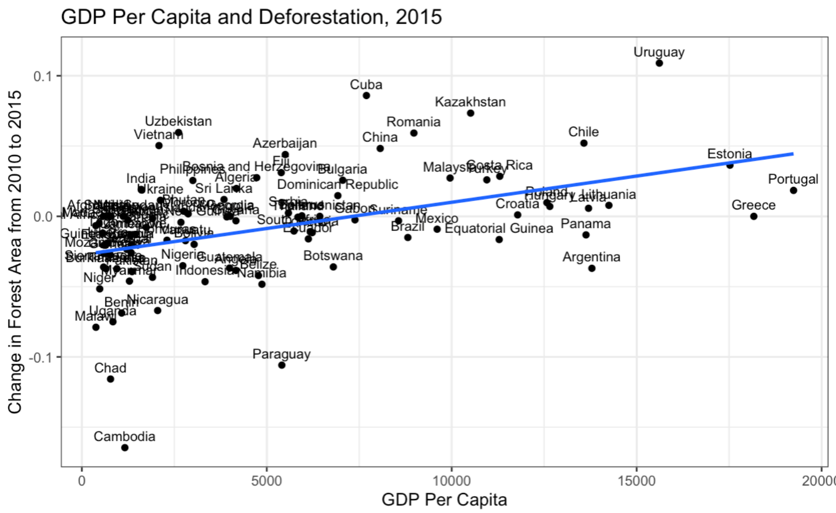


	Model 1
Intercept	-0.012***
	(0.004)
GDP per capita in 2015	0.000***
	(0.000)
Num.Obs.	108
R2	0.064
R2 Adj.	0.056

* p < 0.1, ** p < 0.05, *** p < 0.01

As a first step, we ran a regression on GDP per capita as an independent variable. There did not seem to be any clear pattern as a whole, but there seems to be a threshold: countries with more than US$20,000 GDP per capita generally have little to no change in forest areas over the six years.

5. GDP per capita (countries with forest and with less than US$20,000 GDP per capita)

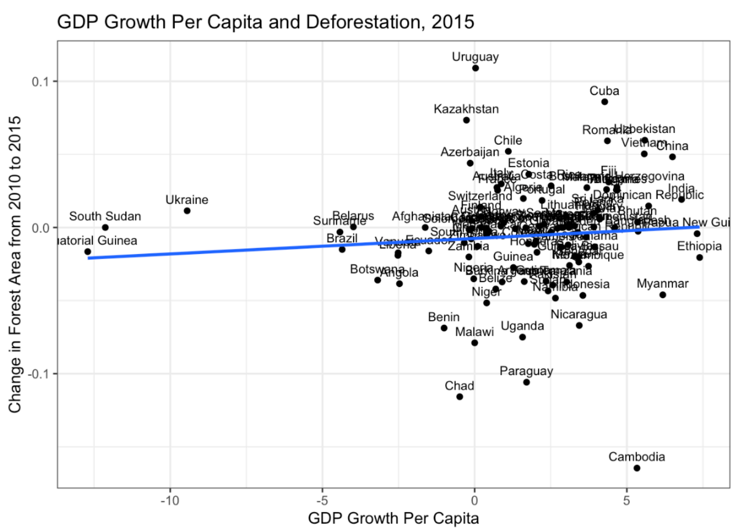


	Model 1
Intercept	-0.027***
	(0.006)
GDP per capita in 2015	0.000***
	(0.000)
Num.Obs.	94
R2	0.195
R2 Adj.	0.186

* p < 0.1, ** p < 0.05, *** p < 0.01

Following the outcome of the analysis above, we filtered our dataset with a threshold value of US$20,000 in GDP per capita. Now the relationship is clearer, but the coefficient implies the effect of GDP per capita is weak despite the statistical significance (p < 0.01). We decided to look for other candidate variables.

6. GDP growth per capita (countries with forest)

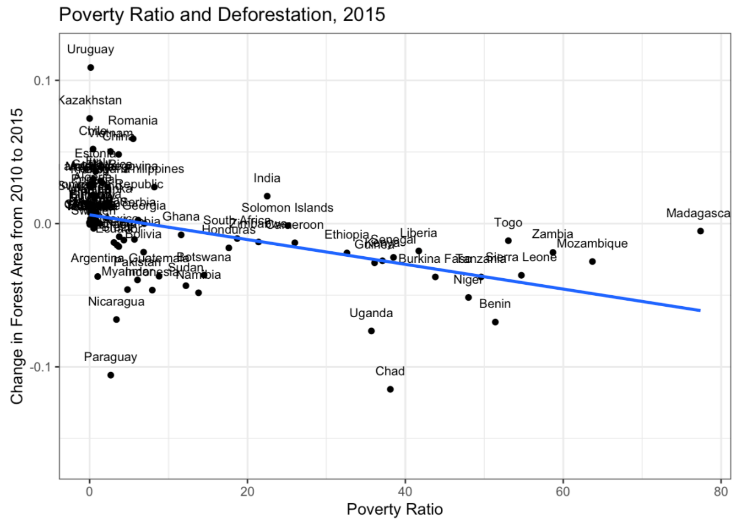


	Model 1
Intercept	-0.008*
	(0.004)
GDP growth per capita in 2015	0.001
	(0.001)
Num.Obs.	107
R2	0.009
R2 Adj.	-0.001

* p < 0.1, ** p < 0.05, *** p < 0.01

Next, we tried GDP growth per capita instead of GDP per capita too see if acceleration/stagnation of growth would affect the degree of deforestation/reforestation. The result was not clear and removal of outliers (such as Equatorial Guinea, South Sudan, Ukraine, and Cambodia) does not seem to help our analysis. We moved ahead with other variables.

7. Poverty ratio (countries with forest)



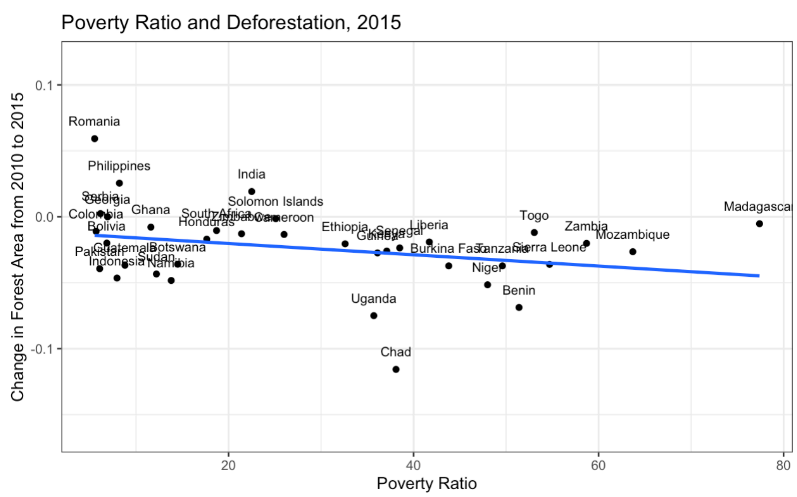
	Model 1
Intercept	0.006
	(0.004)
Poverty ratio (2011-2015 average)	-0.001***
	(0.000)
Num.Obs.	85
R2	0.209
R2 Adj.	0.200

* p < 0.1, ** p < 0.05, *** p < 0.01

We ran a regression on poverty ratio. People under poverty is defined by the World Bank as the people with an income less than $1.90 per day. Although the coefficient was subtle, it seems there is a weak negative correlation between the poverty ratio and forest area change (= the more people a country has, the more alarming deforestation is).

However, we suspected that the statistical significance (p < 0.01) may have resulted from the heavy weight of middle-income to high-income countries where the extreme poverty is almost non-existent, as you can see the density of plots around 0 in poverty ratio. We decided to take a closer look at the problem, as summarized below.

8. Poverty ratio (countries with forest and poverty ratio of 5% or higher)

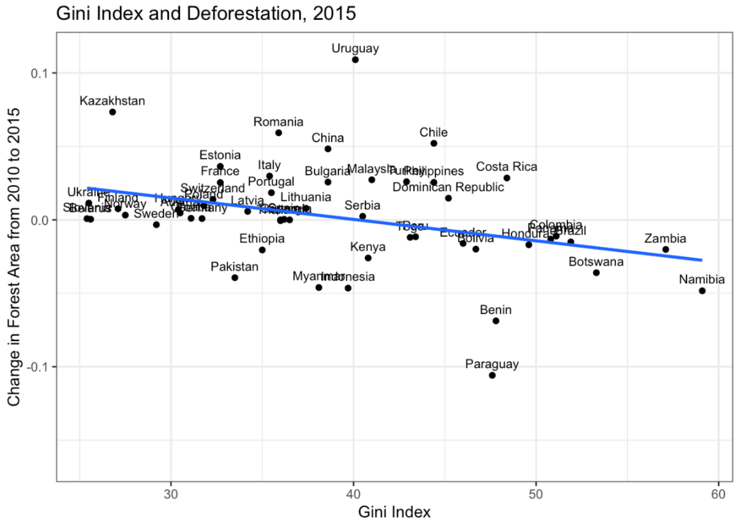


	Model 1
Intercept	-0.012
	(0.009)
Poverty ratio (2011-2015 average)	0.000*
	(0.000)
Num.Obs.	35
R2	0.080
R2 Adj.	0.052

* p < 0.1, ** p < 0.05, *** p < 0.01

As you can see, the coefficient became closer to a flat line with smaller R-squared values. Our careful analysis suggests that we should not conclude that there is a clear relationship between poverty ratio and deforestation.

9. Gini Index (countries with forest)



	Model 1
Intercept	0.059***
	(0.022)
Gini Index in 2015	-0.001**
	(0.001)
Num.Obs.	52
R2	0.125
R2 Adj.	0.108

* p < 0.1, ** p < 0.05, *** p < 0.01

Gini Index represents the degree of inequality within a country by measuring the steepness of the income distribution curve when you place poorest on the left and richest on the right of the x axis in a cumulative way. The higher the index value is, the wider gap a country has.
Although the correlation is still not very strong as shown in the R-squared values, this time we can confirm a negative trend (i.e. the wider the gap between rich and poor is in a country, the more alarming deforestation is).

10. Does Gini Index explain the difference in the effect of democratization on deforestation?

Lastly, we evaluated whether Gini Index explains the difference in the effect of democratization on deforestation. We did two distinct approach:

(1) Pick up the best and worst 20 countries respectively in terms of Gini Index values and consider them as a binary treatment (i.e. worst 20 countries received "1" while the best 20 countries received "0") and calculate the average treatment effect as difference-in-differences variable in democratization-deforestation analysis. We set the confidence level of 95% and alpha value of 0.05.
(2) Run a multivariable regression for all countries we have the data for Gini Index.

As a result, from (1) we obtained the p-value of 1.998, which is far beyond the set alpha value. Hence we could not reject the null hypothesis i.e. Gini Index as a binary treatment does not explain the difference within the democratization-deforestation analysis.

On the other hand, result from (2) suggested there was a statistical significance ($p < 0.05$) between the two variables: Democracy Index and Gini Index, as shown in the table on the right.

	Model 1
(Intercept)	0.246**
	(0.099)
Democracy.Index.in.2015	-0.028*
	(0.014)
Gini.Index.in.2015	-0.007**
	(0.003)
Democracy.Index.in.2015 × Gini.Index.in.2015	0.001**
	(0.000)
Num.Obs.	52
R2	0.215
R2 Adj.	0.166

* p < 0.1, ** p < 0.05, *** p < 0.01

Conclusion

There was a correlation between the Democracy Index and change in forest areas from 2010 to 2015 for the countries with the forest area of 1 million hectares or more. While the trend was generally positive, we tried to analyze if there was any country other than Kenya where democratization adversely affected the deforestation issue. While no clear correlation was observed in agricultural land, GDP per capita, GDP growth per capita or poverty ratio, Gini Index showed a negative trend on change in forest area. Our examination on the average treatment effect of Gini Index as a binary treatment did not show significant effect to explain the difference-in-differences in democratization-deforestation analysis. The multivariable linear regression, on the other hand, suggested that there was a statistical significance ($p < 0.05$) between the two variables: Democracy Index and Gini Index.

Primary literature

Jacqueline M. Klopp (2012): Deforestation and democratization: patronage, politics and forests in Kenya, Journal of Eastern African Studies, 6:2, 351-370

The Economist Intelligent Unit Limited (2020): Democracy Index 2019 - A year of democratic setbacks and popular protest

Data sources

- Democracy Index dataset was obtained from the report "Democracy Index 2019." The Democracy Index is based on five categories: electoral process and pluralism; the functioning of government; political participation; political culture; and civil liberties.
- Deforestation dataset was obtained from the Statistical Department of the United Nations: https://unstats.un.org/unsd/envstats/qindicators.cshtml
- Other datasets, namely Gini Index, GDP per capita, GDP growth per capita, agricultural land, and poverty ratio from the World Bank: https://databank.worldbank.org/home.aspx.