Strategic environmental commitment and climate change in Africa: Evidence on mining and deforestation*

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Abstract

This paper addresses two issues on the link between mining, deforestation and environmental policy in Africa using a panel data of 35 African countries spanning over 2001-2017. First, we study the relationship between mining and deforestation. Our findings suggest that mining increases deforestation while environmental policy contributes to reduce deforestation in mineral resource-rich countries. An increase in mineral rent by a one-point percentage of GDP leads to forest loss of about 50 km^2. Moreover, regional economic community has heterogeneous effects on deforestation consistent with the coordination policies. Second, we test the implication of these results for uncoordinated environmental policies using two measures: a *de jure* and a *de facto* environmental policy. Our results support that countries adopt a strategic behavior in response to the environmental policy of their neighbors. A 1% increase in neighbors' environmental commitment increases one's own environmental commitment by 0.3% and 0.8% for *de jure* and *de facto* respectively. We document that this strategic behavior leads to a race to the top for *de jure* environmental policy and a race to the bottom *de facto* environmental policy. As African countries increasingly engage in *de jure* environmental enforcement, their *de facto* efforts to mitigate climate change are slackening.

Keywords: Deforestation, climate change, mining, environmental policy.
JEL Codes: C23, P48, Q23, Q54

1 Introduction

Forest is the most important "natural brake" to climate change (Gibbs et al., 2007; Malhi et al., 2002). It stores 30% of current total carbon emissions from fossil fuels and industry (IPCC, 2001).[1] When a forest is destroyed or degraded, an important store of carbon dioxide is released into the atmosphere. Lawrence and Vandecar (2015) show that "completely deforesting the tropics could result in global warming equivalent to that caused by burning of fossil fuels since 1850". In Africa for instance, deforestation causes about 70% of total greenhouse gas emissions (Gibbs et al., 2007).

Yet, forests are under threat of human activities in many countries around the world. Mining activities are the fourth driver of deforestation globally, induce 7% of forest lost in developing

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[1]IPCC: Intergovernmental Panel on Climate Change

countries (Hosonuma et al., 2012; Potapov et al., 2017) and raise enormous environmental concerns (Edwards et al., 2014; Durán et al., 2013). Jenkins and Yakovleva (2006) state that "the discovery, extraction and processing of mineral resources are widely regarded as one of the most environmentally and socially disruptive activities undertaken by business".

By contrast to advanced economies, developing regions face a double challenge. They have to conciliate their development imperatives with the environmental concerns. The extractive sector and particularly the mining industry is at the heart of these challenges. The mining sector provides a unique opportunity for African countries to mobilize revenue domestically for financing development as stated in the Africa Mining Vision (African Union, 2009). Indeed, Africa possesses around 30% of the world mineral resources (Edwards et al., 2014) with an enormous growth potential (Taylor et al., 2009). For instance, from 1999 to 2016, African Extractive Industries Transparency Initiative (EITI) countries have accumulated more than US$700 billion as direct tax revenue from the extractive companies (EITI, 2018). According to Collier (2010), "the economic future of Africa will be determined by whether this opportunity is seized or missed". How African countries can escape this double edge-sword dilemma? This study aims to shed light on how to address it.

The purpose of this paper is twofold. First, we study the effect of mining activity on deforestation and the role of environmental policies in that respect. Second, given the opportunity offered by the extractive sector in terms of domestic revenue mobilization, states might strategically interact with each other, to attract foreign investment in the mining sector. In the absence of coordination, this strategic behavior may lead to a kind of "Prisoner's Dilemma" and deters any climate mitigation policy. This temptation is stronger in the African context where countries lack competitiveness and capital is scarce (Onwuekwe, 2006). While Oman (1999) emphasizes that states competition for foreign firms' location tends to be intense in a specific industry and intra-regional, there is no evidence on such strategic interaction in Africa. Environmental policy is subject to a game of the kind and more so, since the environmental costs are relegated to future generations.

Mobilizing mining revenue for development is already challenging. A skeptical view widely dominates the literature on the potential contribution of the mining sector to economic development. Abundant natural resources yield poor economic outcomes (Sachs and Warner, 1995, 1999, 2001), exert adverse effects on governance and institutional quality (Ross, 2001), deter political stability (Bhavnani and Lupu, 2016) and fuel conflicts (Collier et al., 2004; Ross, 2004; Berman et al., 2017). Recent literature shows that the curse is not a destiny and well design policies matter (Brunnschweiler, 2008; Brunnschweiler and Bulte, 2008; James, 2015). However, significant environmental costs would be unbearable for future generations in the context of climate change. Understanding how mining activities affect deforestation and how states strategically interact in their environmental policy is an important step to designing better environmental coordination mechanisms and common enforcement to escape an environmental race to the bottom.

Our paper contributes to the literature in three main aspects. First, we examine the effect of mining on deforestation in Africa. While studies on the local impact of mining activities including air, water and soil pollution exist (Akiwumi and Butler, 2008; Hilson, 2002; Porgo and Gokyay, 2017), contributions on deforestation are scant. Hund et al. (2017) and Abernethy et al. (2016) recognize that the mining sector is one of the main drivers of deforestation in the Democratic Republic of Congo and in the Congo Basin. Hund et al. (2017) explore possibilities for the extractive sector to contribute to the Reduction of Emissions from Deforestation and forest Degradation and improving carbon stocks (REDD+). They do not assess the impact of mining on deforestation. To the best of our knowledge, our study is the first attempt to estimate the extent to which mining affects deforestation in Africa while considering spatial autocorrelation across countries in Africa.

Second, we examine how mining affects environmental policy and how states strategically interact. Previous studies only focus on competition among the US states and within the European Union (Fredriksson and Millimet, 2002; Konisky, 2007), partly because of the lack of data on environmental policy in developing countries[2]. We contribute to this literature not only by using a sample of developing countries in Africa but also by including in our strategic interaction model both time and space dynamics of environmental policy. Considering time a space dynamic allows us to disentangle the direct and indirect effects in both the long-run and the short-run. We also control for country exposure to climate shocks.

Finally, we distinguish *de jure* and *de facto* environmental policies. *de jure* policy refers to country adherence to international environmental treaties. *de facto* environmental policy represents the actual environment control. The advantage of this distinction is that in poor institutional quality context and asymmetric power between states and foreign investors, a wide gap can exist between environmental policies on paper and in practice. This is important in environmental policy since the climate cost is global and relegated to future generations. Indeed, the effectiveness of the legal enforcement of environmental standards depends on the institutional environmental environment and the administrative capacity to implement these standards.

We use a panel data of 35 African countries over the period 2001-2017. Relying on spatial econometrics specifications, we establish three key results. First, we show that mining activity increases deforestation in Africa. An increase in mineral rent by a one-point percentage of GDP leads to forest loss of about 50 km^2. However, environmental policy contributes to reducing deforestation in EITI[3] member states. We also find evidence of heterogeneity among countries depending on regional economic community they belong to. Economic communities such as the ECOWAS[4] and the WAEMU[5] are associated with lower deforestation while others (ECCAS and SADC)[6] are associated with higher deforestation. These heterogeneities may be driven by difference in policy coordination. Second, we test the implication of these results for uncoordinated environmental policies. We find that countries adopt a strategic behavior in response to the environmental policy of their neighbors. A 1% increase (decreases) in neighbors' environmental enforcement increases (decreases) in one's own adherence by 0.3% and 0.8% respectively for *de jure* and *de facto* environmental policy. Third, we find a race to the top for *de jure* environmental policy while countries exhibit a race to the bottom in their *de facto* environmental policy. Consequently, countries' strategic behaviors lead to an increasing in *de jure* environmental enforcement, while their *de facto* environmental enforcement is weakening.

The rest of the paper is organized as follows. We discuss the related literature in section 2. Section 3 describes the data. In section 4, we present the econometric specifications and the results of the effects of mining on deforestation. Section 5 discusses the methodology and the results of the strategic interaction models and the test of the races hypothesis. Section 6 undertakes robustness checks of the results. Section 7 derives policy implications and future research prospects.

2 Related literature

In this section, we discuss some empirical evidences related to mining activities, deforestation and environmental policies with a specific focus on climate change. The references cited below are by no means exhaustive.

[2]See Konisky and Woods (2012) for extensive discussion on environmental policy measures.

[3]The Extractive Industries Transparency Initiative

[4]Economic Community of West African States

[5]West African Economic and Monetary Union

[6]ECCAS: Economic Community of Central African States; SADC: Southern African Development Community

2.1 Mining, deforestation and climate shocks

Evidence suggests that deforestation contributes to climate change (Moutinho and Schwartzman, 2005; Shukla et al., 1990). Climate and vegetation coexist in a dynamic equilibrium such that a perturbation of either or both components could alter the equilibrium. In a simulated model, Shukla et al. (1990) show that deforestation of the Amazonian forest causes "a significant increase in surface temperature and a decrease in evapotranspiration and precipitation over Amazonia". Also, the authors predict that the forest chance of renewal is limited since the length of the dry season increases. Deforestation disrupts not only the ecosystem's natural ability to store carbon dioxide emissions; it also contributes to them.

From exploration to resource refinement, extractive activities disrupt the landscape and the environment. Deforestation is one of the main consequences of this disruption. Yet, the literature on the effects of mining on deforestation is still scant, especially in Africa. Most of the empirical studies on mining and deforestation are concentrated on the Amazonian forest and Brazil. However, the world's second-largest tropical forest is in Africa and the mining effect on deforestation might be particularly sizable in the context of weak enforcement capability and a weak institutional framework. Under the pollution haven hypothesis (PHH)[7], some empirical studies show that laxity in environmental regulation attracts highly-polluting industries (Dean et al., 2009; Xing and Kolstad, 2002).

According to Sonter et al. (2017), the effect of mining on deforestation is sizable and underestimated worldwide. Mining activities affect deforestation both directly and indirectly through different channels. Directly, processing and infrastructure development and extraction, particularly for strip mining removes the overburden on a significant area that may be forested. Indirectly, mining activities affect deforestation through three major channels (Sonter et al., 2017). First, toxins and solid metals released during mining operations might remain for a long time after the mining closure and cause soil erosion hence, significant forest loss in the surrounding area. The argument that mining companies occupy a small area (less than 1% of the world terrestrial land surface (Bridge, 2004)) may be delusional. Several studies show that adopting an ecosystem perspective, mining activities can have an impact on the forest on a large scale. Sonter et al. (2017) estimate that mining causes deforestation up to 70 km beyond the mining lease boundaries in the Amazonian forest. Using the propensity score matching method they found that mining activities cause 11.67 km^2 of deforestation between 2005 and 2015. This surface represents 9% of all Amazon and 12 times the deforestation that occurs within mining leases boundaries. Second, infrastructure establishment, both for extraction and transport might lead to forest loss. Third, mining affects population spatial distribution through displacement and urban expansion as a response to increasing labor demand and the development of other activities surrounding the mineral commodity supply chains.

Combes et al. (2015) use a sample of developing countries over the period 1990-2010 and find a positive relationship between mineral rents and deforestation. The authors argue that mineral extraction is space -consuming and might invade forest area. Bridge (2004) identifies tree major environmental impacts of mining: modifying physical landscape; waste pollution and driving regional and global environmental disruption. Waste pollution includes physical (ingress of particulates in the atmosphere, water and land) and chemical pollution (chemical products used during the mineral processing).

One common policy response to mining driven forest damage is setting protected areas. However, Durán et al. (2013) show that even protected areas (PA) are under threat. "7% of mines for four key metals directly overlaps with the protected area and a further 27% lies within 10 km of a PA boundary. Moreover, those PA with mining activity within their boundaries constitute around 6% of the total area coverage of the global terrestrial protected area system, and those with mining activity within or up to 10 km from their boundary constitute nearly

[7] The "pollution haven hypothesis" is the idea that environmental policies could affect pollution-intensive activities location. See Kellogg (2006) for more details.

14% of the total area".

Overall, the literature emphasizes that mining activities disrupt the environment and weaken the ecosystem's natural ability to mitigate climate change.

2.2 Strategic interaction in environmental policy: A race to the bottom or a race to the top ?

Strategic interactions[8] in environmental policy stem from both international trade literature and environmental politics literature (Engel, 1996; Levinson, 2003; Olney, 2013; Potoski, 2001; Wood, 1991). Since environmental policies are major sources of comparative advantage in international trade and in foreign direct investment locations, states respond to their competitors' behaviors. A race to the bottom occurs when countries strategically respond to each other by lowering their environmental standards (Konisky, 2007). In response to lax environmental policies of their competitors, countries react by lowering their environmental standards. Since the intuition of the race to the bottom is straightforward, it occupies a large body of the literature (Fredriksson and Millimet, 2002; Konisky, 2007). However, a race to the top can also happen.

A race to the top occurs when countries imitate each other in their environmental enforcement. Indeed, environmental standards increase with the level of development (Olney, 2013). As long as counties' economic conditions improve, also does the demand for higher environmental standards. Moreover, stringent environmental standards may lead to innovation (Porter and Van der Linde, 1995).

Regarding the race to the bottom, Konisky (2007) emphasizes that: "Regulatory competition among state governments suggests that their regulatory behavior is interdependent. While this assumption is fundamental to the race to the bottom theory, it has received scant attention in empirical studies. Instead, most of the literature focuses on whether firm economic investment decisions are sensitive to inter-jurisdictional differences in the stringency of environmental regulation". Using annual state-level pollution regulation data from 1985 to 2000, Konisky (2007) found that environmental regulatory behavior is influenced by the interactions with the competing states for economic investment. Such interaction is more likely to take place between resource-rich countries with limited investment capacity. In China, Hong et al. (2019) argue that local governments tend to prioritize economic growth to environmental quality. Fredriksson and Millimet (2002) find that in the US, states improve their environmental standards in response to an improvement in their neighbors with relatively already stringent regulations. However, an increase in environmental standards by states with relatively lax policy has no effect on their neighbors. Barrett (1994) argues that, in a context of imperfectly competitive international markets, governments have the incentive to set low environmental standards for businesses operating in those markets.

Summing up, the literature on the effect of mining on deforestation in African remains limited. The role of environmental policy and spatial interactions are neglected. This study aims to fill this gap.

3 Data and main indicators

The dataset covers 35 African countries over the period 2001-2017. The list of countries is provided in Table 1. Deforestation data availability limited the period to 2001-2017. We gather the data from different sources. In the following subsection, we describe the data and presents some descriptive analyses. Data sources and variables' definition are given in Table A2.

[8]See Brueckner (2003) for review on strategic interaction models.

3.1 Deforestation

Deforestation is "stand-replacement disturbance or a change from a forest to a non-forest state" (Hansen et al., 2013). We measure deforestation using the forest cover loss at different thresholds of three cover (greater than 20%; 30% and 50% capony cover) compiled by Hansen et al. (2013). Hansen et al. (2013) data are given by geographic coordinates that we convert into country-level data. The authors use earth observation satellite imagery data at a spatial resolution of 30 meters to quantify gross forest cover loss. Using different canopy covers allows us to take into account the sensitivity of forest measurement to different three cover thresholds (Grainger, 2008). The type of forest is classified following the canopy cover thresholds in percentage. The higher percentages correspond to the closed forest while lower correspond to open forest. Since the measurement methodology of forest loss and forest gain differ, the net cover loss cannot be used (Combes et al., 2018). These data are more reliable compared to the FAO forest cover data (Combes et al., 2018; Grainger, 2008). Using the FAO dataset, Grainger (2008) shows that it is difficult to construct a reliable trend and "evidence for a decline is unclear". Deforestation data consider forest loss induced by both natural and economic activities.

The average forest loss is 0.66, 0.74 and 0.57 thousand of km^2 for canopy cover greater than 20%, 30% and 50% respectively. The minimum forest loss is zero for all canopy cover.The maximum are respectively 14.9, 14.65 and 13.77 thousand of km^2 in the sample. The standard deviations are respectively 1.49, 1.74 and 1.54.

3.2 Environmental policy

By contrast to developed countries where environmental policy data exist for quite a long period (OECD environmental policy dataset for instance), measuring environmental policy in Africa is challenging. To the best of our knowledge, there is no dataset on environmental policy in Africa over a significant period. The environmental performance index dataset is released biennially in even-numbered over the period 2006-2018 (Wendling et al., 2018) and cannot be assembled into a panel data because of methodological change. Also, the World Bank CPIA environmental sustainability rating started in 2005. The challenge is how to proxy environmental policy in Africa in a context of lack of data. To deal with these issues, we refer to two different measures of environmental policy in Africa: domestic environmental commitment which is a *de facto* measure of country environmental policy and international environmental commitment which is a *de jure* measure.

We follow the same methodology as Combes et al. (2016) to compute a *de facto* environmental policy measure. The authors build an indicator called "domestic efforts for climate mitigation (DECM)" which is the residuals of the regression of per capita CO_2 emissions over a set of control variables (GDP per capita, openness to trade, population, foreign direct investment and foreign aid). They argue that the error term provides a *de facto* measure of domestic effort to climate mitigation because the regression controls exogenous factors that predict the "structural emissions". Therefore, the residuals catch the autonomous climate policy (Combes et al., 2016).

We estimate a dynamic panel model estimated with a System-GMM (Blundell and Bond, 2000) as in Combes et al. (2016). We then normalize the residuals from -10 (lax environmental policy) to +10 (stringent environmental policy). See Table B1 in Appendix for further details.

Figure 1 displays the kernel density estimate of the *de facto* environmental policy measure. We observe three modalities in the distribution showing heterogeneities of the *de facto* measure of environmental policy in the sample.

The *de jure* environmental policy is a count of country adhesion to international treaties. Although international treaties may not be binding, they are deemed to be more contingent than the domestic laws. Also, country commitment to international enforcement is a good signal of their environmental policy. We expect country environmental commitments to reduce deforestation.

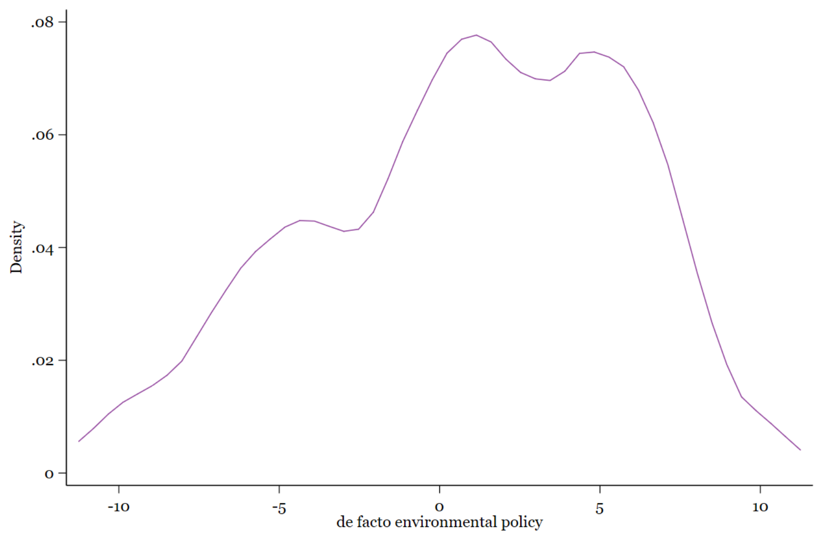

Figure 1: Kernel density estimate of *de facto* environmental policy

Figure 2 displays the box plots of the *de jure* environmental policy in three years periods, except the last box which is two years. We observe an increase in the quartiles over time. The median is around 75.

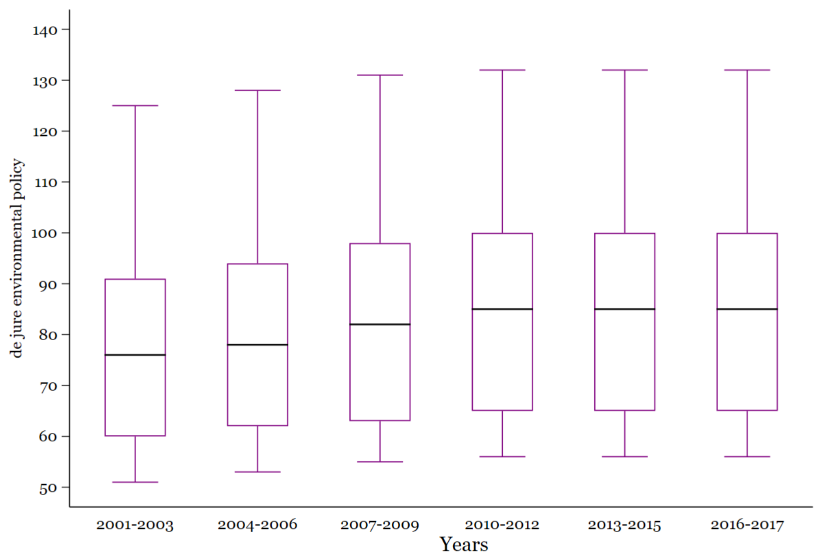

Figure 2: Box plots of the *de jure* environmental policy

Figure 3 shows a contrasted evolution of the year average of the two environmental policies. Countries' adhesion to international environmental treaties (*de jure*) increases over the period 2001 to 2017 while the domestic environmental enforcement (*de facto*) decreases. African countries are committing in international environmental treaties but these commitments seem to be ineffective in terms of actual policies. The nonbinding nature of treaties may explain these trajectories.

3.3 Mineral resources rent

Because we are interested in mining activities we do not consider the other extractive resources such as oil and natural gas. Mining is more prevalent in forest areas than oil and gas extraction

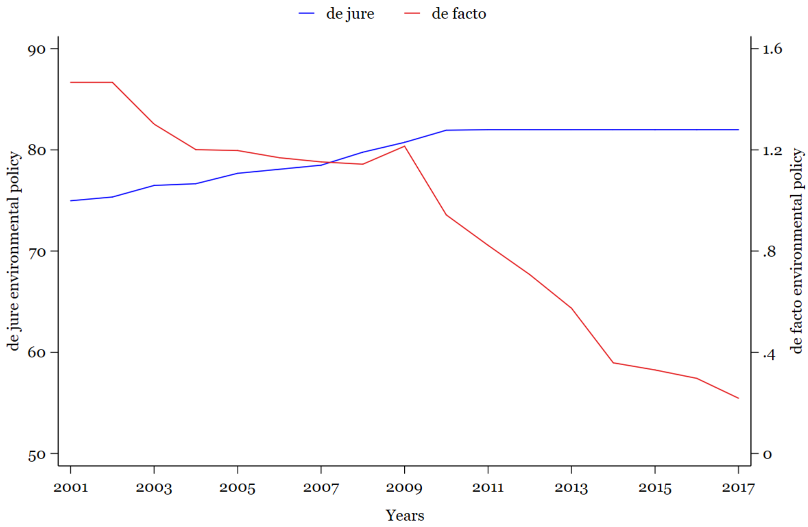

Figure 3: Average environmental policy

(Hund et al., 2017). The increasing weight in African economies of the mining sector comes with substantial environmental issues. We use mineral resource rents as % of GDP as our measure mining activities. Some alternative measures could be the subsoil wealth computed by the World Bank, and mining concession. However, these datasets are limited in terms of time and country coverage. The subsoil dataset is not available yearly while the dataset on mining concession data cover only a few countries. Subsequently, we resort to resource rents. The data are from the World Bank World Development Indicators.

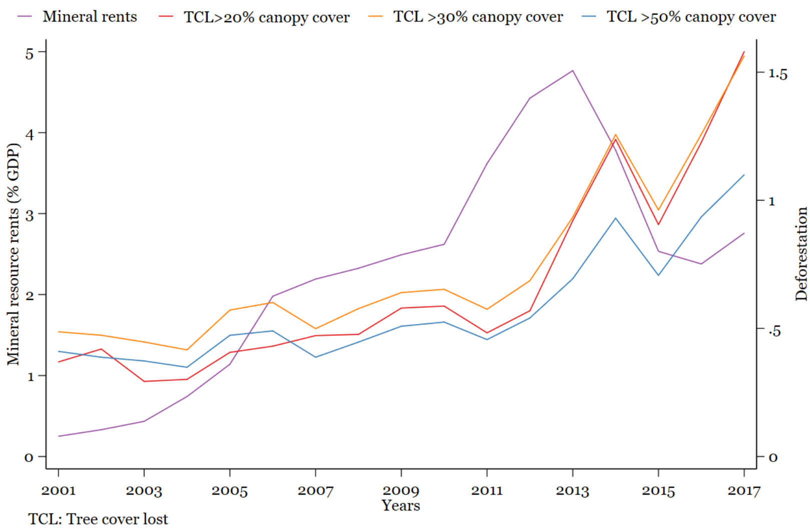

Figure 4: Mining and deforestation

Figure 4 displays the evolution of the sample average of mineral resource rents as a percent of GDP and deforestation (tree cover loss greater than 20%, 30% and 50% canopy cover). It shows a clear co-movement between mineral rents and deforestation over the period 2001-2017.

Figure 5 present the maps of the country average over the period 2001-2017 of deforestation (tree cover loss at canopy cover >20%) and mineral resource rents. Except for Mali, we observe spatial correlation between the mineral resource rents of the countries in the sample and their deforestation. Countries with high mineral resource rents display greater forest loss.

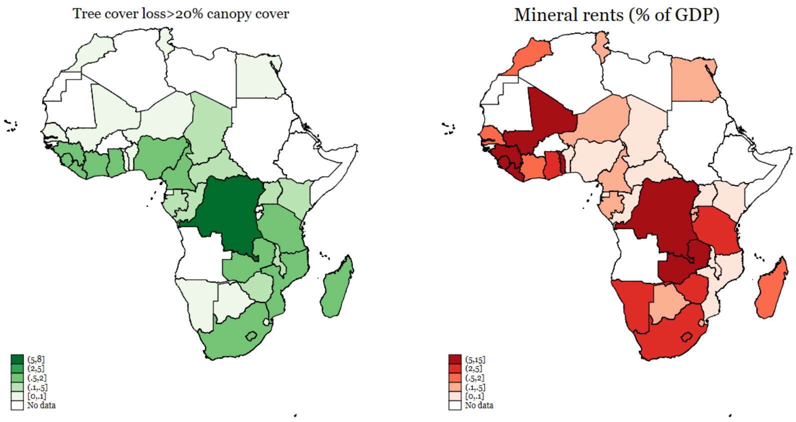

Figure 5: Average deforestation and mineral resource rents

3.4 Other variables

Temperature and precipitation shocks: to control for the effect of climate shocks we use the absolute value of the deviation of the temperature, respectively precipitation, to its long-run average. Temperature (precipitation) shocks are natural events that can exacerbate deforestation. Data on temperature and precipitation are from the University of East Anglia Climatic Research Unit.

GDP per capita: We control for both GDP per capita and GDP per capita square. The intuition is that the level of economic development affect deforestation. Including the square allows us to test the environmental Kuznets Curve hypothesis. In the early stage of economic development, deforestation increases and starts to decrease since the country reaches a certain level of development. In this sense, we expect an inverted U-shape relation between deforestation and GDP per capita.

EITI membership: the Extractive Industries Transparency Initiative "is a global standard for the good governance of oil, gas and mineral resources. It seeks to address the key governance issues in the extractive sectors". The EITI membership is a dummy variable equal to 1 if the country is a member of EITI and 0 otherwise. 16 countries out of 35 of our sample are members of EITI. We expect EITI membership to decrease deforestation since the EITI promotes good practices in the extractive sector. However, the EITI membership is also a signal of extractive resource endowment. As compared to other countries, deforestation may be higher in those countries. The data on country status are extracted from the EITI website.[9]

Democracy index: The democracy index is collected from the Polity IV dataset. It measures the quality of democracy. The index is between -10 (autocratic regime) to +10 (full democracy). It varies from -9 to 9 in our sample. The mean is 1.96, meaning that on average, democracy is weak in Africa. In his strategic interaction model Konisky (2007) controls the political orientation of the state governors. The data are from the Polity IV project database (Marshall and Jaggers, 2002).

Population density: The population density is the number of inhabitants per km^2. Higher population density is expected to be associated with higher deforestation. Population density data are from WDI.

Regional economic community in Africa: Based on our sample, eight regional economic communities across Africa can be defined: The Arab Maghreb Union (AMU); the Common Market for Eastern and Southern Africa (COMESA); the Economic Community of Central African States (ECCAS); the Economic Community of West African States (ECOWAS); the Southern African Development Community (SADC); The West African Economic and Monetary Union (WAEMU); the Economic and Monetary Community of Central Africa (CEMAC) and the West

[9] https://eiti.org/countries Membership status in February 2020

African Monetary Zone (WAMZ). Regional economic communities capture the regional-level effort in environmental regulation. The effect of a given region compared to the others will depend on environmental the existence of regional enforcement. The WAEMU has established a regional mining code since 2003. In 2009 the ECOWAS adopted in 2009 a mining directive. For these two regions where the enforcement at the regional-level exist we expect to have less deforestation compared to the other countries. See Table 1 bellow for details of country membership.

Table 1: Regional Economic Communities in Africa

Regional Economic Community	**Offical State members**	**Member in the sample**	**Frequence**
AMU	Algeria, Libya, Mauritania, Morocco, Tunisia	Morocco, Tunisia	6%
COMESA	Angola, Burundi, Comoros, D. R. Congo, Djibouti, Egypt, Eritrea, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Sudan, Swaziland, Uganda, Zambia, Zimbabwe	Burundi, D. R. Congo, Kenya, Madagascar, Malawi, Rwanda, Uganda, Zambia, Zimbabwe	31%
ECCAS	Burundi, Cameroon, C. Afr. Rep., Chad, D.R.Congo, Equatorial Guinea, Gabon, Rep. Congo, Rwanda, S. Tomé and Princ.	Burundi, Cameroon, C. Afr. Rep., Chad, D.R.Congo, Equatorial Guinea, Gabon, Rep. Congo, Rwanda	26%
ECOWAS	Benin, Burkina Faso, Cape Verde, Côte d'Ivoire, the Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo	Benin, Côte d'Ivoire, Ghana, Guinea, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo	31%
SADC	Angola, Botswana, D.R. Congo, Lesotho, Malawi, Mauritius, Mozambique, Namibia, South Africa, Swaziland, Tanzania, Zambia, Zimbabwe	Botswana, D.R. Congo, Malawi, Mozambique, Namibia, South Africa, Eswatini, Tanzania, Zambia, Zimbabwe	29%
UEMOA	Benin, Burkina Faso, Côte d'Ivoire, Guinea Bissau Mali Niger Senegal Togo	Benin, Côte d'Ivoire, Mali Niger Senegal Togo	17%
CEMAC	Cameroon, Chad, Congo Republique, Centrale Africa Republique, Equatorial Guinea, Gabon	Cameroon, Chad, Congo Republique, Centrale Africa Republique, Equatorial Guinea, Gabon	17%
WAMZ	Cape Verde, the Gambia, Ghana, Guinea, Liberia, Nigeria, Sierra Leone	Ghana, Guinea, Liberia, Nigeria, Sierra Leone	14%

Foreign Direct Investment (FDI):[10] is the annual FDI net inflows to the country. The direction of the relationship between FDI and deforestation is theoretically ambiguous. While lax environmental policies might attract FDI and increase deforestation, foreign investors might bring environmentally friendly technology or align with the environmental standards of the home countries. See Table A1 and A2 in the Appendix for respectively the descriptive statistics and more details in the variables and data sources.

Aid per capita: is the net official development assistance per capita. We use this variable only as a control in the computation of *de facto* policy indicator.

Forest rents: "Forest rents are roundwood harvest times the product of average prices and a region-specific rental rate" (WDI, 2019). This variable account for logging since the data on logging covering our sample is unavailable. Higher forest rents are expected to induce deforestation.

Control of corruption: "Control of corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests" (WGI,2019). Weaker control of corruption leads to environmental degradation.

4 Channeling deforestation, climate shocks and mining

This section presents the econometric specification and the results of our deforestation model.

4.1 Econometric specification

We consider a spatial panel-data error model:

$$F_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \mathbf{z}'_{i(r)}\boldsymbol{\theta} + a_i + u_{it} \tag{1}$$

$$a_i = \phi \sum_{j=1}^{N} \omega_{ij} a_j + \eta_i$$

[10] We would have preferred using the FDI of the mining sector, but unfortunately these data are not available. However, aggregated FDI should not bias the results.

$$u_{it} = \lambda \sum_{j=1}^{N} m_{ijt} u_{jt} + v_{it}, \quad i = 1, \cdots, N; \; t = 1, \cdots, T; \; r = 1, \cdots, R; (j \neq i) \in R$$

where F_{it} is a measure of deforestation by type of canopy cover in country i at time t, a_i are country fixed effects; m_{ijt} is the time variant weight assigned to country j by country i, $(j \neq i)$; ω_{ij} are time invariant weight assigned to country j by country i, $(j \neq i)$; $\mathbf{x}$ is a vector of time variant controls including among others temperature and precipitation shocks,[11] mining rents, countries' environmental commitment, GDP per capita and its square; $\mathbf{z}$ denotes the vector of time invariant regional dummies, $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are vector of parameters of interest to be estimated, ϕ and λ are spatial parameters to be estimated, u_{it} and v_{it} represent idiosyncratic shocks uncorrelated across countries and over time.

Equation 1 is a generalization of the spatial error model, in which the panel effects, represented by the vector $\mathbf{a} = (a_1, \cdots, a_i, \cdots, a_n)'$, are spatially correlated. The vectors $\mathbf{a}$ and $\mathbf{v} = (v_{i1}, \cdots, v_{it}, \ldots, v_{nT})'$ are assumed to be independently normally distributed errors, so the model is necessarily an random effect specification with $\mathbf{a} = (I - \phi W)^{-1}\eta$ with $W \ni \omega_{ij}$ and $\mathbf{u} = (I - \lambda M)^{-1}\mathbf{v}$, with $M \ni m_{ijt}$. In this setting, two spatial matrices were used: the inverse distance W which is a geographic distance, and the population matrix M which account for the size of the country.

Algebraically, an element w_{ij} of W, the geographic distance weighting matrix, takes the following form:

$$\omega_{ij} = \begin{cases} \frac{1/d_{ij}}{\sum_j 1/d_{ij}} & \text{if} \quad j \neq i \\ 0 & \text{otherwise} \end{cases}$$

with d_{ij} being the Euclidean distance between the capitals of countries i and j. The components m_{ijt} of the population matrix M are computed as:

$$m_{ijt} = \begin{cases} \frac{(|POP_{it} - POP_{jt}|)^{-1}}{\sum_j (|POP_{it} - POP_{jt}|)^{-1}} & \text{if} \quad j \neq i \\ 0 & \text{otherwise} \end{cases}$$

where POP denotes the population. The elements of M are based on the absolute difference in population between countries i and j. We take the inverse of the absolute difference so that the weighting matrix attributes a higher weight to countries that have a smaller absolute difference in population.

This specification emphasizes spatial interactions to which environmental quality indicators are subject, in particular deforestation. Brown (2000) stressed the importance of spatial dimension (spatial heterogeneity and externality) in the management of renewable resources. In the case of forest resource management, taking into account heterogeneities of this type such as spatial interdependence, irreversibility, different practices concerning the use of the forest surface and uncertainty may lead to optimal management of the forest surface (Albers, 1996).

While within countries, we may expect deforestation to be spatially dependent, it is hard to defend a spatial correlation across borders. Countries are unlikely to follow each other in deforestation behavior (activities). However, natural drivers of deforestation including unobserved climatic characteristics that influence deforestation may exhibit spatial dependence. For these reasons, we specify a generalized spatial panel random effects (GSPRE) model for the determinants of deforestation (Equations 1). This specification is estimated using the Quasi-Maximum Likelihood Estimator (QMLE). The likelihood function of Equation 1 is provided in Appendix A.3 (Equation E1).

[11] While climate shocks may raise endogeneity concern, due to reverse causality between deforestation and climate shocks, we presume that this feedback effect takes time to occur.

4.2 Results

4.2.1 Deforestation, climate shocks and mining rent

Tables 2a, 2b and 2c report the results of the regression of the determinants of deforestation for tree cover loss at canopy cover greater than 20%, 30% and 50% respectively. From column (1) to (8) in each table, we control for different regional economic communities across Africa (AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ). Because some countries are member of more than one regional economic zone we estimate separate equations to avoid overlapping.

The spatial autocorrelation coefficients in the error terms (ϕ for the spatial fixed effect and λ for the idiosyncratic spatial effect) are in most estimates (depending on regional clusters) positive and significant except for canopy cover$>$ 50% for which lambda is not significant (Table 2c). This result globally confirms the existence of spatial heterogeneity. Countries behave similarly when they share similar unobserved characteristics or unobservable institutional environment. Even though we control for some of these institutional environments by including regional clusters, there are still some factors (fixed and variable) such as the climatic zones that are captured in the spatial autocorrelations of the error terms.

Our variables of interest are mineral resource rents, temperature shocks and environmental policies.

4.2.2 Mineral resources rent

Mining rents increase deforestation in Africa as we presumed. The coefficient vary from 0.0421 (Table 2c column 2) to 0.0573 (Table 2a column 4) and are statistically significant at 1% level. On average, an increase in mining rent by 1% of GDP increases deforestation by 50 km^2. The size of the effect decreases with the canopy cover. We observe that the effect of mining on deforestation is more marked at the canopy cover greater than 20% than it is at canopy cover greater than 30% and 50%. This is expected because the higher the canopy cover the dense the forest, and forest protection policies might come at play for dense forests. Mining activities are space consuming and contribute directly to deforestation (Combes et al., 2015). Moreover, mining can also induce deforestation in the surrounding area (Sonter et al., 2017). The indirect effects may also include mining-induced infrastructures, urbanization and toxic releases (Bridge, 2004). These results are consistent with previous findings that mining activities are among the leading causes of deforestation (Combes et al., 2015).

4.2.3 Climate shocks

To control for climate variability, we use yearly average temperature shocks which is the absolute value of the difference between the yearly temperature (precipitation) and its mean. Temperature and precipitation shocks have a positive impact on deforestation as expected but nonsignificant statistically. Combes et al. (2018) find similar results in several specifications. A plausible explanation is that deforestation may be less sensitive to the yearly variation in climate conditions.

4.2.4 Environmental policy

The effect of environmental policies is statistically nonsignificant whether it is *de jure* (country international environmental treaties participation) or *de facto* ("domestic effort to climate mitigation"). However, the coefficients associated to EITI are positive and significant implying that deforestation is higher in EITI member States than non-EITI member States. This result might be a signal than mining resources increase deforestation since the members are those endowed with natural resources. In these countries both *de facto* and *de jure* environmental policies are effective in reducing deforestation in terms of the size of the coefficients. The coefficients of the interaction term between environmental policy and EITI membership are negative and statistically significant at 1% level. Moreover, within EITI members, *de facto* environmental policy is more effective than *de jure* environmental policy. The coefficients associated with the interaction between EITI and *de jure* environmental policy vary from -0.0405 (Table 2a column 2) to -0.0645 (Table 2b column 1). For *de facto* policy, the coefficients of the interactive term are ten times bigger. They are between -0.609 (Table 2a column 5) -0.443 (Table 2c column 1). These results support that, what matters the most is not that countries engage in international treaties but their actual efforts. Being members of EITI brings more transparency to the extractive sector and contributes to effective government policy in the mining sector regulation. EITI invest the past decade on empowering civil society in its State members. These interventions may contribute to enforcing environmental policy in these countries than in the others. Moreover, existing literature shows that EITI membership improves governance (Villar and Papyrakis, 2017) and revenue mobilization (Mawejje, 2019).

Table 2a: Determinants of deforestation

	Dependent variable: Tree cover loss >20% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0565*****	**0.0543*****	**0.0561*****	**0.0573*****	**0.0551*****	**0.0560*****	**0.0564*****	**0.0555*****
	(0.00946)	(0.00946)	(0.00944)	(0.00940)	(0.00941)	(0.00935)	(0.00946)	(0.00942)
Temperature shocks	0.00523	0.00525	0.00600	0.00532	0.00498	0.00603	0.00515	0.00563
	(0.0169)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0169)	(0.0168)
Precipitation shocks	0.000625	0.000601	0.000620	0.000612	0.000620	0.000603	0.000627	0.000615
	(0.000440)	(0.000440)	(0.000440)	(0.000439)	(0.000440)	(0.000439)	(0.000440)	(0.000440)
de jure environmental policy	0.00213	-0.00263	0.00120	-0.000523	0.00146	-0.00458	0.00109	-0.00258
	(0.0121)	(0.0115)	(0.0117)	(0.0104)	(0.0116)	(0.0105)	(0.0117)	(0.0118)
De faco environmental policy	0.00644	0.0221	0.0112	0.0319	0.0482	0.0368	0.00772	0.0270
	(0.0681)	(0.0643)	(0.0661)	(0.0609)	(0.0668)	(0.0620)	(0.0680)	(0.0663)
EITI membership	**6.038*****	**5.604*****	**5.778*****	**6.303*****	**5.770*****	**5.786*****	**5.963*****	**5.646*****
	(1.286)	**(1.314)**	**(1.302)**	**(1.244)**	**(1.282)**	**(1.222)**	**(1.280)**	**(1.344)**
***de jure* environmental policy x EITI**	**-0.0462*****	**-0.0405*****	**-0.0449*****	**-0.0437*****	**-0.0444*****	**-0.0436*****	**-0.0448*****	**-0.0424*****
	(0.0142)	**(0.0140)**	**(0.0138)**	**(0.0129)**	**(0.0137)**	**(0.0131)**	**(0.0140)**	**(0.0143)**
***de facto* environmental policy x EITI**	**-0.572*****	**-0.579*****	**-0.574*****	**-0.597*****	**-0.608*****	**-0.597*****	**-0.571*****	**-0.588*****
	(0.0851)	(0.0817)	(0.0834)	(0.0793)	(0.0834)	(0.0802)	(0.0852)	(0.0834)
GDP per capita (log)	2.518*	2.573*	2.780**	2.356*	2.509*	2.594*	2.521*	2.639*
	(1.337)	(1.359)	(1.350)	(1.351)	(1.353)	(1.343)	(1.335)	(1.352)
GDP per capita square (log)	-0.172*	-0.164*	-0.189**	-0.164*	-0.167*	-0.176**	-0.172*	-0.175*
	(0.0891)	(0.0905)	(0.0900)	(0.0889)	(0.0899)	(0.0888)	(0.0891)	(0.0899)
FDI	-0.00620*	-0.00600*	-0.00645*	-0.00625*	-0.00627*	-0.00646*	-0.00616*	-0.00621*
	(0.00344)	(0.00344)	(0.00344)	(0.00342)	(0.00343)	(0.00342)	(0.00344)	(0.00343)
ϕ	2.388***	-0.629	0.208	-1.565*	-0.0607	-1.329	2.398***	0.159
	(0.335)	(1.089)	(0.550)	(0.891)	(0.690)	(1.028)	(0.339)	(0.733)
λ	0.397***	0.387***	0.398***	0.408***	0.398***	0.412***	0.399***	0.399***
	(0.0697)	(0.0700)	(0.0688)	(0.0670)	(0.0686)	(0.0673)	(0.0694)	(0.0690)
σ_μ	1.519***	1.439***	1.411***	1.201***	1.400***	1.253***	1.516***	1.476***
	(0.218)	(0.196)	(0.197)	(0.180)	(0.192)	(0.182)	(0.217)	(0.202)
σ_e	0.648***	0.648***	0.648***	0.648***	0.648***	0.647***	0.648***	0.647***
	(0.0198)	(0.0197)	(0.0198)	(0.0198)	(0.0198)	(0.0197)	(0.0198)	(0.0197)
AMU	-0.0495							
	(1.321)							
COMESA		1.047						
		(0.698)						
ECCAS			0.950					
			(0.608)					
ECOWAS				-1.610***				
				(0.370)				
SADC					1.082**			
					(0.550)			
UEMOA						-2.083***		
						(0.579)		
CEMAC							-0.396	
							(0.882)	
WAMZ								-0.231
								(0.981)
Constant	-9.175*	-9.871*	-10.15**	-7.871	-9.486*	-8.566*	-9.066*	-9.344*
	(5.095)	(5.162)	(5.146)	(5.109)	(5.124)	(5.078)	(5.073)	(5.131)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-674.4	-672.3	-672.0	-668.4	-671.5	-669.1	-674.3	-673.1

Notes: Standard errors in parentheses. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$ We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

Table 2b: Determinants of deforestation

	Dependent variable: Tree cover loss >30% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0513*** **	**0.0495*** **	**0.0515*** **	**0.0516*** **	**0.0499*** **	**0.0509*** **	**0.0513*** **	**0.0514*** **
	(0.00972)	(0.00975)	(0.00973)	(0.00966)	(0.00965)	(0.00962)	(0.00972)	(0.00971)
Temperature shocks	0.00534	0.00584	0.00554	0.00618	0.00514	0.00674	0.00546	0.00554
	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)
Precipitation shocks	0.000708	0.000685	0.000713	0.000689	0.000696	0.000680	0.000707	0.000706
	(0.000454)	(0.000454)	(0.000454)	(0.000453)	(0.000453)	(0.000453)	(0.000454)	(0.000454)
de jure environmental policy	0.0216	0.00726	0.0222*	0.00774	0.0136	0.00400	0.0180	0.0177
	(0.0134)	(0.0140)	(0.0127)	(0.0121)	(0.0129)	(0.0122)	(0.0128)	(0.0126)
De faco environmental policy	-0.0225	-0.0172	-0.0275	-0.00960	0.0205	-0.00518	-0.0184	-0.0202
	(0.0704)	(0.0690)	(0.0703)	(0.0656)	(0.0689)	(0.0655)	(0.0704)	(0.0704)
EITI membership	**7.253*** **	**5.939*** **	**7.157*** **	**6.519*** **	**6.200*** **	**5.974*** **	**7.102*** **	**7.187*** **
	(1.419)	**(1.617)**	**(1.384)**	**(1.424)**	**(1.443)**	**(1.437)**	**(1.423)**	**(1.419)**
***de jure* environmental policy x EITI**	**-0.0645*** **	**-0.0506*** **	**-0.0630*** **	**-0.0522*** **	**-0.0551*** **	**-0.0519*** **	**-0.0612*** **	**-0.0625*** **
	(0.0157)	**(0.0167)**	**(0.0149)**	**(0.0149)**	**(0.0152)**	**(0.0152)**	**(0.0154)**	**(0.0153)**
***de facto* environmental policy x EITI**	**-0.565*** **	**-0.559*** **	**-0.562*** **	**-0.576*** **	**-0.597*** **	**-0.576*** **	**-0.570*** **	**-0.568*** **
	(0.0864)	(0.0871)	(0.0861)	(0.0830)	(0.0847)	(0.0833)	(0.0864)	(0.0865)
GDP per capita (log)	2.490*	2.700*	2.529*	2.640*	2.520*	2.816**	2.481*	2.468*
	(1.413)	(1.420)	(1.410)	(1.410)	(1.418)	(1.411)	(1.414)	(1.412)
GDP per capita square (log)	-0.172*	-0.176*	-0.178*	-0.181*	-0.169*	-0.189**	-0.171*	-0.170*
	(0.0942)	(0.0946)	(0.0940)	(0.0936)	(0.0944)	(0.0938)	(0.0942)	(0.0942)
FDI	-0.00667*	-0.00635*	-0.00681*	-0.00657*	-0.00656*	-0.00666*	-0.00661*	-0.00659*
	(0.00358)	(0.00357)	(0.00358)	(0.00355)	(0.00356)	(0.00355)	(0.00357)	(0.00357)
ϕ	1.437***	-0.492	1.472***	-1.286	-0.498	-1.367	1.444***	1.477***
	(0.294)	(1.445)	(0.300)	(0.899)	(0.868)	(1.100)	(0.294)	(0.290)
λ	0.280***	0.278***	0.280***	0.292***	0.285***	0.295***	0.283***	0.284***
	(0.0763)	(0.0773)	(0.0762)	(0.0759)	(0.0762)	(0.0761)	(0.0764)	(0.0764)
σ_μ	1.709***	1.769***	1.664***	1.567***	1.633***	1.597***	1.745***	1.729***
	(0.234)	(0.233)	(0.228)	(0.214)	(0.214)	(0.222)	(0.235)	(0.234)
σ_e	0.668***	0.667***	0.668***	0.666***	0.667***	0.666***	0.667***	0.668***
	(0.0203)	(0.0202)	(0.0203)	(0.0202)	(0.0202)	(0.0201)	(0.0202)	(0.0203)
AMU	-1.269							
	(1.458)							
COMESA		0.910						
		(1.064)						
ECCAS			1.462					
			(0.914)					
ECOWAS				-1.706***				
				(0.483)				
SADC					1.591***			
					(0.573)			
UEMOA						-2.239***		
						(0.728)		
CEMAC							0.165	
							(0.977)	
WAMZ								0.746
								(1.004)
Constant	-10.39*	-10.62**	-10.91**	-9.322*	-10.32*	-9.786*	-10.15*	-10.20*
	(5.342)	(5.360)	(5.354)	(5.307)	(5.322)	(5.287)	(5.341)	(5.335)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-691.7	-691.2	-690.8	-688.1	-688.6	-688.7	-692.1	-691.8

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

4.2.5 Regional clusters

African countries are engaged in regional economic communities in the last three decades. In these organizations, some policy harmonization has been put into place including the mining sector regulation. We capture these supranational regulations controlling for these regional dummies. Tables 2a, 2b, and 2c report similar pattern with regard to our regional dummies. The coefficients of AMU are negative but not statistically significant. Also, those associated with COMESA are positive and not significant. Similarly, the coefficient of ECCAS is positive but significant at 10% level only in Table 2c (canopy cover >50%). Being members of these three regions does not affect significantly deforestation as compared to other regions. The coefficients associated with the SADC region is positive and significant. The coefficients vary from 1.1 (Table 2a) to 1.6 (Table 2b). This means that deforestation is higher in SADC member states compared to others. Indeed, since 1990, Southern Africa experienced the highest rate of forest cover loss in Africa.[12]

[12] https://www.sadc.int/themes/meteorology-climate/climate-change-mitigation/

Table 2c: Determinants of deforestation

	Dependent variable: Tree cover loss >50% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0439*** **	**0.0421*** **	**0.0442*** **	**0.0444*** **	**0.0424*** **	**0.0433*** **	**0.0440*** **	**0.0429*** **
	(0.00892)	(0.00894)	(0.00892)	(0.00880)	(0.00886)	(0.00882)	(0.00892)	(0.00888)
Temperature shocks	0.00226	0.00273	0.00241	0.00346	0.00217	0.00354	0.00243	0.00286
	(0.0156)	(0.0155)	(0.0156)	(0.0155)	(0.0155)	(0.0156)	(0.0156)	(0.0156)
Precipitation shocks	0.000683	0.000658	0.000685	0.000637	0.000671	0.000651	0.000680	0.000667
	(0.000423)	(0.000422)	(0.000423)	(0.000422)	(0.000422)	(0.000422)	(0.000422)	(0.000422)
de jure environmental policy	0.0178	0.00457	0.0187*	0.00105	0.0104	0.00243	0.0148	0.00657
	(0.0119)	(0.0124)	(0.0113)	(0.00985)	(0.0116)	(0.0108)	(0.0115)	(0.0121)
De faco environmental policy	-0.0695	-0.0646	-0.0764	-0.0568	-0.0338	-0.0499	-0.0661	-0.0562
	(0.0645)	(0.0628)	(0.0644)	(0.0545)	(0.0633)	(0.0594)	(0.0646)	(0.0633)
EITI membership	**6.187*** **	**5.038*** **	**6.086*** **	**5.378*** **	**5.324*** **	**5.141*** **	**6.070*** **	**5.244*** **
	(1.273)	**(1.430)**	**(1.233)**	**(1.286)**	**(1.301)**	**(1.286)**	**(1.279)**	**(1.400)**
***de jure* environmental policy x EITI**	**-0.0574*** **	**-0.0450*** **	**-0.0561*** **	**-0.0433*** **	**-0.0493*** **	**-0.0467*** **	**-0.0548*** **	**-0.0474*** **
	(0.0142)	**(0.0151)**	**(0.0134)**	**(0.0131)**	**(0.0139)**	**(0.0138)**	**(0.0140)**	**(0.0148)**
***de facto* environmental policy x EITI**	**-0.453*** **	**-0.448*** **	**-0.448*** **	**-0.460*** **	**-0.482*** **	**-0.470*** **	**-0.458*** **	**-0.461*** **
	(0.0792)	(0.0789)	(0.0787)	(0.0708)	(0.0775)	(0.0750)	(0.0792)	(0.0781)
GDP per capita (log)	2.040	2.181	2.061	2.280*	2.060	2.305*	2.026	2.215*
	(1.318)	(1.327)	(1.314)	(1.301)	(1.325)	(1.316)	(1.319)	(1.324)
GDP per capita square (log)	-0.156*	-0.155*	-0.162*	-0.166*	-0.151*	-0.166*	-0.155*	-0.161*
	(0.0878)	(0.0885)	(0.0875)	(0.0856)	(0.0882)	(0.0873)	(0.0879)	(0.0881)
FDI	-0.00652*	-0.00612*	-0.00671**	-0.00624*	-0.00635*	-0.00637*	-0.00646*	-0.00628*
	(0.00338)	(0.00338)	(0.00338)	(0.00335)	(0.00337)	(0.00336)	(0.00338)	(0.00338)
ϕ	1.439***	-0.495	1.461***	-3.800***	-0.326	-1.408	1.442***	0.0269
	(0.296)	(1.320)	(0.302)	(0.176)	(0.821)	(1.092)	(0.296)	(0.868)
λ	0.0732	0.0692	0.0737	0.0796	0.0705	0.0789	0.0743	0.0737
	(0.0869)	(0.0875)	(0.0869)	(0.0865)	(0.0872)	(0.0870)	(0.0870)	(0.0873)
σ_μ	1.497***	1.542***	1.438***	1.220***	1.460***	1.396***	1.527***	1.564***
	(0.205)	(0.203)	(0.198)	(0.160)	(0.191)	(0.193)	(0.206)	(0.204)
σ_e	0.627***	0.625***	0.627***	0.625***	0.625***	0.625***	0.626***	0.625***
	(0.0189)	(0.0188)	(0.0189)	(0.0188)	(0.0188)	(0.0188)	(0.0189)	(0.0188)
AMU	-1.136							
	(1.276)							
COMESA		0.763						
		(0.822)						
ECCAS			1.440*					
			(0.786)					
ECOWAS				-1.497***				
				(0.329)				
SADC					1.244**			
					(0.534)			
UEMOA						-1.927***		
						(0.624)		
CEMAC							0.249	
							(0.857)	
WAMZ								-0.379
								(1.034)
Constant	-7.680	-7.789	-8.133	-7.112	-7.662	-7.314	-7.486	-7.552
	(4.956)	(4.968)	(4.960)	(4.878)	(4.953)	(4.916)	(4.959)	(4.966)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-647.3	-646.6	-646.1	-648.7	-644.8	-644.1	-647.6	-646.9

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

The effect of ECOWAS membership on deforestation is negative and significant. One might think that this negative and significant effect stems from common environmental policies. ECOWAS set a mining directive since 2009 as a guideline for its member States. To the best of our knowledge, there is no similar coordination in the mining sector in Africa. This might induce countries to raise their environmental standards specifically in the mining sector. However, a closer look shows that the negative and significant coefficient is driven by the WEAMU members. When we divide ECOWAS into WAEMU and Non-WAEMU members (WAMZ), we observe that the WAEMU membership has a negative and significant effect on deforestation while the WAMZ membership is not significant. In fact, since 2003 the WEAMU member States establish a community mining code. Moreover, the WAEMU mining code, in its articles 11 and 18, explicitly enforces environmental regulation including environmental impact evaluation, encourages "set up a monitoring plan as well as a rehabilitation program for the environment" (Art.18).[13] Policy harmonization is advanced in the WAEMU compared to the

[13] http://www.droit-afrique.com/upload/doc/WAEMU/WAEMU-Code-minier-communautaire-2003.pdf

other regions.

Based on these results, we suspect strategic interactions between States in Africa regarding their environmental policy. Such strategic interactions may lead to a "Prisoner's Dilemma" and hence an environmental race to the bottom. However, with regional coordination, it may also lead to a race to the top where countries align their environmental policy to the best standards. These interactions are likely to occur with natural resources-endowed countries with but little investment capacity. Therefore, environmental policies may be key interest of competition between countries to attract investments.

Overall, we find evidence that mining increases deforestation in Africa and environmental policy matters at least in EITI member countries. Moreover, the results support that *de facto* environmental policy is more effective than *de jure* environmental policy when countries are EITI members. The results are robust regarding different canopy covers.

5 Environmental strategic behavior and asymmetric effects

5.1 Econometric specification

The race to the bottom theory implies that, confronted with economic competition, countries are inclined to relax their environmental standards to attract mobile capital. Coupled with strategic behavior such as the 'Prisoner's Dilemma' governments may try to gain competitive advantage over other countries. If all countries behave similarly, the equilibrium strategy will be the continued relaxing of environmental commitment. The race to the bottom argues that the equilibrium outcome is suboptimal, since countries would be better off collectively setting a high level of commitments rather than relaxing them (Konisky, 2007). To assess the presence of competition among countries in environmental regulatory behavior, we consider a spatial-temporal dynamic regression where a country's behavior as a function of other countries' behaviors. The model takes the form:

$$\begin{aligned} E_{it} &= \tau E_{it-1} + \delta \sum_{j=1}^{N} \omega_{ij} E_{jt} + \mathbf{x}_{1it}' \boldsymbol{\beta} + \boldsymbol{\theta} \sum_{j=1}^{N} \omega_{ij} \mathbf{x}_{2jt}' \qquad (2) \\ &\quad + a_i + \gamma_t + u_{it}, \qquad i = 1, \cdots, N;\ t = 1, \cdots, T;\ j \neq i \end{aligned}$$

where E_{it} is a measure of environmental commitment (*de jure* vs. *de facto* environmental policy), u_{it} is a normally distributed error term, ω_{ij} are the weight assigned to country j both for the autoregressive component E_{it-1} and for the spatially lagged control variable $\mathbf{x}_2$, a_i is the individual fixed effect, and γ_t denotes the time effect.

The variable of primary interest in this model is the strategic interaction or spatial lag term $\sum_{j=1}^{N} \omega_{ij} E_{jt}$. This term represents a weighted average of environmental commitment in neighboring states. Detecting the presence of a strategic interaction requires testing for the significance of δ. A statistically significant and positive coefficient suggests that one state's environmental commitment effort is a function of other states' environmental commitment efforts. A statistically significant and negative spatial coefficient would imply that there is strategic substitution effect among countries. The null hypothesis is that there is no effect, which implies a lack of environmental competition, thereby undermining both the race to the bottom and the race to the top arguments.

While estimating Equation (2) establishes whether there is strategic interaction among countries, the race to the bottom (vs. to the top) suggests a specific asymmetric dynamics among countries. More specifically, we should observe a state responding to its competitors only in situations where its own environmental commitment might put it at a disadvantage for attracting economic investment relative to these competitors. Following Fredriksson and Millimet (2002), such asymmetric effects model is given by:

$$E_{it} = \tau E_{it-1} + \delta_0 D_{it} \sum_{j=1}^{N} \omega_{ij} E_{jt} + \delta_1 (1 - D_{it}) \sum_{j=1}^{N} \omega_{ij} E_{jt} \quad (3)$$
$$+ \mathbf{x}'_{1it}\boldsymbol{\beta} + \boldsymbol{\theta} \sum_{j=1}^{N} \omega_{ij} \mathbf{x}'_{2jt} + a_i + \gamma_t + u_{it}, \qquad i = 1, \cdots, N, \ t = 1, \cdots, T \ j \neq i$$

where:

$$D_{it} = \begin{cases} 1 & \text{if} \quad E_{it} > \sum_{j=1}^{N} \omega_{ij} E_{jt}, \quad j \neq i \\ 0 & \text{otherwise} \end{cases}$$

Strategic interaction consistent with the race to the bottom assumes country responsiveness to competitor countries in years in which one's own environmental commitment effort is greater than one's competitors, but not in years in which it is lower. This means that we expect a positive and significant coefficient δ_0, but not δ_1 or when the two parameters are positive and significant, $\delta_0 > \delta_1$. As a result, Equation (3) assumes that strategic interaction occurs only when the average stringency of competitors' environmental commitment is lower than the state's own level. The likelihood function of Equations 2 and 3 is provided in Appendix A.3 (Equation E2).

5.1.1 Direct and indirect effects

The space-time dynamic structure of the model in Equations (2) and (3) allows us to compute direct and indirect effects of the explanatory variables on the dependent variable in the long and short-run. As the model reflects the spatial dependence between countries, a change in an explanatory variable in a given country will affect the country itself (direct effects) and potentially its neighbors (indirect effects) (LeSage and Pace, 2009). Table 3 below provides the computation formula of these effects in a dynamic spatial Durbin model (DSDM) as in Equations (2) and (3).

Table 3: Direct and indirect effects

	Direct effect	Indirect effect
Short-run	$[(I - \delta W)^{-1} \times (\beta + W\theta)]^{\bar{d}}$	$[(I - \delta W)^{-1} \times (\beta + W\theta)]^{\overline{rsum}}$
Long-run	$[((1-\tau)I - \delta W)^{-1} \times (\beta + W\theta)]^{\bar{d}}$	$[((1-\tau)I - \delta W)^{-1} \times (\beta + W\theta)]^{\overline{rsum}}$

Source: Apdated from Elhorst (2014). Note: $\bar{d}$ denotes the operator that calculates the mean diagonal elements of a matrix, $\overline{rsum}$ the operator that calculates the mean row and sum of the non-diagonal elements.

One of the advantages of the DSDM is that it allows estimating the long and short-run effects of our variable of interest on environmental policy response. The short-run effects are the partial derivative of the dependent variable with respect to an explanatory variable at a particular time period; the dynamic aspect of the model (coefficient τ in Equation 2) being ignored. The long-run effects are the partial derivatives of the dependent variable with respect to an explanatory variable at a particular time period while setting $E_{it-1} = E_{it} = E^*$ and $WE_{it} = WE^*$. Long-run effects are similar to a steady-state where environmental policies remain constant over time in all countries.

5.1.2 Estimation strategy and specification tests

The estimation strategy of the dynamic model fits into two categories: instrumental variables or generalized method of moments (IV/GMM) and bias-corrected maximum likelihood (ML) or quasi-maximum likelihood (QML) estimator (Elhorst, 2014; Belotti et al., 2017). The QML estimator and the IV/GMM have the advantage of not relying on the normality of the error term. However, the QML estimator outperforms the IV/GMM because the Jacobian term in the log-likelihood function of ML estimators restricts the spatial coefficient δ to the interval $[1/r_{min}, 1]$ where r_{min} denotes the "most negative purely real characteristic root" of the row-normalized spatial matrix. (Elhorst, 2014). Hence we use the QML estimator in this study. The QML estimator for dynamic spatial models is developed by (Yu et al., 2008; Lee and Yu, 2010; Elhorst, 2014). It is a consistent estimator in the presence of spatially lagged-dependent variables and robust to distributional misspecification (Lee, 2004).[14] Indeed, the temporally and spatially lagged-dependent variables in Equation (2) and (3) raise endogeneity concerns sourced essentially from simultaneity between E_{it} and $\sum_{j=1}^{N} \omega_{ij} E_{jt}$ and omitted variables potentially correlated with E_{it-1}.

Following LeSage and Pace (2009), we test the suitability of the dynamic spatial Durbin model (DSDM) to estimate Equations (2) and (3) against the dynamic spatially autoregressive model (DSAR) and the spatial error model (SEM). The DSDM specification is reduced to a DSAR model if the coefficients of the spatially lagged explanatory variable are not statistically different from zero which amounts to testing the joint nullity of the spatially lagged explanatory variables ($\boldsymbol{\theta} = 0$ in Equation 2). For *de jure* environmental policy, $\chi^2(3) = 79.98$ is significant at 1% level (Prob>χ^2=0.000). For *de facto* environmental policy, $\chi^2(3) = 70.00$ is also significant at 1% level (Prob>χ^2=0.000). Hence we reject the null hypothesis of $\boldsymbol{\theta} = 0$; thus the DSAR specification is rejected.

The DEM is also a special case of the DSDM if $\delta\boldsymbol{\beta} + \boldsymbol{\theta} = 0$ (Equation 2). For *de jure* environmental policy, $\chi^2(3) = 98.29$ is significant at 1% level (Prob>χ^2=0.000). For *de facto* environmental policy, $\chi^2(3) = 75.76$ is also significant at 1% level (Prob>χ^2=0.000). Here again, we reject the null hypothesis of $\delta\boldsymbol{\beta} + \boldsymbol{\theta} = 0$. Hence both the DSAR and the SEM specifications are rejected and DSDM is suitable for our analysis. The DSDM is a fixed effects model.

5.2 Results

5.2.1 Strategic interaction and dynamics of environmental policy

Table 4 presents the results of the strategic interaction model (Equation 2) for both *de jure* and *de facto* environmental policy.

The coefficients of the spatial lagged-variable are positive ($\delta > 0$) and statistically significant at 1% level. This supports a presence of spatial interaction among African countries: stringent (lax) environmental policy in a given country leads to environmental policy enforcement (relaxation) in its neighbors. This result is consistent with other findings in the United States (Fredriksson and Millimet, 2002; Konisky, 2007) and in the European Union (Holzinger and Sommerer, 2011). Using environmental abatement costs, Fredriksson and Millimet (2002) find that the US States are engaged in strategic environmental policymaking interactions. Similarly, in a sample of 48 US States, Konisky (2007) confirms the strategic interaction between States in their environmental policy. We go beyond the time-static model adopted by these authors to consider time dynamics as well in our strategic interaction model. Our results show that the time dynamics also matters in environmental policy. The coefficient of E_{it-1} is positive and strongly significant in both *de jure* and *de facto*.

[14]See the likelihood function Equation E2 in Appendix.

5.2.2 Direct, indirect and total effects

Thanks to the spatial and temporal dynamics structure of the model, we can break down into direct and indirect effects, the impact of the explanatory variables on the environmental policy responses. Indeed, in a given country, variation in any explanatory variables affects the country itself (direct effects) and eventually its neighbors (indirect effects or spillover effects) (LeSage and Pace, 2009; Elhorst, 2014).

We presume that mineral resource rents, GDP growth and FDI have spillover effects on environmental policy. This is confirmed by our specification tests which show that the spatial lags of these variables are statistically significant. Mineral resource rents affect both environmental policy directly and indirectly. The direct effect on *de jure* environmental policy is negative and significant in the short-run while insignificant in the long-run. Also, the indirect effect is negative in the short-run while it is positive in the long-run. In the short-run, an increase in country mineral resource rents decreases not only its willingness to participate in international environmental agreements but also prevents its neighbors to participate. An explanation is that mining resources might be shared across bordering countries (for instance gold in Burkina Faso, Ghana and Mali). In such a case, an increase of the rents in a given country makes its neighbors willing to attract investment and therefore more reluctant to enforce their environmental policy. In the long-run however, the direct effect of mining activities on *de jure* environment policy is statistically nonsignificant. All long-run effects operate through neighbor's environmental policies. In total, mining deteriorates countries willing to participate in international environmental treaties and results in weak *de facto* commitment in the long-run.

GDP growth has spillovers effect on both *de facto* and *de jure* environmental policies. The direct effect of GDP growth on *de jure* environmental enforcement is positive and significant in the short-run but not in the long-run. The indirect effect is positive and significant in the short-run while negative in the long-run. The trade-off between economic growth and environmental protection is not clearly established when it comes to international environmental treaties adhesion. However, this trade-off is clear with *de facto* environmental policy. Countries may be mimicking each other *de jure* environmental policy while still involved in lax environmental commitment. The total effect of GDP growth on *de jure* environmental policy is positive and significant in the short-run and negative in the long-run. For *de facto* policy, it is negative in the short-run and positive in the long-run. Economic growth enforces effective policy in the long-run while it leads to weak enforcement in the short-run.

The spillover effects of FDI on *de jure* environmental policy is not significant. However, on *de facto* environmental policy, the short-run direct and indirect effects are negative and significant. The total effect is negative and statistically significant in the short-run and positive in the long-run. To attract FDI, countries lower their environmental standards. Nevertheless, FDI increase environmental policy (*de facto*) enforcement.

5.2.3 Short-run and long-run effects

The effect of mining rents on *de jure* environmental policy is negative in the short-run and positive in the long-run. Countries with significant mining rents are reluctant to engage in international environmental commitments in the short-run. However, in the long-run mining rents increase *de jure* environmental policy stringency. This is coherent with the nexus between natural resource exploitation and the environment. In the long-run, as citizens' standard of living increases, they value more the quality of the environment and they demand more environmental protection which leads to an increase in international commitment. We observe the opposite when it comes to *de facto* environmental policy. Mining activities increase *de facto* environmental enforcement in the short-run while it leads to lax environmental policy in the long-run.

Table 4: Strategic interactions: Direct and indirect vs. short run and long-run effects

	Dpendent variable *de jure* environmental policy								**Dependent variable: *de facto* environmental policy**							
	Main	Wx	SR direct	SR indirect	SR total	LR direct	LR indirect	LR total	Main	Wx	SR direct	SR indirect	SR total	LR direct	LR indirect	LR total
L.*de jure* environmental policy	0.888***								0.942***							
	(0.0236)								(0.0353)							
Mineral resource rents	-0.0291***	-0.245***	-0.0345***	-0.357***	-0.391***	-0.391	1.949	1.558***	0.00586	0.101***	0.0278**	0.761**	0.789**	-0.0747***	-0.0606**	-0.135***
	(0.00869)	(0.0305)	(0.00882)	(0.0541)	(0.0577)	(3.606)	(3.626)	(0.428)	(0.00498)	(0.0129)	(0.0108)	(0.311)	(0.321)	(0.0272)	(0.0270)	(0.0180)
Temperature shocks	0.0379**		0.0397**	0.0171*	0.0568**	0.414	-0.633	-0.219**	0.00602		0.00814	0.0437	0.0518	0.0256	-0.0342	-0.00859
	(0.0183)		(0.0180)	(0.00906)	(0.0265)	(1.721)	(1.732)	(0.105)	(0.00777)		(0.00887)	(0.0532)	(0.0614)	(0.0286)	(0.0375)	(0.00939)
Precipitation shocks	0.000634		0.000632	0.000277	0.000909	0.00567	-0.00907	-0.00340	0.000438**		0.000519**	0.00271*	0.00322*	0.00158*	-0.00214**	-0.000555**
	(0.000430)		(0.000437)	(0.000207)	(0.000637)	(0.0127)	(0.0134)	(0.00246)	(0.000182)		(0.000218)	(0.00162)	(0.00181)	(0.000840)	(0.00103)	(0.000225)
GDP Growth	0.0144**	0.0660***	0.0160**	0.100***	0.116***	0.188	-0.643	-0.455***	-0.0117***	-0.0684***	-0.0281***	-0.563**	-0.591**	0.0214	0.0791***	0.101***
	(0.00674)	(0.0225)	(0.00662)	(0.0353)	(0.0372)	(1.370)	(1.383)	(0.153)	(0.00432)	(0.0114)	(0.00903)	(0.242)	(0.250)	(0.0242)	(0.0275)	(0.0148)
FDI	0.00145	-0.0134	0.00127	-0.0189	-0.0176	0.0159	0.0520	0.0680	-0.00698***	-0.0292***	-0.0143***	-0.253**	-0.267**	0.00305	0.0428***	0.0458***
	(0.00205)	(0.0138)	(0.00205)	(0.0186)	(0.0190)	(0.0925)	(0.122)	(0.0765)	(0.00223)	(0.00751)	(0.00440)	(0.116)	(0.120)	(0.0143)	(0.0146)	(0.00978)
Democracy index	-0.0631***		-0.0632***	-0.0274**	-0.0906***	-0.643	0.989	0.346***	0.0390***		0.0462***	0.246*	0.292**	0.142***	-0.191***	-0.0491***
	(0.0181)		(0.0189)	(0.0119)	(0.0300)	(2.237)	(2.242)	(0.103)	(0.00621)		(0.00941)	(0.134)	(0.142)	(0.0517)	(0.0563)	(0.00689)
Control of corruption	0.522**		0.519***	0.218**	0.737**	5.199	-8.164	-2.966**	-0.195**		-0.231***	-1.151**	-1.382**	-0.679**	0.930**	0.251**
	(0.203)		(0.201)	(0.0949)	(0.287)	(18.52)	(18.66)	(1.491)	(0.0781)		(0.0842)	(0.487)	(0.550)	(0.322)	(0.383)	(0.100)
Poulation density	-0.0150***		-0.0149***	-0.00635***	-0.0212***	-0.146	0.229	0.0831***	0.0101***		0.0120***	0.0626**	0.0746**	0.0363***	-0.0491***	-0.0128***
	(0.00264)		(0.00270)	(0.00206)	(0.00454)	(0.468)	(0.467)	(0.0210)	(0.000957)		(0.00148)	(0.0278)	(0.0290)	(0.0119)	(0.0120)	(0.00119)
Openness to trade	0.00104		0.00109	0.000456	0.00155	0.00864	-0.0149	-0.00624	-0.00380***		-0.00441***	-0.0226**	-0.0270**	-0.0131***	0.0178***	0.00476***
	(0.00163)		(0.00168)	(0.000726)	(0.00239)	(0.0318)	(0.0373)	(0.0101)	(0.000813)		(0.000931)	(0.00996)	(0.0105)	(0.00499)	(0.00526)	(0.00110)
Forest rent	0.00988		0.00988	0.00408	0.0140	0.0762	-0.133	-0.0572	0.0192***		0.0226***	0.116**	0.138**	0.0678**	-0.0921**	-0.0243***
	(0.0143)		(0.0137)	(0.00583)	(0.0194)	(0.371)	(0.408)	(0.0841)	(0.00713)		(0.00769)	(0.0540)	(0.0601)	(0.0316)	(0.0373)	(0.00848)
δ	0.300***								0.852***							
	(0.0415)								(0.0383)							
σ_e^2	0.470***								0.0960***							
	(0.0539)								(0.0120)							
# Observations	560	560	560	560	560	560	560	560	560	560	560	560	560	560	560	560
Number countries	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Log likelihood	-563.4	-563.4	-563.4	-563.4	-563.4	-563.4	-563.4	-563.4	-126.5	-126.5	-126.5					

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ SR: short-run LR: long-run.

The effect of deforestation on *de jure* environmental policy is negative in the short-run and positive in the long-run. However, the effect on *de facto* environment policy is not statistically significant both direct and indirectly.

Temperature shocks have a positive and significant effect on *de jure* environmental policy, while their effect on *de facto* environmental policy is statistically non-significant. Climate shocks increase countries willingness to engage in international environmental treaties but do not necessarily translate into effective climate mitigation policy. The non-binding nature of international agreements might explain this result. In the short-run, an increase in temperature shocks increases countries' adherence to international environmental agreements.

We also control for political institutions (democracy index), population density, economic growth and FDI. The effect of democracy depends on the measure of environmental policy and the time length. In the short-run, democracy degrades countries adherence in international environmental treaties while its effect, in the long-run, is positive and significant at 1% level. With *de facto* environmental policy, we observe the opposite. Democracy is associated with more enforcement of environmental policy in the short-run while in the long-run democratic countries tend to dedicate less effort to environmental policy enforcement. This contrasted result might be explained by an asymmetry between citizens' demand for environmental protection and government response. In the long-run, governments respond to citizens demand for environmental enforcement by participating in international treaties which is visible than effectively putting effort to mitigate the environmental impact of economic activities. Similarly, Neumayer (2002) find that democracy induces international environmental commitment but not necessarily environmental outcomes. Governments focus mostly on economic growth rather than on the environment.

Population density has a significant effect on *de jure* environmental policy. An increase in population density increases country *de jure* environmental enforcement in the long-run while its effect is negative in the short-run.

Economic growth has also a contrasted effect on *de jure* and *de facto* environmental policy. In the short-run, its effect on *de jure* environmental policy is positive while negative on *de facto* policy. In the long-run, economic growth increases countries *de facto* environmental enforcement policy while it decreases their *de jure* counterpart.

FDI affect only *de facto* environmental policy. In the sort-run, FDI decrease *de facto* environmental policy stringency while in the long-run, they increase environmental enforcement. To attract FDI countries may lower their environmental standards in the short-run. The effect of openness to trade is similar to the one of FDI. An increase in openness to trade decreases *de facto* environmental policy in the short-run and raises environmental standards.

To sum up, we find evidence of strategic interactions between African countries in their environmental policy. However, at this stage of the analysis the direction of the spatial pattern (race to the top or race to the bottom) is still undetermined. For evidence of any environmental race to the bottom or race to the top (asymmetric dynamics among states), we need to estimate Equation 3 (Fredriksson and Millimet, 2002; Konisky, 2007).

5.3 Test of race to the bottom vs. race to the top

Table 5 summarizes the results of the test of the race to the bottom (to the top) for both *de jure* and *de facto* environmental policy. We use the same control variables as in the previous strategic interaction regressions. Evidence of the race to the bottom suggests that δ_0 is positive and significant while δ_1 is not significant (Fredriksson and Millimet, 2002; Konisky, 2007). Indeed, countries react to change in the environmental policy of their neighbors only when their own environmental policy is more stringent than their competitors. Conversely, a race to the top would suggest that δ_1 is positive and significant while δ_0 is not significant. In this case, countries react to neighbors' environmental policy by strengthening their policy only when their standards are lower. An intermediary situation is where both coefficients δ_0 and δ_1 are significant. In this case, we may need to compare to size of the coefficients to determinants the dominants equilibrium. Figures D1 and D2 in Appendix display the distributions of *de jure* and *de facto* environmental policies according to $D_{it} = 0$ and $D_{it} = 1$.

Table 5: Test of the race to the bottom vs. race to the top

	δ_0	δ_1
de jure environmental policy	**0.169*****	0.394***
	(0.0403)	(0.0818)
de facto environmental policy	0.857***	**0.244*****
	(0.0412)	**(0.0786)**

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

For *de jure* environmental policy, δ_0 and δ_1 are all significant at 1% level. However, the size of δ_1 is stronger and more than two times bigger than the size of δ_0. This implies that the strategic interaction is stronger in countries where the *de jure* environmental standards of neighbors are higher. This result supports a clustered race to the top.

For *de facto* environmental policy, δ_0 δ_1 are also significant. However, in that case δ_1 is much lower than δ_0 implying that the strategic interaction is stronger in countries where the *de facto* environmental policy of the neighbors are higher. African countries are engaged in a race to the bottom in their *de facto* environmental policy.

This result explains the contrasted evolution of *de jure* and *de facto* environmental policy presented in Figure 3. While African countries continue to engage in international environmental treaties, their domestic effort to mitigate climate change is decreasing.

6 Robustness checks

In this section, we conduct a series of robustness checks for the results of our three models: the determinants of deforestation, the strategic interaction and the test of the race to the bottom vs. to the top.

6.1 Deforestation

We analyze the sensitivity of the estimates of the determinants of deforestation by adding additional control variables and by using alternative weighting matrices. In fact, spatial regression can be sensitive to the choice of weight matrices. Hence, we check the sensitivity of the estimates to the weighting matrices in the baseline estimates.

6.1.1 Additional controls

Tables F1a, F1b and F1c report the results of the estimates of the determinants of deforestation with control of corruption and forest rents as additional controls. The coefficients associated to both variables are statistically not significant. However, the results are in line with the previous findings. Mining increases deforestation while environmental policies (both *de jure* and *de facto*) are effective in EITI member countries. African regional economic communities have heterogeneous effects on deforestation as shown previously.

6.1.2 Alternative weighting matrices

We replace the inverse distance matrix with a contiguity matrix and the population weighting matrix with the GDP weighting matrix. The contiguity matrix is based on Rook contiguity. We use the same formula, as for the population matrix, to compute the GDP weighting matrix. This matrix captures the economic distance between countries. As shown in the Tables F2a, F2b and F2c, our main results still hold. Comparing the results of Tables F2a, F2b and F2c also shows that our estimates is not sensitive to the choice of the canopy cover. Mining increases deforestation. We observe an Environmental Kuznets Curve in accordance to the previous literature (Combes et al., 2015, 2018). The effects of climate shocks remain nonsignificant while the conclusion on regional economic communities still holds.

6.2 Strategic interaction test of the race to the bottom vs. race to the top

Table 6 summarizes the our robustness analysis.[15] We test the consistency of the strategic interaction and the race results by using alternative weighting matrices. For all our three alternative matrices δ remain positive and significant for both *de jure* and *de facto* environmental policies. The finding that States interact strategically in response to their neighbors' environmental policy is robust. Similarly, the results of a race to the top for *de jure* environmental policy and a race to the bottom for *de facto* environmental policy is robust to change in weighting matrix. For *de jure* environmental policy, δ_0 is not significant for all the matrices while δ_1 is positive and significant. This result supports the race to the top in *de jure* environmental policy. For *de facto* policy δ_0 is significant at 1% level and larger than δ_1: African countries exhibit a race to the bottom in their *de facto* environmental policies.

Table 6: Strategic interaction and races

	de jure environmental policy			*de facto* environmental policy		
Weighting matrices	δ	δ_0	δ_1	δ	δ_0	δ_1
Population	0.0573**	0.0526	0.141***	0.122***	0.143***	0.117*
	(0.0233)	(0.0462)	(0.0336)	(0.0330)	(0.0290)	(0.0621)
GDP per capita	0.0648**	0.0102	0.110***	0.127***	0.106**	0.0739*
	(0.0303)	(0.0552)	(0.0373)	(0.0314)	(0.0521)	(0.0437)
Mineral rent	0.0485*	0.0540	0.127***	0.155***	0.118***	0.00244
	(0.0254)	(0.0405)	(0.0361)	(0.0432)	(0.0385)	(0.0471)

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7 Policy discussion

In the context of climate change, Africa is caught between a double imperative: mobilizing domestic revenue for financing development and protecting the environment. While the mining sector constitutes an opportunity for domestic revenue mobilization (Collier, 2010), it poses at the same time enormous environmental issues (Edwards et al., 2014). Deforestation is one of the environmental costs of mining activities. Indeed, mining activities are the fourth driver of forest landscape loss after industrial agriculture, infrastructure and urban expansion (Hosonuma et al., 2012; Potapov et al., 2017). However, the role of forest in mitigating climate change cannot be overstated according to the Intergovernmental Panel on Climate Change (Netz et al., 2007).

In this paper, we investigate how mining affects deforestation and environmental policies. We use two environmental policy measures for this purpose. A *de jure* environmental policy,

[15] The full estimation tables are available upon request.

which is the adherence of countries to international environmental treaties and a *de facto* measure which is the country's commitment to climate change mitigation proposed by Combes et al. (2016). Relying on a sample of 35 African countries over the period 2001-2017, we show that mining activity increases deforestation in Africa. An increase in mineral rent by a one-point percentage of GDP leads to forest loss of about 50 km^2. However, environmental policy contributes to reducing deforestation in resource-rich countries (member countries of the EITI). We then test the implication of these results for uncoordinated environmental policies. We find that countries adopt a strategic behavior in response to the environmental policy of their neighbors (competitors). These strategic reactions lead either to a race to the bottom where all countries will tend to lower their environmental standards or a race to the top where countries imitate each other in setting stronger environmental standards. We test this hypothesis in third place. For *de jure* environmental policy, our results support a race to the top. Countries respond mostly to the adherence of their competitors to international environmental treaties by joining as well. However, for *de facto* environmental policy, the strategic behavior leads to a race to the bottom.

Three main policy recommendations emerge from these results. First, international environmental treaties must be more binding. As African countries increasingly engage in environmental treaties, their actual commitment to mitigate climate change are slackening. Imaginative solutions that involve setting up clearly defined environmental rating systems (as the notations in finance) can motivate countries to strengthen their environmental standards due to the reputation stakes involved. Such notations have the advantage, not only for putting countries in a virtuous circle of environmental competition but also; they can be used to allocate funding in the Green Climate Fund (GCF) framework for instance.

Second, the coordination of environmental policies is imperative to avoid a race to the bottom. Regional economic communities are appropriate frameworks for such coordination. This coordination can be done by following the example of WAEMU and ECOWAS. However, it must be done through concrete actions and with monitoring and evaluation mechanisms to avoid free-riding. Such coordination can also help avoiding "Prisoner's Dilemma" while designing policies to attract foreign investment. Zhang et al. (2018) support that in China, central coordination enforces local environmental policy.

Third, at the country level, mining is an environmental cost often left to the affected local populations. Countries need to be much more careful about environmental aspects and put in place mechanisms that limit the effects of mining activity on deforestation.

We draw two future research prospects from our findings. First, there is no environmental policy data in developing countries for long period. Moreover, existing institutional quality data weakly document the environmental aspects of governance in developing countries specifically in Africa. Country international environmental treaty participation and domestic effort to climate mitigation are limited environmental policy measures. Future research focusing on developing world governance indicators (WGI) type dataset on environmental governance for developing countries is an important step for sound climate mitigation policies. Second, this study focuses on a sample of countries level analysis of deforestation. However, local case studies can give detailed insights on the extent to which mining activities affect deforestation and how to mitigate it.

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A Appendix

A.1 Descriptive Statistics and description of the variables

Table A1: Descriptive statistics on the pooled data

Variables	mean	st. dev.	min	max
Three cover loss (>20% canopy cover)	0.66	1.49	0.00	14.90
Three cover loss (>30% canopy cover)	0.74	1.74	0.00	14.65
Three cover loss (>50% canopy cover)	0.57	1.54	0.00	13.77
GDP growth	4.68	5.67	-36.04	63.38
Mineral resource rents	2.28	4.56	0.00	46.62
Temperature shocks	2.07	1.77	0.00	15.90
de facto environmental policy	0.91	4.76	-10	10
de jure environmental policy	79.66	29.66	0.00	132
CO_2 emissions per capita	0.98	1.78	0.02	9.84
Democracy index	1.96	5.05	-9	9
Population density	72.64	86	2.22	485.65
GDP per capita (in thousands of USD)	2.26	3.7	0.21	20.51
Total population (millions)	22.4	29.6	0.63	191
Aid per capita	53.24	43.19	-8.27	393.50
Openness to trade	73.01	33.69	20.72	311.35
Foreign Direct Investment (inflows)	4.98	9.52	-4.85	103.34
Control of corruption	-0.67	0.56	-1.83	1.22
Forest rents	6.07	6.06	0	40.43

Notes: Number of countries (N) =35; Waves (T)=17; NT=595

Table A2: Data sources and variables description

Variables	Definition	Type[a]	Sources
Deforestation	Three cover loss at different canopy cover (greater than 20%; 30% 50%)	Cont.	Hansen et al. (2013)
Temperature shocks	Absolute value of the yearly average temperature deviation to its long-run trend	Cont.	University of East Anglia Climatic Research Unit
Mining rents	Mineral rents are the difference between the value of production for a stock of minerals at world prices and their total costs of production. Minerals included in the calculation are tin, gold, lead, zinc, iron, copper, nickel, silver, bauxite, and phosphate.	Cont.	WDI (2019)
de facto environmental policy	An index of environmental policy build upon domestic effort for climate mitigation	Int.	Authors' computation based on Combes et al. (2016)
de jure environmental policy	A count of country adhesion to international environmental treaties	Cont.	Environmental Treaties and Resource Indicators dataset
GDP growth	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars. GDP is the sum of gross value	Cont.	WDI (2019)
Population	Population is the midyear estimate of the total population based on the *de facto* definition of population, which counts all residents regardless of legal status or citizenship.	Cont	WDI (2019)
Openness to trade	Openness to trade is the sum of exports and imports of goods and services (in % of GDP)	Cont.	WDI (2019)
Aid	Aid is the Net official development assistance (ODA) per capita. It consists of disbursements of loans made on concessional terms and grants by official agencies of the members of the Development Assistance Committee (DAC), by multilateral institutions, and by non-DAC countries.	Cont.	WDI (2019)
EITI membership	A dummy variable equal 1 if the country of a member of EITI and 0 otherwise.	Dum.	EITI website
Foreign Direct Investment	Foreign direct investment are the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. It is the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors and is divided by GDP.	Cont.	WDI (2019)
Democracy index	Measures of institutional quality mainly democracy. Polity is ranged from -10 (autocratic) to +10 (full democracy)	Int.	Polity IV Project (2019)
GDP per capita	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes.	Cont.	WDI (2019)
Population density	Population density is midyear population divided by land area in square kilometers. The population is based on the *de facto* definition of population, which counts all residents.	Cont.	WDI (2019)
CO_2 emissions per capita	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.	Cont.	WDI (2019)
Control of corruption	"Control of corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests."	Cont.	WGI(2019)
Forest rents	"Forest rents are roundwood harvest times the product of average prices and a region-specific rental rate."	Cont.	WDI(2019)

[a] Cont.: continuous; Int.: integer.; Dum.: dummy

A.2 Estimation tables

Table B1: System-GMM estimation of *de facto* environmental policy

Dependent variable: Log of CO_2 emissions per capita			
	(1)	(2)	(3)
L.CO2 emissions per capita (log)	0.874***	0.869***	0.880***
	(0.0792)	(0.0807)	(0.0895)
GDP per capita (log)	0.180*	0.215**	0.214*
	(0.0956)	(0.107)	(0.113)
Total population (log)	0.0510**	0.0700**	0.0739**
	(0.0243)	(0.0318)	(0.0342)
Openness to trade (log)	0.139*	0.197***	0.207**
	(0.0724)	(0.0762)	(0.0813)
Foreign Direct Investment (log)		-0.00190	-0.000535
		(0.00957)	(0.00993)
Aid per capita (log)			-0.000790
			(0.0214)
Constant	-2.804***	-3.643***	-3.714***
	(1.010)	(1.343)	(1.334)
Time fixed effects	Yes	Yes	Yes
# Observations	560	537	535
Number of countries	35	35	35
AR(1) p-value	0.000	0.000	0.000
AR(2) p-value	0.510	0.555	0.532
Hansen test p-value	0.142	0.220	0.283
Number of instruments	26	29	32

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.1$ Residuals from the complete specification (column 3) is used to compute the index of *de facto* policy.

Table C1: Race test regression: *de facto*

	Dpendent variable *de facto* environmental policy (for δ_0)							
	Main	Wx	SR direct	SR indirect	SR total	LR direct	LR indirect	LR total
L.*de facto* environmental policy	0.993***							
	(0.0475)							
Mineral resource rents	0.00909	0.108***	0.0553	0.887	0.942	-0.117***	-0.0207	-0.138***
	(0.00648)	(0.00833)	(0.0542)	(0.987)	(1.041)	(0.0130)	(0.0135)	(0.0134)
Temperature shocks	0.00870		0.0128	0.0579	0.0707	0.00895	-0.0207	-0.0117
	(0.0106)		(0.0139)	(0.0967)	(0.108)	(0.00946)	(0.0215)	(0.0122)
Precipitation shocks	0.000743*		0.00101*	0.00504	0.00604	0.000705*	-0.00158*	-0.000878*
	(0.000387)		(0.000612)	(0.00617)	(0.00668)	(0.000397)	(0.000844)	(0.000460)
GDP Growth	-0.0187***	-0.0916***	-0.0625	-0.834	-0.897	0.0881***	0.0414***	0.130***
	(0.00701)	(0.0109)	(0.0538)	(0.998)	(1.051)	(0.0112)	(0.0139)	(0.0129)
FDI	-0.00349	-0.0160***	-0.0114	-0.151	-0.162	0.0149***	0.00768	0.0226***
	(0.00240)	(0.00505)	(0.0114)	(0.211)	(0.222)	(0.00568)	(0.00488)	(0.00577)
Democracy index	0.0297***		0.0400**	0.196	0.236	0.0277***	-0.0630***	-0.0352***
	(0.00950)		(0.0168)	(0.213)	(0.227)	(0.0100)	(0.0205)	(0.0114)
Control of corruption	-0.222**		-0.297**	-1.417	-1.713	-0.205**	0.470***	0.265**
	(0.0951)		(0.136)	(1.597)	(1.706)	(0.0800)	(0.182)	(0.108)
Poulation density	0.0132***		0.0178***	0.0874	0.105	0.0123***	-0.0279***	-0.0156***
	(0.000980)		(0.00540)	(0.0974)	(0.103)	(0.00217)	(0.00245)	(0.00118)
Openness to trade	-0.00218***		-0.00284**	-0.0135	-0.0164	-0.00195***	0.00449***	0.00253***
	(0.000668)		(0.00110)	(0.0146)	(0.0155)	(0.000600)	(0.00136)	(0.000845)
Forest rent	0.0280***		0.0379**	0.188	0.226	0.0263***	-0.0594***	-0.0331***
	(0.00830)		(0.0154)	(0.208)	(0.222)	(0.00884)	(0.0170)	(0.00897)
δ_0	**0.857*** **							
	(0.0412)							
σ_e^2	0.0995***							
	(0.0152)							
# Observations	320	320	320	320	320	320	320	320
Number countries	20	20	20	20	20	20	20	20
Log likelihood	-79.66	-79.66	-79.66	-79.66	-79.66	-79.66	-79.66	-79.66

	Dependent variable: *de facto* environmental policy (δ_1)							
	Main	Wx	SR direct	SR indirect	SR total	LR direct	LR indirect	LR total
L.*de facto* environmental policy	0.825***							
	(0.0323)							
Mineral resource rents	-0.00895	0.0187	-0.00873	0.0236	0.0149	0.0410	0.559	0.600
	(0.0217)	(0.0476)	(0.0208)	(0.0602)	(0.0561)	(1.250)	(11.01)	(11.74)
Temperature shocks	-0.00559		-0.00477	-0.00173	-0.00649	0.00538	0.0175	0.0229
	(0.00982)		(0.00965)	(0.00362)	(0.0131)	(0.459)	(1.785)	(1.850)
Precipitation shocks	0.000183		-0.000123	-0.000215	-0.000337	-0.0232	-0.799	-0.822
	(0.000169)		(0.0313)	(0.0113)	(0.0420)	(1.112)	(14.58)	(15.59)
GDP Growth	0.000413	-0.000919	0.000642	0.000724	0.00137	0.0138	-0.0251	-0.0113
	(0.00579)	(0.00978)	(0.0103)	(0.0160)	(0.0235)	(0.303)	(1.611)	(1.695)
FDI	-0.0292***	-0.0117	-0.0293	-0.0262	-0.0555	-0.157	0.681	0.524
	(0.00492)	(0.0188)	(0.0206)	(0.0295)	(0.0436)	(1.237)	(10.58)	(11.29)
Democracy index	0.00453		0.00436	0.00173	0.00609	0.0331	-0.0864	-0.0533
	(0.00698)		(0.0117)	(0.00434)	(0.0158)	(0.372)	(2.275)	(2.405)
Control of corruption	-0.128		-0.130	-0.0367	-0.167	-0.283	6.771	6.488
	(0.135)		(0.139)	(0.0468)	(0.181)	(7.449)	(97.55)	(104.4)
Poulation density	0.00117		0.00203	0.000982	0.00301	0.0211	-0.189	-0.168
	(0.00461)		(0.0154)	(0.00567)	(0.0208)	(0.623)	(2.905)	(3.042)
Openness to trade	-0.00384*		-0.00408	-0.00135	-0.00544	-0.0297	0.248	0.218
	(0.00204)		(0.0115)	(0.00416)	(0.0154)	(0.495)	(2.745)	(2.896)
Forest rent	0.0174		0.0166	0.00607	0.0227	0.0792	-0.585	-0.506
	(0.0229)		(0.0244)	(0.00912)	(0.0329)	(0.889)	(10.30)	(11.02)
δ_1	**0.244*** **							
	(0.0786)							
σ_e^2	0.0822***							
	(0.0149)							
# Observations	240	240	240	240	240	240	240	240
Number countries	15	15	15	15	15	15	15	15
Log likelihood	-34.31	-34.31	-34.31	-34.31	-34.31	-34.31	-34.31	-34.31

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C2: Race test regression: *de jure*

	Dependent variable *de jure* environmental policy (for δ_0)							
	Main	Wx	SR direct	SR indirect	SR total	LR direct	LR indirect	LR total
L.*de jure* environmental policy	0.873***							
	(0.0349)							
Mineral resource rents	-0.00591	-0.0457	-0.00705	-0.0538	-0.0608*	-0.0734	-0.0716	-0.145
	(0.0110)	(0.0282)	(0.0107)	(0.0334)	(0.0362)	(1.227)	(20.83)	(22.05)
Temperature shocks	0.0866***		0.0893***	0.0181**	0.107***	0.657	-1.708	-1.051
	(0.0227)		(0.0219)	(0.00739)	(0.0278)	(1.561)	(26.41)	(27.96)
Precipitation shocks	0.00152*		0.00153*	0.000327	0.00186*	0.0123	-0.0166	-0.00434
	(0.000795)		(0.000801)	(0.000218)	(0.00100)	(0.0221)	(0.361)	(0.382)
GDP Growth	-0.00483	-0.0158	-0.00521	-0.0193	-0.0246	-0.0401	0.00550	-0.0346
	(0.0120)	(0.0208)	(0.0113)	(0.0246)	(0.0262)	(0.546)	(9.151)	(9.689)
FDI	-0.00269	0.00624	-0.00245	0.00659	0.00414	-0.0167	0.0811	0.0644
	(0.00304)	(0.0157)	(0.00311)	(0.0178)	(0.0186)	(0.270)	(4.543)	(4.812)
Democracy index	-0.0646***		-0.0652***	-0.0140*	-0.0792***	-0.477	1.483	1.006
	(0.0227)		(0.0228)	(0.00787)	(0.0302)	(0.918)	(15.22)	(16.10)
Control of corruption	1.325***		1.306***	0.259**	1.566***	9.960	-18.81	-8.846
	(0.394)		(0.401)	(0.107)	(0.481)	(26.83)	(451.4)	(477.9)
Poulation density	-0.0355***		-0.0356***	-0.00713**	-0.0427***	-0.283	0.333	0.0509
	(0.0107)		(0.0110)	(0.00314)	(0.0134)	(0.637)	(10.65)	(11.28)
Openness to trade	0.00108		0.00109	0.000208	0.00130	0.00834	-0.0118	-0.00350
	(0.00201)		(0.00211)	(0.000437)	(0.00253)	(0.0439)	(0.705)	(0.746)
Forest rent	0.0388		0.0369	0.00776	0.0446	0.270	-0.818	-0.548
	(0.0278)		(0.0279)	(0.00656)	(0.0341)	(0.613)	(9.742)	(10.30)
δ_0	**0.169*** **							
	(0.0403)							
σ^2_e	0.568***							
	(0.0778)							
# Observations	288	288	288	288	288	288	288	288
Number countries	18	18	18	18	18	18	18	18
Log likelihood	-314.0	-314.0	-314.0	-314.0	-314.0	-314.0	-314.0	-314.0

	Dependent variable: *de jure* environmental policy (δ_1)							
	Main	Wx	SR direct	SR indirect	SR total	LR direct	LR indirect	LR total
L.*de jure* environmental policy	0.888***							
	(0.0344)							
Mineral resource rents	-0.0250**	-0.275***	-0.0415***	-0.464***	-0.505***	0.558	0.661	1.220
	(0.0126)	(0.0296)	(0.0115)	(0.102)	(0.103)	(5.721)	(5.786)	(0.832)
Temperature shocks	0.0405		0.0441	0.0300	0.0740	0.155	-0.319	-0.163
	(0.0292)		(0.0292)	(0.0246)	(0.0522)	(1.277)	(1.295)	(0.136)
Precipitation shocks	0.000351		0.000358	0.000271	0.000630	9.31e-05	-0.00116	-0.00106
	(0.000493)		(0.000495)	(0.000373)	(0.000853)	(0.0192)	(0.0195)	(0.00220)
GDP Growth	0.0131***	0.0134	0.0141***	0.0329*	0.0470**	-0.0109	-0.106	-0.117
	(0.00458)	(0.0116)	(0.00479)	(0.0195)	(0.0217)	(0.752)	(0.759)	(0.0947)
FDI	-0.00946	0.0739**	-0.00541	0.113**	0.108**	-0.218	-0.0481	-0.266
	(0.00581)	(0.0292)	(0.00533)	(0.0486)	(0.0490)	(1.182)	(1.196)	(0.292)
Democracy index	-0.0471**		-0.0475**	-0.0325	-0.0799*	0.0535	0.121	0.175*
	(0.0200)		(0.0206)	(0.0217)	(0.0409)	(3.290)	(3.283)	(0.0984)
Control of corruption	0.604***		0.613***	0.397**	1.010***	0.858	-3.333	-2.475
	(0.168)		(0.174)	(0.199)	(0.344)	(30.85)	(30.98)	(2.252)
Poulation density	-0.00747***		-0.00753***	-0.00496**	-0.0125***	-0.00855	0.0381	0.0295
	(0.00183)		(0.00195)	(0.00248)	(0.00414)	(0.310)	(0.311)	(0.0218)
Openness to trade	0.00434		0.00452	0.00288	0.00740	0.00751	-0.0264	-0.0189
	(0.00323)		(0.00317)	(0.00232)	(0.00528)	(0.336)	(0.338)	(0.0257)
Forest rent	0.0127		0.0133	0.00859	0.0219	0.0390	-0.0898	-0.0508
	(0.0130)		(0.0126)	(0.00904)	(0.0211)	(0.774)	(0.785)	(0.0655)
δ_1	**0.394*** **							
	(0.0818)							
σ^2_e	0.315***							
	(0.0649)							
# Observations	272	272	272	272	272	272	272	272
Number countries	17	17	17	17	17	17	17	17
Log likelihood	-219.9	-219.9	-219.9	-219.9	-219.9	-219.9	-219.9	-219.9

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

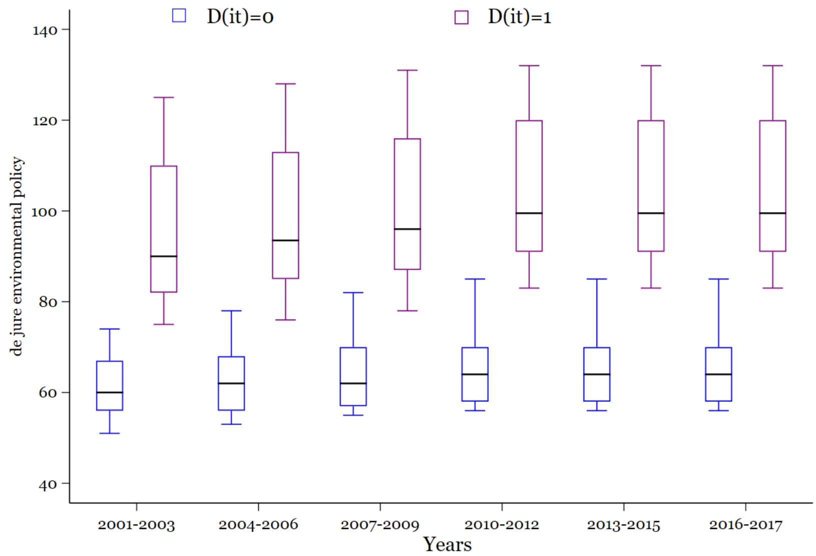

Figure D1: Box plots of *de jure* environmental policy according to $D_{it} = 0$ and $D_{it} = 1$

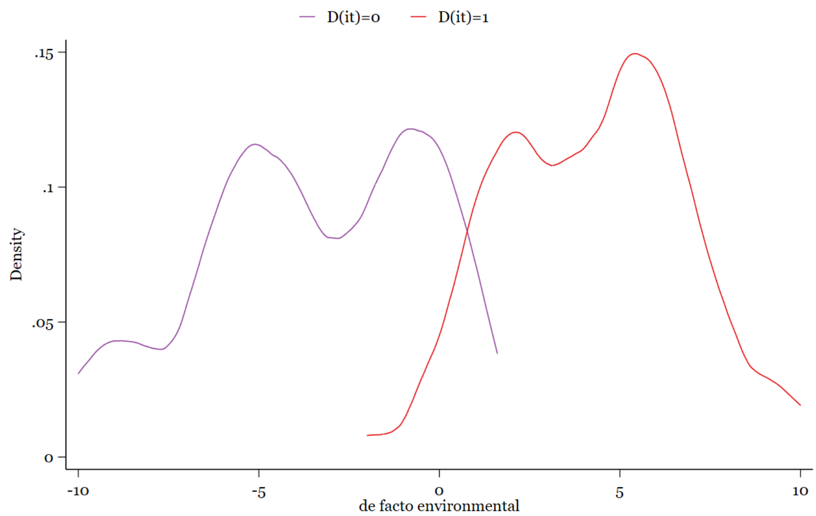

Figure D2: Kernel density estimate of *de facto* environmental policy according to $D_{it} = 0$ and $D_{it} = 1$

A.3 Likelihood functions

The likelihood function of Equation 1, Generalized Spatial Panel Random Effects model (GSPRE) model adapted from Baltagi et al. (2013) is given by:

$$\begin{aligned} L(\beta, \theta) &= -\frac{NT}{2}\ln 2\pi - \frac{1}{2}\ln\det\left[T\sigma_\mu^2(A'A)^{-1} + \sigma_\upsilon^2(B'B)^{-1}\right] \\ &- \frac{T-1}{2}\ln\det\left[\sigma_\upsilon^2(B'B)^{-1}\right] - \frac{1}{2}(F - X\beta)'\Omega_u^{-1}(F - X\beta), \end{aligned} \tag{E1}$$

where $\theta = (\sigma_\upsilon^2, \sigma_\mu^2, \phi, \lambda)$, $A = I_n - \phi W$ and $B = I_n - \lambda M$

We refer the reader to Baltagi et al. (2013) for more details on the properties of the function and the underlying assumptions.

The likelihood function of Equation 2, our spatial dynamic fixed effects model adapted from Yu et al. (2008) is:

$$L_{n,T}(\theta, \alpha_n) = -\frac{nT}{2}\ln 2\pi - \frac{nT}{2}\ln\sigma^2 + T\ln|S_n(\lambda)| - \frac{1}{2\sigma^2}\sum_{t=1}^{T} V'_{nt}(\zeta)V_{nt}(\zeta), \tag{E2}$$

where $V_{nt}(\zeta) = S_n(\lambda)E_{nt} - \tau E_{n,t-1} - \delta W_n E_{n,t-1} - X_{nt}\beta - \alpha_n$. $\theta = (\delta', \lambda, \sigma^2)'$ and $\zeta = (\delta', \lambda, \alpha'_n)'$

We refer the reader to Yu et al. (2008) for more details on the properties of the function and the underlying assumptions.

A.4 Robustness of the estimates of the determinants of deforestation

Table F1a: Determinants of deforestation with additional controls

	Dependent variable: Tree cover loss >20% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0565*** **	**0.0542*** **	**0.0560*** **	**0.0575*** **	**0.0552*** **	**0.0559*** **	**0.0564*** **	**0.0556*** **
	(0.00953)	**(0.00950)**	**(0.00950)**	**(0.00949)**	**(0.00949)**	**(0.00941)**	**(0.00952)**	**(0.00949)**
Temperature shocks	0.00570	0.00581	0.00646	0.00599	0.00594	0.00672	0.00561	0.00638
	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)
Precipitation shocks	0.000614	0.000582	0.000608	0.000612	0.000627	0.000588	0.000615	0.000612
	(0.000442)	(0.000441)	(0.000441)	(0.000440)	(0.000441)	(0.000439)	(0.000442)	(0.000441)
de jure environmental policy	0.00189	-0.00320	0.000843	-0.000752	0.00186	-0.00503	0.000698	-0.00267
	(0.0121)	(0.0115)	(0.0118)	(0.0104)	(0.0116)	(0.0105)	(0.0117)	(0.0118)
De faco environmental policy	0.00798	0.0292	0.0161	0.0329	0.0533	0.0432	0.00920	0.0302
	(0.0685)	(0.0647)	(0.0665)	(0.0624)	(0.0670)	(0.0630)	(0.0684)	(0.0666)
EITI membership	**5.981*** **	**5.511*** **	**5.734*** **	**6.279*** **	**5.854*** **	**5.737*** **	**5.885*** **	**5.665*** **
	(1.307)	**(1.322)**	**(1.317)**	**(1.269)**	**(1.298)**	**(1.245)**	**(1.303)**	**(1.355)**
***de jure* environmental policy x EITI**	**-0.0462*** **	**-0.0404*** **	**-0.0451*** **	**-0.0441*** **	**-0.0458*** **	**-0.0440*** **	**-0.0445*** **	**-0.0432*** **
	(0.0143)	**(0.0140)**	**(0.0139)**	**(0.0130)**	**(0.0138)**	**(0.0132)**	**(0.0141)**	**(0.0143)**
***de facto* environmental policy x EITI**	**-0.562*** **	**-0.573*** **	**-0.570*** **	**-0.591*** **	**-0.606*** **	**-0.595*** **	**-0.559*** **	**-0.584*** **
	(0.0881)	(0.0821)	(0.0846)	(0.0808)	(0.0846)	(0.0811)	(0.0884)	(0.0849)
GDP per capita (log)	2.841**	2.893**	3.005**	2.576*	2.705*	2.779**	2.868**	2.880**
	(1.410)	(1.416)	(1.409)	(1.400)	(1.411)	(1.396)	(1.408)	(1.413)
GDP per capita square (log)	-0.190**	-0.183*	-0.203**	-0.177*	-0.176*	-0.188**	-0.192**	-0.188**
	(0.0929)	(0.0934)	(0.0932)	(0.0917)	(0.0932)	(0.0917)	(0.0928)	(0.0933)
Population density	-0.000601	-0.000796	-0.000536	5.05e-05	0.000678	-0.000390	-0.000702	1.43e-05
	(0.00224)	(0.00192)	(0.00198)	(0.00168)	(0.00193)	(0.00175)	(0.00225)	(0.00203)
FDI	-0.00599*	-0.00575*	-0.00625*	-0.00612*	-0.00599*	-0.00622*	-0.00593*	-0.00598*
	(0.00345)	(0.00345)	(0.00345)	(0.00343)	(0.00345)	(0.00343)	(0.00345)	(0.00344)
Control of corruption	-0.123	-0.134	-0.101	-0.110	-0.167	-0.113	-0.128	-0.137
	(0.152)	(0.150)	(0.153)	(0.146)	(0.152)	(0.147)	(0.152)	(0.151)
Forest rents	-0.000855	-0.00416	-0.00359	-3.84e-05	-0.000192	-0.00673	-0.00103	-0.00159
	(0.0158)	(0.0156)	(0.0157)	(0.0155)	(0.0156)	(0.0155)	(0.0158)	(0.0158)
ϕ	2.379***	-0.825	0.224	-1.550*	-0.178	-1.364	2.387***	0.166
	(0.330)	(1.159)	(0.547)	(0.888)	(0.745)	(1.033)	(0.333)	(0.745)
λ	0.407***	0.403***	0.409***	0.411***	0.394***	0.424***	0.410***	0.404***
	(0.0744)	(0.0739)	(0.0740)	(0.0726)	(0.0741)	(0.0731)	(0.0743)	(0.0748)
σ_μ	1.511***	1.420***	1.411***	1.203***	1.395***	1.248***	1.504***	1.477***
	(0.223)	(0.201)	(0.202)	(0.186)	(0.194)	(0.186)	(0.223)	(0.206)
σ_e	0.647***	0.647***	0.647***	0.647***	0.647***	0.646***	0.647***	0.647***
	(0.0198)	(0.0198)	(0.0198)	(0.0198)	(0.0198)	(0.0197)	(0.0198)	(0.0198)
AMU	-0.0337							
	(1.316)							
COMESA		1.173*						
		(0.703)						
ECCAS			0.918					
			(0.624)					
ECOWAS				-1.594***				
				(0.372)				
SADC					1.157**			
					(0.543)			
UEMOA						-2.094***		
						(0.576)		
CEMAC							-0.466	
							(0.879)	
WAMZ								-0.199
								(1.010)
Constant	-10.54*	-11.16**	-11.02**	-8.820*	-10.62**	-9.206*	-10.49*	-10.44*
	(5.404)	(5.431)	(5.403)	(5.337)	(5.366)	(5.329)	(5.378)	(5.400)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-674.0	-671.8	-671.7	-668.1	-670.8	-668.7	-673.9	-672.7

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

Table F1b: Determinants of deforestation with additional controls

	Dependent variable: Tree cover loss >30% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0511*** **	**0.0491*** **	**0.0512*** **	**0.0512*** **	**0.0496*** **	**0.0503*** **	**0.0511*** **	**0.0511*** **
	(0.00979)	**(0.00981)**	**(0.00979)**	**(0.00974)**	**(0.00973)**	**(0.00968)**	**(0.00979)**	**(0.00977)**
Temperature shocks	0.00577	0.00626	0.00584	0.00654	0.00586	0.00715	0.00591	0.00601
	(0.0172)	(0.0171)	(0.0172)	(0.0171)	(0.0171)	(0.0171)	(0.0172)	(0.0172)
Precipitation shocks	0.000705	0.000672	0.000704	0.000691	0.000708	0.000670	0.000706	0.000699
	(0.000456)	(0.000456)	(0.000456)	(0.000454)	(0.000455)	(0.000454)	(0.000456)	(0.000456)
de jure environmental policy	0.0213	0.00673	0.0220*	0.00769	0.0134	0.00386	0.0177	0.0175
	(0.0134)	(0.0141)	(0.0128)	(0.0121)	(0.0128)	(0.0123)	(0.0129)	(0.0127)
De faco environmental policy	-0.0195	-0.0137	-0.0247	-0.0103	0.0210	-0.00280	-0.0151	-0.0169
	(0.0708)	(0.0692)	(0.0707)	(0.0672)	(0.0689)	(0.0668)	(0.0709)	(0.0707)
EITI membership	**7.260*** **	**5.901*** **	**7.149*** **	**6.582*** **	**6.306*** **	**6.020*** **	**7.120*** **	**7.195*** **
	(1.428)	**(1.662)**	**(1.395)**	**(1.443)**	**(1.441)**	**(1.455)**	**(1.436)**	**(1.428)**
***de jure* environmental policy x EITI**	**-0.0648*** **	**-0.0506*** **	**-0.0631*** **	**-0.0527*** **	**-0.0561*** **	**-0.0524*** **	**-0.0616*** **	**-0.0629*** **
	(0.0157)	**(0.0171)**	**(0.0150)**	**(0.0150)**	**(0.0152)**	**(0.0153)**	**(0.0155)**	**(0.0153)**
***de facto* environmental policy x EITI**	**-0.565*** **	**-0.559*** **	**-0.562*** **	**-0.578*** **	**-0.598*** **	**-0.580*** **	**-0.571*** **	**-0.568*** **
	(0.0884)	(0.0886)	(0.0879)	(0.0844)	(0.0853)	(0.0843)	(0.0885)	(0.0885)
GDP per capita (log)	2.571*	2.796*	2.603*	2.583*	2.457*	2.762*	2.541*	2.568*
	(1.494)	(1.502)	(1.490)	(1.479)	(1.486)	(1.478)	(1.497)	(1.493)
GDP per capita square (log)	-0.176*	-0.181*	-0.182*	-0.177*	-0.163*	-0.186*	-0.174*	-0.176*
	(0.0983)	(0.0985)	(0.0981)	(0.0974)	(0.0981)	(0.0975)	(0.0985)	(0.0983)
Population density	0.000154	-0.000160	-9.73e-05	0.000537	0.00129	0.000244	0.000301	4.81e-05
	(0.00214)	(0.00215)	(0.00214)	(0.00180)	(0.00188)	(0.00182)	(0.00216)	(0.00218)
FDI	-0.00648*	-0.00612*	-0.00664*	-0.00643*	-0.00630*	-0.00644*	-0.00642*	-0.00638*
	(0.00359)	(0.00359)	(0.00359)	(0.00357)	(0.00358)	(0.00357)	(0.00359)	(0.00359)
Control of corruption	-0.0741	-0.0667	-0.0527	-0.0367	-0.108	-0.0417	-0.0762	-0.0806
	(0.160)	(0.159)	(0.160)	(0.158)	(0.159)	(0.158)	(0.160)	(0.159)
Forest rents	-0.00306	-0.00616	-0.00420	-0.00353	-0.00203	-0.00802	-0.00292	-0.00414
	(0.0162)	(0.0162)	(0.0162)	(0.0159)	(0.0160)	(0.0159)	(0.0162)	(0.0162)
ϕ	1.436***	-0.572	1.471***	-1.257	-0.629	-1.369	1.443***	1.476***
	(0.294)	(1.593)	(0.300)	(0.901)	(0.894)	(1.100)	(0.295)	(0.290)
λ	0.283***	0.285***	0.284***	0.287***	0.275***	0.296***	0.284***	0.288***
	(0.0792)	(0.0803)	(0.0792)	(0.0800)	(0.0797)	(0.0806)	(0.0796)	(0.0797)
σ_μ	1.720***	1.777***	1.675***	1.583***	1.628***	1.610***	1.757***	1.739***
	(0.239)	(0.240)	(0.233)	(0.219)	(0.217)	(0.226)	(0.240)	(0.238)
σ_e	0.667***	0.666***	0.668***	0.666***	0.666***	0.665***	0.667***	0.667***
	(0.0203)	(0.0202)	(0.0203)	(0.0202)	(0.0202)	(0.0201)	(0.0203)	(0.0203)
AMU	-1.246							
	(1.469)							
COMESA		0.966						
		(1.174)						
ECCAS			1.449					
			(0.929)					
ECOWAS				-1.698***				
				(0.491)				
SADC					1.667***			
					(0.563)			
UEMOA						-2.251***		
						(0.737)		
CEMAC							0.132	
							(0.992)	
WAMZ								0.778
								(1.022)
Constant	-10.77*	-10.98*	-11.20**	-9.175	-10.35*	-9.543*	-10.47*	-10.65*
	(5.692)	(5.731)	(5.695)	(5.601)	(5.609)	(5.584)	(5.689)	(5.685)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-691.6	-691.0	-690.8	-688.0	-688.2	-688.5	-691.9	-691.6

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

Table F1c: Determinants of deforestation with additional controls

	Dependent variable: Tree cover loss >50% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0433*** **	**0.0413*** **	**0.0435*** **	**0.0433*** **	**0.0415*** **	**0.0421*** **	**0.0434*** **	**0.0421*** **
	(0.00897)	**(0.00899)**	**(0.00897)**	**(0.00886)**	**(0.00891)**	**(0.00887)**	**(0.00897)**	**(0.00893)**
Temperature shocks	0.00219	0.00265	0.00223	0.00305	0.00224	0.00342	0.00237	0.00283
	(0.0156)	(0.0155)	(0.0156)	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)
Precipitation shocks	0.000676	0.000644	0.000673	0.000631	0.000674	0.000637	0.000676	0.000663
	(0.000424)	(0.000423)	(0.000424)	(0.000422)	(0.000422)	(0.000422)	(0.000423)	(0.000422)
de jure environmental policy	0.0175	0.00441	0.0188*	0.00119	0.00961	0.00210	0.0146	0.00574
	(0.0121)	(0.0124)	(0.0114)	(0.00990)	(0.0116)	(0.0108)	(0.0116)	(0.0123)
De faco environmental policy	-0.0673	-0.0624	-0.0751	-0.0617	-0.0361	-0.0510	-0.0641	-0.0560
	(0.0650)	(0.0633)	(0.0648)	(0.0584)	(0.0635)	(0.0609)	(0.0651)	(0.0637)
EITI membership	**6.208*** **	**5.056*** **	**6.105*** **	**5.531*** **	**5.381*** **	**5.211*** **	**6.113*** **	**5.246*** **
	(1.283)	**(1.440)**	**(1.242)**	**(1.300)**	**(1.306)**	**(1.285)**	**(1.291)**	**(1.408)**
***de jure* environmental policy x EITI**	**-0.0573*** **	**-0.0448*** **	**-0.0560*** **	**-0.0432*** **	**-0.0492*** **	**-0.0465*** **	**-0.0550*** **	**-0.0470*** **
	(0.0143)	**(0.0152)**	**(0.0135)**	**(0.0131)**	**(0.0140)**	**(0.0138)**	**(0.0141)**	**(0.0149)**
***de facto* environmental policy x EITI**	**-0.464*** **	**-0.460*** **	**-0.460*** **	**-0.466*** **	**-0.489*** **	**-0.481*** **	**-0.471*** **	**-0.472*** **
	(0.0810)	(0.0800)	(0.0802)	(0.0747)	(0.0785)	(0.0766)	(0.0810)	(0.0794)
GDP per capita (log)	1.751	1.916	1.772	1.858	1.684	1.908	1.693	1.854
	(1.392)	(1.397)	(1.386)	(1.361)	(1.388)	(1.377)	(1.396)	(1.393)
GDP per capita square (log)	-0.140	-0.140	-0.146	-0.141	-0.129	-0.143	-0.137	-0.140
	(0.0914)	(0.0917)	(0.0911)	(0.0891)	(0.0914)	(0.0906)	(0.0916)	(0.0917)
Population density	0.000466	0.000203	0.000168	0.000614	0.00123	0.000588	0.000679	0.000829
	(0.00187)	(0.00181)	(0.00186)	(0.00134)	(0.00164)	(0.00152)	(0.00188)	(0.00173)
FDI	-0.00653*	-0.00607*	-0.00676**	-0.00623*	-0.00624*	-0.00628*	-0.00648*	-0.00623*
	(0.00340)	(0.00340)	(0.00340)	(0.00337)	(0.00339)	(0.00338)	(0.00340)	(0.00339)
Control of corruption	0.0701	0.0662	0.0948	0.106	0.0324	0.0807	0.0709	0.0631
	(0.151)	(0.150)	(0.151)	(0.143)	(0.151)	(0.148)	(0.152)	(0.151)
Forest rents	-0.00748	-0.0104	-0.00853	-0.00725	-0.00764	-0.0121	-0.00727	-0.00854
	(0.0147)	(0.0147)	(0.0147)	(0.0144)	(0.0146)	(0.0145)	(0.0147)	(0.0147)
ϕ	1.437***	-0.497	1.455***	-3.800***	-0.393	-1.484	1.439***	-0.0507
	(0.297)	(1.319)	(0.303)	(0.176)	(0.840)	(1.065)	(0.298)	(0.917)
λ	0.0684	0.0664	0.0695	0.0673	0.0621	0.0718	0.0681	0.0663
	(0.0881)	(0.0886)	(0.0881)	(0.0883)	(0.0885)	(0.0885)	(0.0883)	(0.0886)
σ_μ	1.520***	1.562***	1.453***	1.228***	1.476***	1.405***	1.549***	1.587***
	(0.211)	(0.209)	(0.203)	(0.163)	(0.196)	(0.196)	(0.212)	(0.208)
σ_e	0.626***	0.624***	0.626***	0.624***	0.624***	0.624***	0.625***	0.624***
	(0.0189)	(0.0188)	(0.0189)	(0.0188)	(0.0188)	(0.0187)	(0.0189)	(0.0188)
AMU	-1.129							
	(1.299)							
COMESA		0.750						
		(0.873)						
ECCAS			1.506*					
			(0.803)					
ECOWAS				-1.522***				
				(0.332)				
SADC					1.276**			
					(0.536)			
UEMOA						-1.979***		
						(0.622)		
CEMAC							0.312	
							(0.877)	
WAMZ								-0.430
								(1.045)
Constant	-6.374	-6.542	-6.802	-5.442	-6.117	-5.570	-6.039	-5.956
	(5.299)	(5.320)	(5.289)	(5.125)	(5.242)	(5.196)	(5.301)	(5.295)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-647.0	-646.3	-645.7	-648.2	-644.3	-643.5	-647.3	-646.5

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

Table F2a: Determinants of deforestation with different matrices

	Dependent variable: Tree cover loss >20% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0461*****	**0.0451*****	**0.0465*****	**0.0482*****	**0.0460*****	**0.0470*****	**0.0461*****	**0.0461*****
	(0.00930)	**(0.00929)**	**(0.00931)**	**(0.00931)**	**(0.00928)**	**(0.00926)**	**(0.00931)**	**(0.00928)**
Temperature shocks	0.00733	0.00667	0.00745	0.00695	0.00657	0.00737	0.00737	0.00727
	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0169)	(0.0168)	(0.0168)
Precipitation shocks	0.000722	0.000703	0.000720	0.000730	0.000739	0.000716	0.000722	0.000728
	(0.000451)	(0.000451)	(0.000451)	(0.000451)	(0.000451)	(0.000451)	(0.000451)	(0.000451)
de jure environmental policy	0.00300	0.00185	0.00468	0.00399	0.00724	0.00103	0.00168	0.00167
	(0.0129)	(0.0118)	(0.0119)	(0.0111)	(0.0117)	(0.0113)	(0.0119)	(0.0118)
De faco environmental policy	0.0515	0.0549	0.0436	0.0675	0.0721	0.0713	0.0522	0.0563
	(0.0695)	(0.0679)	(0.0691)	(0.0649)	(0.0698)	(0.0676)	(0.0694)	(0.0690)
EITI membership	**6.346*****	**6.031*****	**6.328*****	**6.575*****	**6.544*****	**6.289*****	**6.282*****	**6.229*****
	(1.419)	**(1.422)**	**(1.378)**	**(1.332)**	**(1.335)**	**(1.391)**	**(1.401)**	**(1.396)**
***de jure* environmental policy x EITI**	**-0.0484*****	**-0.0432*****	**-0.0485*****	**-0.0462*****	**-0.0499*****	**-0.0471*****	**-0.0472*****	**-0.0459*****
	(0.0155)	**(0.0151)**	**(0.0146)**	**(0.0140)**	**(0.0143)**	**(0.0146)**	**(0.0149)**	**(0.0149)**
***de facto* environmental policy x EITI**	**-0.640*****	**-0.634*****	**-0.633*****	**-0.657*****	**-0.657*****	**-0.656*****	**-0.641*****	**-0.646*****
	(0.0862)	(0.0838)	(0.0861)	(0.0831)	(0.0860)	(0.0846)	(0.0865)	(0.0860)
GDP per capita (log)	2.155	2.039	2.251	1.713	1.931	1.894	2.122	2.069
	(1.493)	(1.491)	(1.487)	(1.478)	(1.480)	(1.481)	(1.489)	(1.490)
GDP per capita square (log)	-0.128	-0.116	-0.139	-0.109	-0.115	-0.116	-0.125	-0.123
	(0.0984)	(0.0983)	(0.0982)	(0.0968)	(0.0975)	(0.0973)	(0.0980)	(0.0981)
Population density	0.00244	0.00187	0.00213	0.00286	0.00289	0.00242	0.00249	0.00278
	(0.00200)	(0.00194)	(0.00200)	(0.00179)	(0.00194)	(0.00191)	(0.00203)	(0.00199)
FDI	-0.00598*	-0.00577	-0.00625*	-0.00622*	-0.00599*	-0.00614*	-0.00594	-0.00596
	(0.00363)	(0.00363)	(0.00364)	(0.00362)	(0.00363)	(0.00363)	(0.00364)	(0.00363)
Control of corruption	-0.0522	-0.0571	-0.0210	-0.0357	-0.0850	-0.0349	-0.0528	-0.0553
	(0.161)	(0.160)	(0.163)	(0.157)	(0.162)	(0.159)	(0.163)	(0.161)
Forest rents	0.00173	0.000684	0.000384	0.00361	0.00352	-0.00126	0.00183	0.00313
	(0.0161)	(0.0161)	(0.0161)	(0.0160)	(0.0161)	(0.0161)	(0.0161)	(0.0162)
ϕ	0.0288	-0.265	-0.0123	-0.426	-0.00787	-0.265	0.0239	-0.0769
	(0.246)	(0.327)	(0.250)	(0.273)	(0.278)	(0.311)	(0.253)	(0.290)
λ	0.140*	0.143*	0.143*	0.157*	0.143*	0.165**	0.141*	0.138*
	(0.0822)	(0.0820)	(0.0821)	(0.0816)	(0.0809)	(0.0835)	(0.0823)	(0.0818)
σ_μ	1.581***	1.521***	1.537***	1.345***	1.468***	1.419***	1.584***	1.581***
	(0.224)	(0.217)	(0.220)	(0.204)	(0.210)	(0.209)	(0.224)	(0.221)
σ_e	0.667***	0.667***	0.667***	0.667***	0.667***	0.667***	0.667***	0.666***
	(0.0201)	(0.0201)	(0.0201)	(0.0202)	(0.0201)	(0.0201)	(0.0201)	(0.0201)
AMU	-0.349							
	(1.336)							
COMESA		1.147						
		(0.737)						
ECCAS			0.808					
			(0.645)					
ECOWAS				-1.581***				
				(0.434)				
SADC					1.313**			
					(0.617)			
UEMOA						-1.728***		
						(0.626)		
CEMAC							0.0219	
							(0.856)	
WAMZ								-0.616
								(0.944)
Constant	-9.091	-9.146	-9.504*	-6.727	-8.984	-7.394	-8.911	-8.639
	(5.746)	(5.716)	(5.722)	(5.659)	(5.654)	(5.689)	(5.715)	(5.718)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-683.8	-682.8	-683.1	-679.7	-681.5	-680.9	-683.8	-683.6

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

Table F2b: Determinants of deforestation with different matrices

	Dependent variable: Tree cover loss >30% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0430*** **	**0.0424*** **	**0.0433*** **	**0.0440*** **	**0.0428*** **	**0.0434*** **	**0.0431*** **	**0.0430*** **
	(0.00944)	**(0.00945)**	**(0.00944)**	**(0.00940)**	**(0.00940)**	**(0.00939)**	**(0.00944)**	**(0.00942)**
Temperature shocks	0.00744	0.00735	0.00760	0.00752	0.00666	0.00786	0.00763	0.00752
	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Precipitation shocks	0.000781*	0.000770*	0.000779*	0.000782*	0.000798*	0.000773*	0.000782*	0.000784*
	(0.000457)	(0.000457)	(0.000457)	(0.000457)	(0.000457)	(0.000457)	(0.000457)	(0.000457)
de jure environmental policy	0.0169	0.0101	0.0153	0.0104	0.0162	0.00902	0.0117	0.0106
	(0.0144)	(0.0135)	(0.0135)	(0.0126)	(0.0133)	(0.0130)	(0.0135)	(0.0134)
De faco environmental policy	-0.00242	-0.00228	-0.00881	0.00650	0.0260	0.0110	0.00171	0.00344
	(0.0719)	(0.0712)	(0.0721)	(0.0691)	(0.0709)	(0.0701)	(0.0718)	(0.0714)
EITI membership	**6.897*** **	**6.389*** **	**6.818*** **	**6.745*** **	**6.724*** **	**6.551*** **	**6.670*** **	**6.531*** **
	(1.603)	**(1.668)**	**(1.564)**	**(1.521)**	**(1.526)**	**(1.616)**	**(1.606)**	**(1.597)**
***de jure* environmental policy x EITI**	**-0.0616*** **	**-0.0533*** **	**-0.0587*** **	**-0.0536*** **	**-0.0579*** **	**-0.0553*** **	**-0.0570*** **	**-0.0547*** **
	(0.0170)	**(0.0171)**	**(0.0161)**	**(0.0158)**	**(0.0161)**	**(0.0165)**	**(0.0165)**	**(0.0166)**
***de facto* environmental policy x EITI**	**-0.610*** **	**-0.607*** **	**-0.607*** **	**-0.627*** **	**-0.634*** **	**-0.628*** **	**-0.616*** **	**-0.617*** **
	(0.0868)	(0.0869)	(0.0868)	(0.0848)	(0.0853)	(0.0854)	(0.0869)	(0.0866)
GDP per capita (log)	2.275	2.213	2.314	1.989	1.926	2.104	2.186	2.168
	(1.529)	(1.531)	(1.528)	(1.520)	(1.523)	(1.523)	(1.530)	(1.529)
GDP per capita square (log)	-0.146	-0.139	-0.152	-0.133	-0.124	-0.137	-0.140	-0.139
	(0.101)	(0.101)	(0.101)	(0.0999)	(0.100)	(0.100)	(0.101)	(0.101)
Population density	0.00168	0.00154	0.00150	0.00226	0.00251	0.00198	0.00197	0.00209
	(0.00199)	(0.00202)	(0.00201)	(0.00185)	(0.00189)	(0.00191)	(0.00200)	(0.00198)
FDI	-0.00665*	-0.00639*	-0.00678*	-0.00668*	-0.00655*	-0.00659*	-0.00650*	-0.00649*
	(0.00370)	(0.00369)	(0.00370)	(0.00369)	(0.00369)	(0.00369)	(0.00370)	(0.00369)
Control of corruption	-0.00484	-0.00656	0.0185	0.0146	-0.0438	0.00693	-0.00767	-0.01000
	(0.165)	(0.164)	(0.166)	(0.163)	(0.165)	(0.164)	(0.166)	(0.165)
Forest rents	-0.000996	-0.00167	-0.00194	0.000107	0.00114	-0.00285	-0.000685	2.13e-05
	(0.0161)	(0.0161)	(0.0161)	(0.0160)	(0.0161)	(0.0161)	(0.0161)	(0.0162)
ϕ	0.0720	-0.0908	0.0762	-0.281	-0.0917	-0.176	0.0576	-0.0208
	(0.252)	(0.339)	(0.250)	(0.271)	(0.286)	(0.303)	(0.253)	(0.291)
λ	0.0552	0.0575	0.0569	0.0625	0.0623	0.0672	0.0571	0.0562
	(0.0840)	(0.0847)	(0.0843)	(0.0844)	(0.0834)	(0.0855)	(0.0846)	(0.0844)
σ_μ	1.806***	1.839***	1.795***	1.694***	1.679***	1.747***	1.854***	1.853***
	(0.246)	(0.243)	(0.243)	(0.226)	(0.225)	(0.231)	(0.247)	(0.244)
σ_e	0.677***	0.676***	0.677***	0.676***	0.677***	0.676***	0.676***	0.676***
	(0.0204)	(0.0203)	(0.0204)	(0.0203)	(0.0204)	(0.0203)	(0.0203)	(0.0203)
AMU	-1.520							
	(1.509)							
COMESA		0.719						
		(0.937)						
ECCAS			0.985					
			(0.807)					
ECOWAS				-1.658***				
				(0.578)				
SADC					1.722***			
					(0.641)			
UEMOA						-1.770**		
						(0.790)		
CEMAC							0.155	
							(0.978)	
WAMZ								-0.615
								(1.087)
Constant	-9.619	-9.363	-9.850*	-7.515	-8.933	-8.075	-9.103	-8.863
	(5.857)	(5.867)	(5.874)	(5.809)	(5.788)	(5.833)	(5.859)	(5.867)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-696.4	-696.6	-696.1	-694.0	-693.7	-694.8	-696.9	-696.7

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.

Table F2c: Determinants of deforestation with different matrices

	Dependent variable: Tree cover loss >50% Canopy cover							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral resource rents	**0.0402*** **	**0.0397*** **	**0.0407*** **	**0.0410*** **	**0.0400*** **	**0.0405*** **	**0.0405*** **	**0.0402*** **
	(0.00865)	**(0.00867)**	**(0.00865)**	**(0.00861)**	**(0.00863)**	**(0.00861)**	**(0.00866)**	**(0.00863)**
Temperature shocks	0.00427	0.00422	0.00450	0.00426	0.00363	0.00468	0.00455	0.00438
	(0.0151)	(0.0151)	(0.0151)	(0.0151)	(0.0152)	(0.0152)	(0.0151)	(0.0151)
Precipitation shocks	0.000660	0.000650	0.000654	0.000657	0.000674	0.000649	0.000659	0.000660
	(0.000419)	(0.000419)	(0.000419)	(0.000419)	(0.000419)	(0.000419)	(0.000419)	(0.000419)
de jure environmental policy	0.0123	0.00620	0.0113	0.00544	0.0115	0.00486	0.00750	0.00622
	(0.0129)	(0.0121)	(0.0119)	(0.0112)	(0.0121)	(0.0117)	(0.0120)	(0.0121)
De faco environmental policy	-0.0733	-0.0716	-0.0835	-0.0609	-0.0520	-0.0584	-0.0697	-0.0669
	(0.0657)	(0.0651)	(0.0653)	(0.0626)	(0.0654)	(0.0640)	(0.0654)	(0.0653)
EITI membership	**5.763*** **	**5.361*** **	**5.596*** **	**5.536*** **	**5.676*** **	**5.468*** **	**5.525*** **	**5.403*** **
	(1.408)	**(1.452)**	**(1.363)**	**(1.350)**	**(1.348)**	**(1.431)**	**(1.417)**	**(1.429)**
***de jure* environmental policy x EITI**	**-0.0542*** **	**-0.0471*** **	**-0.0512*** **	**-0.0457*** **	**-0.0512*** **	**-0.0483*** **	**-0.0502*** **	**-0.0478*** **
	(0.0152)	**(0.0152)**	**(0.0143)**	**(0.0142)**	**(0.0144)**	**(0.0149)**	**(0.0148)**	**(0.0151)**
***de facto* environmental policy x EITI**	**-0.474*** **	**-0.475*** **	**-0.468*** **	**-0.495*** **	**-0.495*** **	**-0.495*** **	**-0.482*** **	**-0.482*** **
	(0.0792)	(0.0789)	(0.0786)	(0.0768)	(0.0784)	(0.0776)	(0.0791)	(0.0789)
GDP per capita (log)	2.025	1.955	2.085	1.720	1.734	1.854	1.919	1.930
	(1.395)	(1.398)	(1.390)	(1.387)	(1.394)	(1.390)	(1.397)	(1.396)
GDP per capita square (log)	-0.153*	-0.145	-0.162*	-0.136	-0.135	-0.142	-0.146	-0.146
	(0.0918)	(0.0919)	(0.0915)	(0.0911)	(0.0917)	(0.0914)	(0.0917)	(0.0918)
Population density	0.000852	0.000792	0.000602	0.00147	0.00150	0.00120	0.00123	0.00122
	(0.00174)	(0.00176)	(0.00172)	(0.00159)	(0.00169)	(0.00165)	(0.00175)	(0.00174)
FDI	-0.00644*	-0.00619*	-0.00666*	-0.00640*	-0.00637*	-0.00633*	-0.00634*	-0.00626*
	(0.00340)	(0.00340)	(0.00340)	(0.00339)	(0.00340)	(0.00339)	(0.00340)	(0.00340)
Control of corruption	0.0766	0.0715	0.111	0.0820	0.0483	0.0785	0.0796	0.0688
	(0.150)	(0.150)	(0.152)	(0.148)	(0.151)	(0.149)	(0.152)	(0.150)
Forest rents	-0.00690	-0.00741	-0.00801	-0.00574	-0.00549	-0.00845	-0.00655	-0.00628
	(0.0144)	(0.0144)	(0.0144)	(0.0143)	(0.0144)	(0.0143)	(0.0144)	(0.0144)
ϕ	0.0977	-0.0336	0.0423	-0.313	0.0308	-0.155	0.0512	0.00288
	(0.251)	(0.316)	(0.254)	(0.277)	(0.278)	(0.305)	(0.259)	(0.314)
λ	-0.0728	-0.0694	-0.0726	-0.0649	-0.0651	-0.0625	-0.0711	-0.0702
	(0.0877)	(0.0882)	(0.0879)	(0.0880)	(0.0875)	(0.0888)	(0.0880)	(0.0880)
σ_μ	1.563***	1.597***	1.517***	1.462***	1.497***	1.514***	1.602***	1.609***
	(0.212)	(0.210)	(0.205)	(0.194)	(0.202)	(0.198)	(0.212)	(0.212)
σ_e	0.624***	0.624***	0.624***	0.624***	0.624***	0.624***	0.624***	0.624***
	(0.0188)	(0.0188)	(0.0188)	(0.0188)	(0.0188)	(0.0188)	(0.0188)	(0.0188)
AMU	-1.375							
	(1.316)							
COMESA		0.535						
		(0.775)						
ECCAS			1.199*					
			(0.666)					
ECOWAS				-1.484***				
				(0.493)				
SADC					1.324**			
					(0.634)			
UEMOA						-1.588**		
						(0.687)		
CEMAC							0.426	
							(0.855)	
WAMZ								-0.422
								(1.016)
Constant	-6.980	-6.698	-7.252	-4.925	-6.384	-5.597	-6.401	-6.310
	(5.327)	(5.338)	(5.319)	(5.281)	(5.285)	(5.300)	(5.336)	(5.350)
# Observations	595	595	595	595	595	595	595	595
Number of countries	35	35	35	35	35	35	35	35
Log likelihood	-646.0	-646.3	-645.0	-643.5	-644.4	-644.3	-646.4	-646.5

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ We estimate the same equation from column (1) to (8), controlling respectively AMU, COMESA, ECCAS, ECOWAS, SADC, WAEMU, CEMAC and WAMZ.