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Can Resource-backed Loans Mitigate Climate Change ?

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Abstract

Resource-backed loans are used today by many resource-rich countries as an effective means of providing public goods and services. However, this type of financing can undermine environmental sustainability (e.g., forest cover loss, CO2 emissions, pollution, ecological collapse, material footprint, etc.). In this paper, we first use propensity score matching, which allows for self-selection bias in signature policies, coarsened exact matching, and the entropy balancing method to test whether resource-backed loans have a causal impact on forest cover loss in 64 developing countries from 2004 to 2018. Through a series of econometric and alternative specification tests, we find that resource-backed loans increase forest cover loss. Nevertheless, when we disaggregate resource-backed loans to run the regressions, we find that mineral, tobacco, and cocoa-backed loans increase forest cover, while oil- backed loans have no significant direct impact on forest cover. We recommend that signatory countries and those considering signing resource-backed loans put in place a very strong compensation mechanism, such as introducing taxes or reforming the current tax system in resource-backed loan agreements, to protect biodiversity and mitigate the environmental impacts of these loans. Signatory countries must ensure full transparency of resource-backed loans to make the characteristics of the loans more fluid, avoiding a situation of budgetary debauchery.

Keywords : • Resource-backed loans • Resource rents • Forest cover loss • Resource taxation • Environment • Climate Change • Propensity score matching.
JEL Codes : O13, H81, C12, Q54, Q01.

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1 Introduction

Etymologically, natural capital includes the stocks of natural resources, land, and ecosystems that are essential for the sustainability of economic development (Bank, 2005) and poverty reduction in developing countries (Celentano et al., 2012 ; Wunder, 2001). Several countries have developed thanks to the exploitation and transformation of their natural capital wealth (Halland et al., 2016). Today, many developing countries are using their original endowment of natural capital in the form of oil, gas, minerals, etc. To access the financial market and obtain funds for their economic development goals. On this occasion, some countries in sub-Saharan Africa and Latin America have turned to a new type of financing called resource-backed loans market to circumvent the difficulties of accessing markets and raising funds to finance public goods and services (Mihalyi et al., 2022).

Basically, resource-backed loans are financings provided to a government or public enterprise, with repayment either directly in the form of natural resources (in kind), such as Oil or minerals, or from revenues generated by those resources, or repayment is secured by future revenues related to the natural resources, or the reserves of the natural resources serve as collateral for the loan (Mihalyi et al., 2020, 2022).

As these loans depend on natural resources, this may increase countries' dependence on natural resources. However, heavy dependence on natural resources can lead to serious environmental problems (Combes et al., 2018). Indeed, the literature has shown that natural resource exploitation and economic activities through mining and gas rents (Kinda and Thiombiano, 2021), access to domestic credit (Combes et al., 2018), public debt (Culas, 2006) exert strong pressure on the environment through land conversion, climate change, deforestation, and biodiversity loss. Statistically, the mining industry in Carajas, Brazil, has resulted in an annual deforestation of 6.100 km^2 through the conversion of timber to supply smelters (Kricher, 1999 ; Moran et al., 1994). According to Sonter et al. (2017), mining activities caused 11.67 km^2 of deforestation in the Amazon forest between 2005 and 2015. Global forest change data show that approximately 2032 hectares of forest area were lost between 2004 and 2018, broken down by country and by percentage of tree canopy greater than 20% (Hansen et al., 2013). A recent study by the Food and Agriculture Organization showed that about 420 million hectares of forest have been lost to conversion to other land uses since 1990 (Fao and Unep, 2020). This report shows that the rate of deforestation between 2015 and 2020 was estimated at 10 million hectares per year, compared to 16 million hectares per year in the 1990s. This means that the global primary forest area has decreased by more than 80 million hectares since 1990 (Fao and Unep, 2020).

Moreover, in recent years, these statistics have drawn the attention of governments, interest groups, civil society, and academia to the issue of climate change. Many studies have attempted to examine how macroeconomic variables affect deforestation in developed and developing countries (Holden, 1997 ; Holden et al., 1994 ; Reed, 2019 ; Reed, 2013 ; Kahn and McDonald, 1995 ; Combes et al., 2018 ; Kinda and Thiombiano, 2021 ; Galinato and Galinato, 2016 ; Galinato and Galinato, 2012 ; Keenan et al., 2015 ; Fao and Unep, 2020). Very few authors have addressed the impact of the composition of debt (external and domestic) on deforestation. In fact, the effect of debt on deforestation can differ depending on the type of debt. For example, resource-backed loans with conditions attached to their repayment may encourage governments to overexploit resources in order to meet their obligations as they come due. This could accelerate the rate of natural resource depletion and increase the loss of vegetation cover (deforestation).

In addition, resource-backed loans, especially those backed by minerals, can accelerate the pace of mineral production to meet countries' energy needs, such as the production of electric bacteria. Therefore, resource-backed loans could affect the country's environmental standards by accelerating the deforestation threshold. Another channel through which resource-backed loans can affect deforestation is through the volatility of natural resource costs. This is because resource-backed loans are typically denominated in U.S. dollars, so a collapse in commodity prices increases the face value of these loans and induces borrowing countries to exploit more natural resources to meet loan repayments (Mihalyi et al., 2022). Resource-backed loans are usually invested in large public infrastructure projects such as roads, schools, social housing, water dams, etc., which sometimes require the destruction of forests to implement.

However, these investments made through resource-backed loans could generate additional tax revenues that could be used to finance green projects and improve environmental quality to achieve the Sustainable Development Goals (Coulibaly et al., 2022). Similarly, the countries that take resource-backed loans, especially those in Latin America that benefit from debt relief in favour of the environment, the so-called "debt for nature swaps," tend to focus the repayment of their loans on oil, whose exploration and exploitation does not directly affect forest cover. In fact, the "debt for nature swaps" are intended to reduce pressure on deforestation (Kahn and McDonald, 1995).

Overall, the theoretical impact of natural resource-backed loans on deforestation is ambiguous, which should motivate an estimate of the empirical impact of these loans on forest cover to shed light on the debate over resource-backed loans and global warming. Yet, the emerging literature on the environmental impacts of sovereign debt (Akam et al., 2021 ; Culas, 2003 ; Kahn and McDonald, 1995 Katircioglu and Celebi, 2018 ; Bese, 2021) and the socioeconomic impact of resource-backed loans (Mihalyi et al., 2020 ; 2022 ; Horn et al., 2021 ; Rivetti, 2021) has reported relatively silent on the impact of resource-backed loans on deforestation for African and Latin American economies. This is surprising because the mechanism by which resource-backed loans affect deforestation is different in practical terms from the mechanisms by which other, non-resource-backed loans or debt affect forest cover. Not to mention the extent of deforestation and forest degradation that continues at alarming rates and contributes significantly to ongoing biodiversity loss, global warming, and environmental crises (Fao and Unep, 2020). One possible explanation for this difference is that resource-backed loans force governments to exploit resources, especially land resources. Unlike other credits, there is no implicit pressure or obligation to use force on the forest layer. To our knowledge, there have been four studies of the economic impacts of resource-backed loans, for developing countries (Mihalyi et al., 2020 ; 2022 ; Rivetti, 2021). None of these four examined the impact of resource-backed loans on deforestation in signatory countries. The opacity of resource-backed loans, i.e., the non-transparency of loans, would explain the fact that no previous study has examined impacts on forest cover because resources backed loans are not included in government budget statistics for most signatory countries and therefore may not reflect actual published statistics.

For all the above reasons, this paper fills an important gap in both the literature on the socioeconomic impacts of resource-backed loans and the literature on the determinants of natural capital, particularly forest cover, as it is, to our knowledge, the first paper to estimate the impact of resource-backed loans on deforestation for a panel of two regions of the world (sub-Saharan Africa and Latin America). Particular attention is paid to the environmental impacts of resource-backed loans in order to enrich the policy debate on climate change and natural resource exploitation. In other words, resource-backed loans is a form of external credit or man-made capital, and increased access to it is a means to increase the stock of man-made capital (Combes et al., 2018). Thus, our research question is : **Does increased access to man-made capital through the provision of external credit (resource-backed loans) lead to increased or decreased use of natural capital ?**

Contrary to Combes et al. (2018) and Antle et al. (2006), our intuition is that resource-backed loans may not have a homogeneous impact because of their composition [1] may not have a more homogeneous impact on forest cover than domestic credit and public spending (Combes et al., 2018) and public debt (Culas, 2003). Deforestation is the subject of a large literature. The topic has been the subject of a major debate in economics since the mid-1980s, in which two paradigms confronted each other. The first dealt with the relationship between economic growth and the environment using Kuznets' environmental curves, while the second focused on explanations for deforestation. Although these issues have been extensively studied from an empirical perspective (Angelsen, 1999 ; Bhattarai and Hammig, 2001 ; Van and Azomahou, 2007), no consensus has yet emerged. In light of the existing literature, our work examines the impact of resource-backed loans on the

1. The official report of the Natural Resource Governance Institute (NRGI) shows that there are now 52 resource-backed loans, composed of 43 credits backed by oil, 6 by minerals, 2 by cocoa, and 1 by tobacco.

environment through deforestation.

The contribution of this study to the literature is twofold. First, we add to the literature on efficient use of natural resources and deforestation (Perman et al., 2003 ; Makunga and Misana, 2017 ; Allen and Barnes, 1985 ; Dove, 1993 ; Bese, 2021 Bojang et al., 2011 ; Njoroge et al., 2011 ; Motel et al., 2009 ; Delacote and Angelsen, 2015 ; Combes et al., 2018 ; Combes et al., 2015 ; Kinda and Thiombiano, 2021 ; Culas, 2003 ; Ranjan, 2019, etc.), focusing on environmental compliance and the clean development model. Second, we focus specifically on resource-backed loans, as its impact on borrowing countries' economies in particular and on climate change in general has been largely unexplored. To this end, we specifically address the link between resource-backed loans and deforestation, which to our knowledge has never been studied. We are the first to examine the impact of this type of loans on vegetation cover in a context of climate change that is so troubling for all countries in the world. Therefore, identifying the transmission channels of deforestation-backed loans is critical to enrich and guide policy discussions on this issue.

Our results first suggest that natural resource-backed loans exert high pressure on forest cover, i.e., significantly increase deforestation in countries that have taken these loans compared to those that have not (i), using a propensity score matching (PSM) method. (ii) when we disaggregate resource-backed loans to run the regressions, we find that mineral, tobacco, and cocoa-backed loans increase forest cover, while oil- backed loans have no significant direct impact on forest cover. (iii) By exploring the transmission channels, our results show that public debt, natural resource depletion, and commodity prices have a positive and statistically significant effect on forest cover loss in signatory countries. (iv) The results also suggest that resource-backed loans have a positive and statistically significant effect on forest cover loss in signatory Sub-Saharan African countries, in contrast to Latin American countries where no significant effect was found.

The rest of the paper is structured as follows. Section 2 presents the stylized facts and the review of the existing literature on the subject is presented in Section 3. Then, Section 4 describes the methodology with successively a presentation of data and the empirical identification strategy used to estimate the impact of natural resource-backed loans on deforestation. The results are presented in Section 5 while in Section 6 we study the sensitivity and heterogeneity of these results respectively. Section 7 presents the transmission channels. Finally, Section 8 concludes the study and presents key policy recommendations from the findings.

2 Stylized facts

In this section, we present some stylized facts that characterize resource-backed loans, natural resource deposits, and the extent of deforestation in developing countries from 2004 to 2018.

2.1 Resource-backed loans

Historically, resource-backed loans has been around since the resource boom of the early millennium. The idea was to facilitate access to financial markets for resource-rich developing countries that had difficulty obtaining financing for economic development. In the 1980s, only Angola had shown interest in this type of financing to fund its military expenditures. Today, it is clear that this type of financing has attracted the attention of several developing countries. According to the NRGI report, there are 52 resource-backed loans in two regions [2] of the world (see Figure 3).

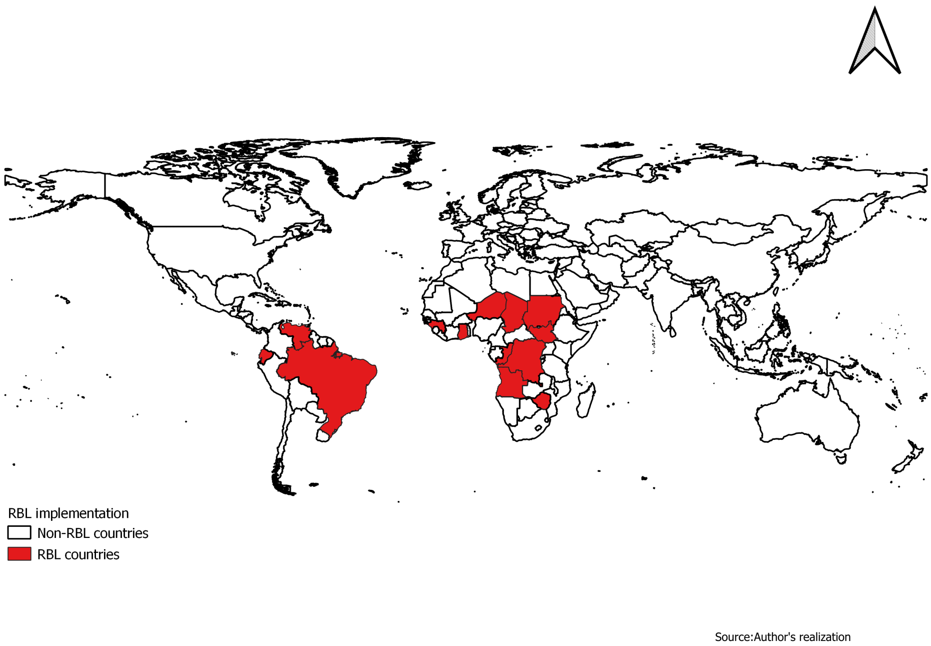


FIGURE 1 – **Location of countries signatories to RBL in the world.**

In addition, 30 of the 52 resource-backed loans identified in developing countries during 2004-2018 went to African countries, while the remaining 22 went to Latin American countries (Mihalyi et al., 2020). A total of 14 countries [3] in these two regions have subscribed to these loans totaling \$164 million, including \$98 million for Latin American countries and \$66 million for Sub-Saharan African countries (Mihalyi et al. ; 2020 ; 2022). The NRGI report indicates that the largest beneficiary of these loans is Guinea Conakry, which subscribed \$200 million in 2017, backed by bauxite. This amount was equivalent to about 200% of the country's GDP at that time (Mihalyi et al., 2020). The country has used this large sum to build multi-sectoral infrastructure, including the Coyah-Dabola road, the Conakry road network and sanitation, and university buildings. It should be

2. Sub-Saharan Africa and Latin America
3. These 14 countries are : Angola, Brazil, Chad, Democratic Republic of Congo, Ecuador, Ghana, Guinea, Niger, Republic of Congo, Sao Tome and Principe, Sudan, South Sudan, Venezuela and Zimbabwe (for more details, see Mihalyi et al., 2020 ; 2022 and Coulibaly et al., 2022).

noted that most of these resource-backed loans were provided by China. In fact, China is the leader in terms of market share due to its unconditional aid policy and donations to developing countries. Following the signing of the $20 million agreement, China and the Guinean state agreed to disburse the sum gradually between 2017 and 2036, in return for which Guinea will grant mining concessions to Chinese companies. The Chinese companies that receive mining concessions and agreements will help repay this large financing programme for Guinea, according to the Guinea EITI [4] 2017.

The second largest recipient of resource-backed loans in Africa is the Republic of Congo, with a total of $1.6 million in 2006, representing 20.7% of the country's GDP at the time. This amount was used for the implementation of infrastructure, the repayment of which must be made over a period of 20 years with oil (Mihalyi et al., 2020). Besides these two countries, the Democratic Republic of Congo is the third largest beneficiary. The country has subscribed resource-backed loans with China amounting to 3.000 million dollars or about 16% of its GDP in 2008. The repayment of this sum must be made through the exploitation and sale of copper & cobalt. In Latin America, Venezuela is the largest beneficiary with a contribution of 23.3% of GDP in the period 2004 to 2018. The country signed its largest agreement in 2010 for an amount of 20255 million dollars, equivalent to about 7% of its GDP in that year. This amount of money was used to implement major projects. These include the financing of infrastructures : electricity, heavy industry, housing, agricultural projects, 6 million dollars at the discretion of Venezuela ; associated with the construction of highways and power plants (Mihalyi et al., 2020). In conclusion, Ecuador and Brazil are behind Venezuela with a share of 15% and 1.4% of GDP, respectively, in the period 2004-2018.

Unlike African countries, all Latin American countries have linked their loan payments to oil. It should be noted, however, that non-oil-backed loans taken out during 2004-2018 are higher than oil-backed loans (see Table 1).

TABLE 1 – The share of resources used in repayment agreements in total resource-backed loans over the period 2004-2018.

	Resource-backed loans signed by Minerals, Tobacco and Cocoa	Resource-backed loans signed by Oil	Total
The share of resource-backed loans in GDP	227%	185%	412%
	or about 55% of total GDP	or about 45% of total GDP	

Source : Author's calculation based on NRGI, Mihalyi et al. (2020) dataset.

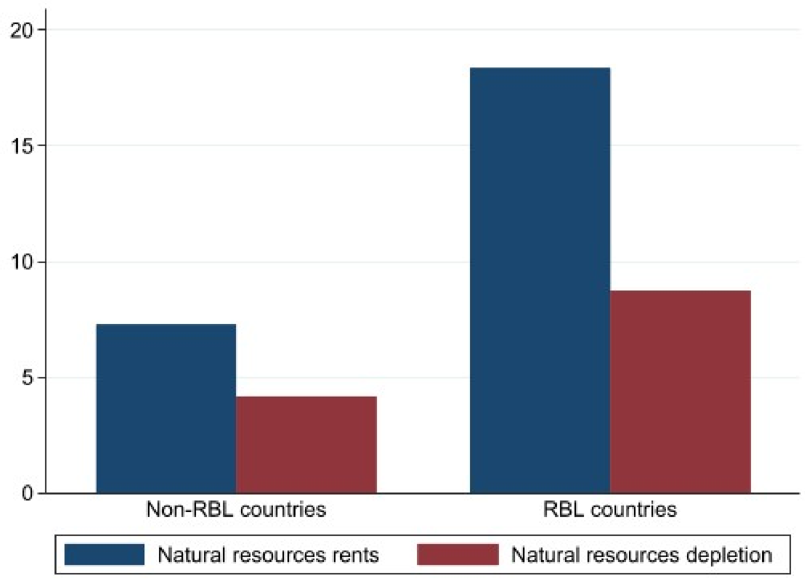
4. Extractive Industries Transparency Initiative report (see :https://www.reuters.com/article/us-guinea-mining-china/china-to-loan-guinea-20-billion-to-secure-aluminium-ore-idUSKCN1BH1YT)

Our intuition in this paper is that resource-backed loans will not only accelerate resource depletion, but can also degrade vegetation cover. Therefore, it would be detrimental to look at the evolution of natural resource rent mobilization, resource depletion, and the deforestation variable over time.

2.2 Resource-backed loans, rents, natural resources depletion and loss forest cover.

We therefore examine natural resource rent capture and natural resource extraction for countries with resource-backed loans versus countries without resource-backed loans over the period 2004 to 2018. Figure 2 shows that the rate of natural resource depletion is higher in countries with resource-backed loans than in countries without resource-backed loans (twice). Countries that have taken a resource-backed loan have, on average, a resource depletion rate of 8.74% of GNI in contrast to countries that have not taken a loan, which have, on average, only 4.18% of GNI during 2004-2018 (see Figure 2). As for the total rent, it is very high in the subscribing countries, averaging about 18% of GDP compared to 7% of GDP in the non-subscribing countries. Similar to Figure 3, forest loss is higher in signatory countries than in non-signatory countries.

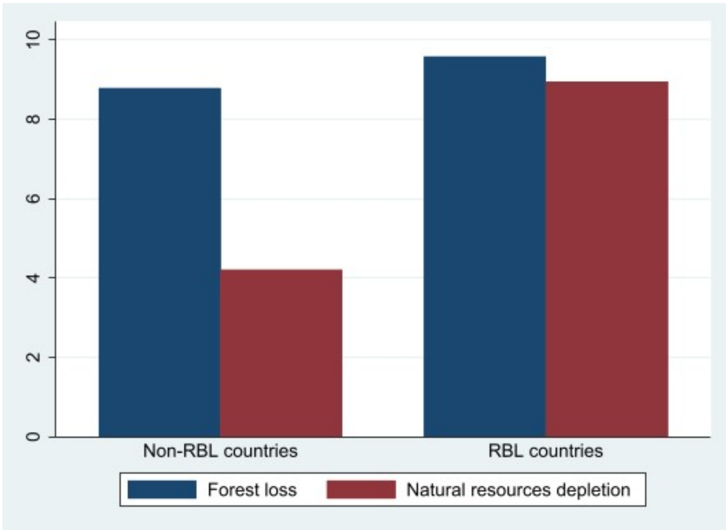
FIGURE 2 – **Average of natural resource rent and resource depletion.**



Source : Author's construction

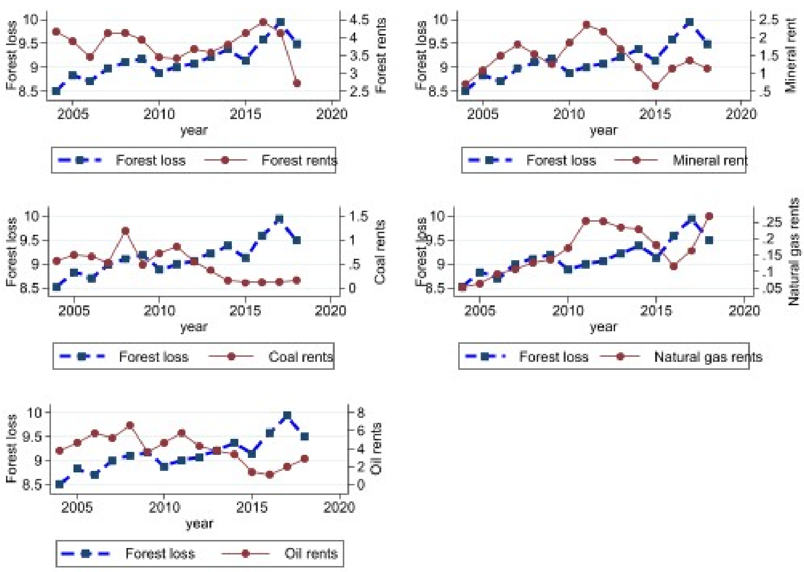
This observation suggests that resource-backed loans are associated with greater resource exploitation. Since we have illustrative evidence that resource-backed loans are likely to be associated with greater resource exploitation, we examine the extent of deforestation in countries with resource-backed loans and in countries without resource-backed loans agreements. As shown in Figure 2, pressure on forest cover is greater in countries with resource-backed loans than in countries without resource-backed loans from 2004 to 2018. In Figure 4, we highlight rents and forest loss.

FIGURE 3 – **Average of forest loss and natural resources.**



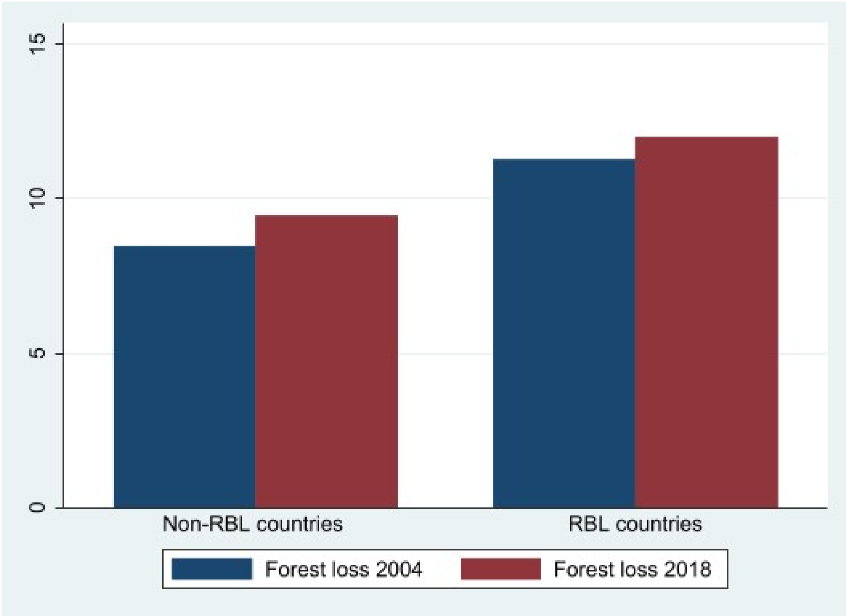
Source : Author's construction

FIGURE 4 – **Average of resources rents and forest cover loss.**



Source : Author's construction

Figure 5 – **Average trend of forest cover loss from 2004 to 2018.**



Source : Author's construction

3 Related literature

The literature on the macroeconomic impacts of resource-backed loans is nascent and short (Mihalyi et al., 2020 ; 2022 ; Rivetti, 2021; Coulibaly et al., 2022), and that on deforestation is nonexistent. To do so, we link our literature to two channels through which resource-backed loans could affect forest cover, namely the handful of studies that estimate the effects of external debt and public spending, resource rents on deforestation.

3.1 Public debt, resource-backed loans and forest cover.

We begin the discussion by asking how resource-backed loans affect deforestation through the external debt channel, since these loans are a special type of external debt. Culas (2006) estimated the relationship between debt and deforestation through a cross-country regression analysis using a set of panel data from 23 African countries between 1971 and 1994, and the results show that debt and deforestation are positively related in tropical developing countries. The author recommends reducing the debt burden of developing countries to expand opportunities for better environmental governance. These findings are consistent with those of Shandra et al. (2008), which used a cross-country model to estimate the impact of debt on deforestation in 62 countries from 1990 to 2005. These authors find that debt and structural adjustment increase deforestation. However, the increasing number and density of international nongovernmental organisations is reducing deforestation.

In the same vein, Gullison and Losos (1993) examined the role of foreign debt in deforestation in Latin America. They found that external debt has contributed to economic stagnation and an associated increase in poverty in Latin America, which in turn has led to degradation of marginal lands affecting forest cover. The authors suggest that debt could be exchanged for forestry [5] and agricultural sector reform, which would have a very positive impact on forest conservation and management. Using instrumental variable methods, Lawell et al. (2018) estimates the global relationship between income and pollution over the period 1980 to 2012. They find that debt service may be correlated with deforestation as countries liquidate natural assets to pay their debts. Boly et al. (2022), however, have found a long-term complementary relationship and a short-term substitution relationship between sovereign debt and the environment. The authors note that in the short run, government debt generates new resources that can be invested in mitigating activities, improving the quality of the environment [6]. In contrast, the government must pay down the debt burden.

3.2 Public expenditure and forest cover.

Resource-backed loans could help governments increase public spending to finance public goods and services. However, such spending has been shown to have negative environmental consequences. Indeed, an increase in public spending could trigger the clearing of forest land for agricultural production in the short term, which would increase deforestation. Galinato and Galinato (2012) found, using a theoretical model, that increased public spending and the expansion of social safety nets in developing countries significantly affect forest cover. In fact, increased deforestation and carbon dioxide emissions are caused by land use change. These results are consistent with those of Combes et al. (2018), which uses both a theoretical model and the generalized method of moments (GMM) to estimate the impact of public spending and credit on forest cover loss in 63 developing countries during 2001-2012. The results show that public spending has a positive impact on forest cover.

López et al. (2011), however, have modelled the environmental impact of the composition of public spending. The results show that shifting the composition of public spending toward social and public goods reduces pollution. This improves the quality of the environment. Conversely, increasing total public spending without changing its composition does not reduce pollution.

The collapse of commodity prices can be attributed to two consequences of resource-backed loans on the loss of forest cover. First, resource-backed credits may jeopardize public debt situation Horn et al. (2021) and prevent the country from mobilizing fiscal resources to finance public expenditures related to climate change. Second, the loss of

5. e.g., debt-for-nature swaps.
6. e.g financing green projects or low carbon policies.

fiscal revenues due to price rip-offs will increase the face value of the debt as it is denominated in U.S. dollars, forcing countries to increase their exploitation activities to comply with the trade. This will adversely affect forest cover, as activities related to natural resource exploitation and exploration increase forest cover loss in resource-rich countries. To illustrate, Kinda and Thiombiano (2021) conducted a theoretical analysis, supported by empirical evidence, and found an adverse effect of extractive industry rents on forest cover, but pointed out that the effects are not homogeneous depending on the type of rent. They argue that maximizing rents is strongly associated with deforestation and that this can be offset by adopting a «polluter pays» model. Recent impact studies on resource-backed loans, such as. Coulibaly et al. (2022), have shown that resource-backed loans improves debt dynamics over a seven-year period after signing due to the investments made and the tax revenues generated by those investments, which would allow for the financing of public expenditures directed toward green projects related to climate change or investments that meet environmental standards.

4 Data and Methodology

4.1 Data

4.1.1 Resource-backed loans variable

We use information about the existence of a resource-backed loan from NRGI. To date, NRGI remains the only institution that provides reliable and solid evidence on the existence and many details of resource-backed loans in developing countries.

A team of researchers led by Mihalyi, D., Adam, A. and Hwang, J. collected as much information as possible on resource-backed loans to obtain a somewhat larger database. They compiled two original dataset maintained by institutions dedicated to researching China's overseas activities : the China-Africa loans dataset produced by the China-Africa Research Initiative (CARI) at Johns Hopkins SAIS and the China-Latin America financial database of the Inter-American Dialogue and Global Development Policy Center at Boston University (Mihalyi et al., 2020). Next, the authors supplemented these databases with additional literature searches to present their dataset. It should be noted that the data on these resource-backed loans are not fully comprehensive due to the relative opacity of these transactions (Rivetti, 2021). There could certainly be other resource-backed loans in both regions than those listed by the authors as they are limited by publicly available information (Mihalyi et al., 2020). However, it is the most comprehensive dataset on resource-backed loans for African and Latin America economies over a long period. Based on this information, we construct a binary variable that takes the value 1 if country i at a period t has taken out a resource-backed loan and 0 otherwise.

4.1.2 Forest Cover Loss variable

Following Combes et al. (2018) and Kinda and Thiombiano (2021), we use forest cover data from global forest change. The global forest change contains a dataset mainly from the University of Maryland Department of Geographic Sciences and has recently been published and made freely available by Hansen et al. (2013). In this dataset, trees are defined as vegetation over 5 m in height expressed as a percentage per output grid cell as "2000% tree cover". Secondly, "loss of forest cover" is defined as a stand-replacing disturbance, or a change from a forested to a non-forested state. As for the 'Forest Cover Gain' is defined as the inverse of loss, or a non-forest to forest change entirely within the period 2000–2012. And finally, 'Forest Loss Year' is a disaggregation of total 'Forest Loss' to annual time scales (Hansen et al., 2013). Although all of these data based on Landsat satellite imagery published by Hansen et al. (2013) may suffer from potential bias from inaccuracies in distinguishing between forests and plantations at the local level (Tropek et al., 2014), it remains a potentially valuable source of information on forest cover. In contrast to Combes et al. (2018) using a canopy cover >10% and Kinda and Thiombiano (2021), canopy cover >20%, this study considers a forest as any area with more than 25% trees in 2000, thus excluding all areas with a lower percentage of trees. We will use other cover thresholds in the robustness tests to take into account the forest typology.

4.1.3 Matching variables

Following the literature, we select some variables that can affect the level of deforestation (the key drivers). First, we capture the effect of the **credit variable** which is measured by domestic credit provided by the banking sector as a percentage of GDP. It has been shown in the literature that the more credit the private banking sector provides to agents, the more agricultural activities intensify. Consequently, deforestation accelerates the more (Combes et al., 2018 ; Culas, 2003). In the short term, its sign is positive on deforestation. However, in the long term, if income from agricultural activities is reinvested in conservation and environmental protection, it will have a negative effect on deforestation. We control for the effect of **net official development assistance (ODA)**, which includes the disbursement of loans and grants to promote the economic development and well-being of countries and territories[7]. Just like at Kinda and Thiombiano (2021), we expect a negative impact of the net ODA received on the loss of forest cover. Similarly, we control for **gross capital formation, or gross domestic investment**, which consists of expenditures on the acquisition of fixed assets in the economy and net changes in the level of inventories in our model. Secondly, we add **public expenditure** which measures government consumption expenditure as a percentage of GDP. Previous studies have found significant positive impacts on deforestation (Galinato and Galinato, 2016 ; Gupta and

7. Defined by the World Bank in the context of the construction of the ODA variable in the dataset

Barman, 2009 ; López et al., 2011 ; Combes et al., 2018 ; Kinda and Thiombiano, 2021). In our study we expect a positive effect on deforestation.

The effect of **natural resource rents** are controlled. This variable measures the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents as percent of GDP. Kinda and Thiombiano (2021), in their recent study they found a significant positive effect of resource rents, excluding forest rents, on deforestation. We believe that its sign on deforestation will be positive in our study.

Finally, we capture the effect of **natural resource depletion**, which is the sum of net forest depletion, energy depletion, and mineral depletion [8]. Its sign on deforestation is ambiguous because it depends on the level of depletion of natural resources.

4.2 Methodology

4.2.1 Identification strategy

In this study, we investigate whether signing a resource-backed loan has led to significant loss of forest cover. To do this, we need to compare the level of deforestation in countries that have signed up to resource-backed loans against non-signatories. This allows us to see more clearly the causal impact of resource-backed loans. Indeed, this comparison can be affected by a selection bias. Furthermore, treated and untreated individuals are not identical and their differences, in addition to being treated, may act as confounding factors if they impact their deforestation level.

In addition, the outcome of treated and control individuals may differ even in the absence of treatment. Table 2 below shows a simple comparison of our covariates by treatment group (treated and untreated). A clear difference is observed between the different units treated at the level of our covariates due, for example, to the macroeconomic conditions of the countries, thus leading to an endogeneity problem that may bias our conclusions. We solve this endogeneity by using a matching technique.

4.2.2 Propensity score matching

We follow the impact assessment methodology, which consists of assessing the average treatment effect on treated persons (ATT) proposed by Rosenbaum and Rubin (1983). Indeed, the PSM is a two-step process : first, using a probit model, we generate for each country a propensity score p(x), which estimates the probability that this country, with its vector of characteristics, will take out a resource-backed loan. Thus :

8. Net forest depletion is unit resource rents times the excess of round wood harvest over natural growth. However, Energy depletion is the ratio of the value of the stock of energy resources to the remaining reserve lifetime. About Mineral depletion, it's the ratio of the value of the stock of mineral resources to the remaining reserve lifetime (see World Bank definition for more details).

Table 2 – Characteristic of treatment and control groups

Variables	[1] Mean in treated	[2] Mean in Untreated	[3]=[2]-[1] Difference
Natural resources depletion	10,74	4,35	-6,39***
Natural resources rents	18,77	7,92	-10,85***
Log GFC	3,15	3,09	-0,06
Log Credit	2,6	2,9	0,3***
Expenditure	14,72	14,18	-0,54
Oda	3,41	5,2	1,79***

Note : In this table of matching covariates, country-year observations where an resource-backed loans exists (the treatment group) are in column [1] and country-year observations where no resource-backed loans exists (the potential control group) are in column [2]. Column [3] reports the differences in means between the treatment and control groups. *** p<0.01, ** p<0.05, * p<0.1

$$\text{p}(X)=\Pr(T=1|X)=\text{E}(T/X)$$

Where, T= {0 ;1} is the binary variable indicating whether the country has signed a resource-backed loan and X is the vector of observed characteristics before treatment. Table 3 reports the main descriptive statistics of the variables used for matching.

Table 3 – Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variable					
Log Forest loss	890	8.987	3.261	0	15.498
Treatment variable					
Resource-backed loans	960	0.139	0.346	0	1
Control variables					
Log Credit	932	2.891	0.905	-4.903	4.666
Oda	946	5.852	7.74	-2.313	92.141
Log GFC	811	3.093	0.398	0.422	4.375
Expenditure	800	14.135	5.975	2.047	79.169
Natural resources rents	947	9.426	10.573	0	62.697
Natural resources depletion	922	5.136	8.393	0	71.291

Second, we assess the impact of resource-backed loans by estimating the average treatment effect on treated countries (ATT), expressed as follows :

$$ATT=E[(Y_{i_1}-Y_{i_0})|T_i=1]=E[(Y_{i_1}|T_i=1)]-E[(Y_{i_0}|T_i=1)] \tag{1}$$

Ti (treatment) is a dummy variable or RBL equal to 1 for country i that has a resource-backed loan, and zero otherwise. Y_{i_1} captures the forest loss when the country signed an resource-backed loan, and Y_{i_0} is the forest loss that would have been observed if the country had not signed an resource-backed loan. The problem is that we cannot observe Y_{i_1} and Y_{i_0} simultaneously. Here, there is a counterfactual problem that arises.

One solution would be to compare average deforestation levels between signatory and non-signatory countries to get around this difficulty. However, this approach assumes that the allocation of treatment is random. Then, the assumption would be ad hoc because the choice to contract an resource-backed loan may be dictated by some omitted variables (macroeconomic situation, good governance, degree of vulnerability to exogenous shocks etc.) that also affect forest cover loss, which would lead to a self-selection bias. For this purpose, Rosenbaum and Rubin (1983) and Smith and Todd (2005) propose to replace in Equation 1 the unobservable term $E[(Y_{i_0}|T_{i_1})]$ by the observable term $E[(Y_{i_0}|T_{i_0}, Xi)]$ to satisfy the conditional independence assumption. This gives us the following equation :

$$ATT{=}E[(Y_{i_1}|RBL_i{=}1, X_i)] - E[(Y_{i_0}|RBL_i{=}0, X_i)] \tag{2}$$

A second assumption based on the existence of a common support, also called the overlap condition, must be verified (0 < p(X) <1). This hypothesis assumes that for each treated country, there is at least one comparable untreated country with a fairly similar propensity score. We finally obtain the following equation :

$$ATT{=}E[E\{Y_{i_1}|RBL_i{=}1, p(X_i)\} - E[(Y_{i_0}|RBL_i{=}0, p(X_i))] \tag{3}$$

4.2.3 Selection of matching algorithms

In practice, treated countries are matched to untreated countries according to their propensity scores using different matching methods and the ATT is the difference in deforestation level results between treated and untreated countries matched on similar propensity score criteria. It is also possible to match each treated country with more than one control country. Thus, we match each treated country with the two and then the three closest neighbours in terms of propensity score. However, it should be noted that with this method, it's possible for a treated country to be matched with one or more control countries with a very distant propensity score leading to a poor match and potentially biased results. Dehejia and Wahba (2002) proposed a radius calibre matching method to resolve this bias. This method consists of matching each treated country with all control countries that are within a well-defined neighbourhood threshold, called a caliper. In our study, we use a low $(\mathbf{r} = \mathbf{0.005})$, medium $(\mathbf{r} = \mathbf{0.05})$ and high $(\mathbf{r} = \mathbf{0.01})$ calibre. Finally, we use two last algorithms : kernel matching and local regression matching. The first associates each treated unit with a counterfactual equal to the average of all untreated

TABLE 4 – Estimation of the propensity score

Dependent variable : RBL	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Log Credit	-0.0143	-0.0604	-0.0651	0.0385	-0.0192	0.0659	-0.0769	0.0482	-0.0123
	(0.1004)	(0.1017)	(0.1066)	(0.1104)	(0.1091)	(0.1092)	(0.0991)	(0.1066)	(0.1030)
Oda	-0.0690***	-0.0809***	-0.0878***	-0.0626***	-0.0515***	-0.0725***	-0.0459***	-0.0737***	-0.0757***
	(0.0165)	(0.0184)	(0.0183)	(0.0172)	(0.0172)	(0.0166)	(0.0161)	(0.0171)	(0.0172)
Log GFC	-0.0373	0.0375	0.0231	0.0207	0.0031	-0.3141*	0.0395	-0.0772	-0.0675
	(0.1573)	(0.1775)	(0.1649)	(0.1690)	(0.1739)	(0.1770)	(0.1589)	(0.1596)	(0.1590)
Expenditure	0.0277***	0.0266**	0.0236*	0.0249**	0.0552***	0.0364***	0.0291***	0.0231**	0.0361***
	(0.0098)	(0.0105)	(0.0124)	(0.0109)	(0.0129)	(0.0106)	(0.0099)	(0.0098)	(0.0113)
Natural resources rents	0.0859***	0.1120***	0.1171***	0.0893***	0.0828***	0.0785***	0.0756***	0.0902***	0.0831***
	(0.0113)	(0.0135)	(0.0139)	(0.0119)	(0.0121)	(0.0118)	(0.0116)	(0.0117)	(0.0114)
Natural resources depletion	-0.0548***	-0.0819***	-0.0885***	-0.0563***	-0.0309**	-0.0532***	-0.0487***	-0.0557***	-0.0518***
	(0.0127)	(0.0157)	(0.0160)	(0.0131)	(0.0140)	(0.0130)	(0.0131)	(0.0131)	(0.0128)
Public Debt		0.0203***							
		(0.0068)							
Log Gdp per capita			-0.0525*						
			(0.0269)						
Public Debt (t-1)				0.0153**					
				(0.0068)					
Log Demographic growth					0.4805***				
					(0.0628)				
Rich countries						0.6382***			
						(0.1787)			
Minerals reserve horizon							0.9162***		
							(0.1876)		
Rainfall shocks								-0.0031***	
								(0.0011)	
Temperature shocks									0.0499**
									(0.0237)
Constant	-1.6774***	-1.8683***	-1.3160**	-2.0737***	-10.3363***	-1.4788**	-1.8996***	-1.3586**	-2.8938***
	(0.5598)	(0.6077)	(0.6166)	(0.5984)	(1.3070)	(0.5744)	(0.5573)	(0.5790)	(0.8100)
Pseudo R2	0.1894	0.2368	0.2325	0.2062	0.3112	0.2103	0.2229	0.2024	0.1968
Observations	776	771	742	722	776	776	761	776	776

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1

units weighted by a weight inversely proportional to their distance from the treated unit considered. The second is a generalised version of the kernel estimator, but the difference is that it includes a linear term in the propensity score of a treated unit (Heckman et al., 1998).

5 Results

This section presents our main results. We present the propensity score estimates in subsection 5.1. Subsection 5.3 then presents the (ATT) estimation results.

5.1 Discussion of propensity scores

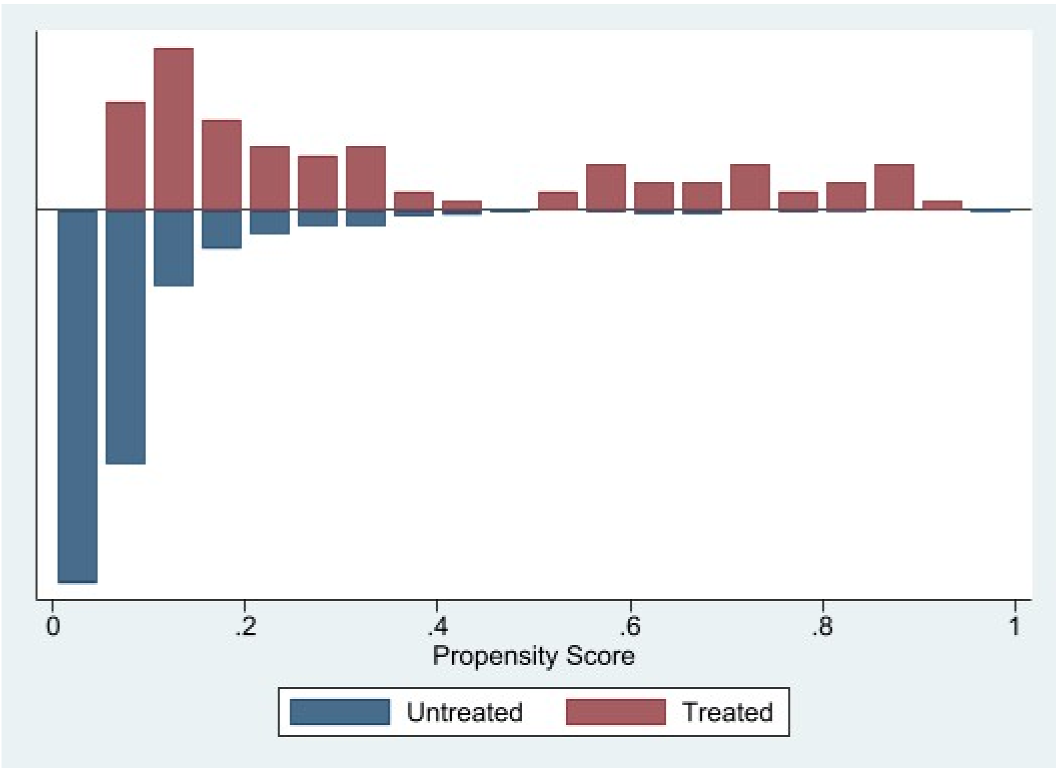
In Table 4, we present the results of the probit model used to predict the propensity scores for the matching algorithms. In column [1], we report the results of our basic model. Net official development assistance and natural resource depletion reduce the probability of a country signing a resource-backed loan. However, natural resources rents and final consumption expenditure are positively correlated with resource-backed loans. The overall regression fit is acceptable with a Pseudo R^2 of 0.1894 for our baseline model.

5.2 Quality of matching

We start checking the quality of our results with probabilities close to 0. Indeed, the Figure 6 shows that most of our treated individuals have a probability very close to 0. It would be very easy to match treated units with low propensity scores but not so easy to match treated units with a high propensity score. Note that there is no consensus in the literature on the best test to judge the effectiveness of this test (Chapel, 2022).

Following Simone and Bazilian (2019), we re-estimate our propensity score only for matched individuals and compare the obtained Pseudo R^2 with the one obtained before the matching process. If the matching worked well, the pseudo R^2 of the probit model with only matched individuals had to be reduced considerably and turned out to be very low. This is the case in our study as we see in Table 5 that it has gone from 0.1894 to almost 0. Some authors rely instead on the standardised bias which calculates the percentage bias on each covariate. The bias must have decreased significantly compared to the pre-matching bias for each covariate, and the closer it is to 0, the more efficient our matching is. Finally, the p-value associated with the standardised bias must be greater than the critical value of 10% (Rosenbaum and Rubin, 1983). This is the case in our study.

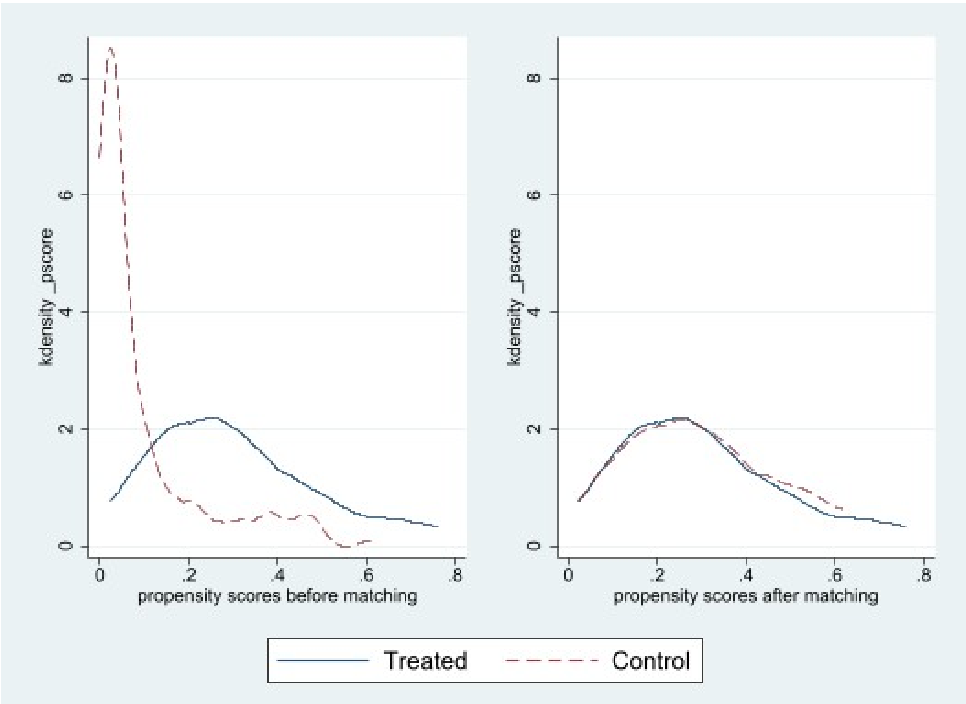
FIGURE 6 – **Graphs of propensity score by treatment status.**



Source : Author's construction

The Figure 7 shows the distributions of estimated propensity score before and after matching (left and right respectively). Before matching, the common support appears to be quite large, but the graph shows that treated units with a high propensity score may not be matched because of the small number of nearby control units. After matching, the distribution of propensity score in the treated and untreated group is similar, which proves that the treated units were indeed matched with untreated units having a similar propensity score in our matches. Given that we have this graphical evidence our results are not matching bias, we can safely move on to analyse the results.

FIGURE 7 – **Common support before and after matching.**



Source : Author's construction

5.3 Matching results

The Table 5 below presents the results of the ATT. The estimated coefficients are all positive and significant, with a magnitude ranging from 1.64 (N-nearest-Neighbors Matching) to 1.41 (Kernel Matching) percentage points. These results indicate that the signing of a resource-backed loan has contributed to increased deforestation in the recipient countries. A simple explanation for these results would be the formal obligations on debtor countries to repay its loan with natural resources. This would push countries to accelerate their resource, which in turn affects forest cover. In addition, infrastructure projects such as the construction of highways, hydroelectric dams, schools, social housing etc. created by resource-backed loans have also contributed to the loss of vegetation cover in the recipient countries.

Another channel is the accumulation effect of loans and the possibility of renegotiating loans in case of difficulty. In fact, the more the country has the possibility of renegotiating the maturity of these loans in a situation of inability to pay, the longer the repayment period increases and the extractive activities continue to intensify. As a result, the loss of forest cover accelerates further.

Table 5 – Average Treatment Effect on Treated (ATT)

Dependent Variable :	1-Nearest Neighbor	2-Nearest Neighbor	3-Nearest Neighbor	Radius Matching			Local lineair regression	Kernel
Log forest loss		Matching		r=0.005	r=0.05	r=0.01	Matching	Matching
Baseline								
ATT	1.6365***	1.5401***	1.4751***	1.5311**	1.4389***	1.6501***	1.3083***	1.4115***
	(0.5976)	(0.5547)	(0.4171)	(0.6206)	(0.3466)	(0.5059)	(0.3645)	(0.4142)
Observations	727	727	727	727	727	727	727	727
Treated	92	92	92	92	92	92	92	92
Untreated	635	635	635	635	635	635	635	635
Matching Quality								
Pseudo-R2	0.010	0.008	0.009	0.087	0.007	0.051	0.010	0.007
Rosenbaum bounds sensitivity test	2.05	2.15	2.5	1.85	2.5	2.1	2.4	2.45
Standardized bias (p-value)	0.860	0.905	0.894	0.014	0.937	0.120	0.860	0.946

Bootstrapped standard errors based on 50 replications in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6 Robustness test

6.1 Modification of sample

The main objective of the theory of clean development is to meet environmental standards. In order to combat illegal and abusive deforestation, several developing countries have introduced restrictions on the export of timber both at national and international level. These bans aim to reduce the export of forest products, which could have a significant effect on the level of deforestation (Burgess et al., 2012 and Resosudarmo et al., 2006). Forest Trends has identified 72 countries in their database that actually restrict or have restricted the international export of one or more forest products. The extent of deforestation in those countries imposing one or more of these measures may differ whether or not it is addressed in our sample. To obtain a homogeneous sample and robust results, we excluded all countries that have adopted export bans on forest products. The results of the ATT are reported in Table 6 row ([2]-[4]). In row [2], we report the results of excluding countries that have adopted forest product export ban. Then we move to the countries that have introduced a domestic natural forest logging ban in row [3]. Finally, in row [4], we exclude countries that have introduced a sawnwood Export Ban. Our results remain robust (see Table 6).

6.2 Adding control variables

After modifying the sample, we also consider increasing the specificity of the baseline model to test the robustness of our results. To do this, we control across several additional variables that are likely to be positively or negatively correlated with both resource-backed loans and forest cover (Table 6, row [5]-[12]). These variables are : public debt, GDP per capita, public debt(t-1), demographic growth, rich countries, Minerals reserve horizon, Rainfall shocks and Temperature shocks. We begin the explanation and discussion of this modification in controlling the effect of the public debt. Indeed, the literature has shown that an unsustainable level of debt leads to a high rate of tropical deforestation mainly through the clearing of forest land for agricultural expansion (Culas, 2003). In fact, heavy external debt can reduce the country's standing in the conventional financial market, pushing it towards China to sign a resource-backed loan agreement (Mihalyi et al., 2020), the repayment of which will require abusive deforestation. The variable GDP per capita measure measures the level of aggregate national wealth created over a period of time per capita. The higher level of GDP can help governments finance their development goals without resorting to resource-backed loans, financing green projects that will have a significant impact on forest cover. However, Its impact on deforestation remain ambiguous according to the literature. Combes et al. (2018) found a positive and significant impact of GDP on deforestation. In contrast Foster and Rosenzweig (2003), in their study on India show that neither the expansion of agricultural productivity nor rising wages have increased local forest cover.

We control for the effect of demographic growth. This variable can have an impact on the horizon and depletion of natural resources, the size of housing and farms. An increase in population fuels demand for arable land, fuel-wood and charcoal (Kinda and Thiombiano, 2021). Secondly, we monitor the effect of natural resource endowments (minerals, gas, oil etc.) on deforestation. In fact, natural resource endowment can easily attract foreign multinationals to rich countries (Manyika et al., 2013). This could accelerate not only resource depletion but also deforestation. This variable is dummy, taking the value of 1 if the country is classified as rich in natural resources and 0 otherwise according to the IMF classification. In addition, the mineral reserve horizon is controlled in our model. Our intuition on this variable is based on the assumption that a long resource horizon leads to long exploitation and keeps the extractive industries going for a long time. This would further increase the loss of forest cover. Mineral reserve is a dummy variable equals 1 if a country's reserve horizon is greater than the median of all mineral-exporting countries, based on BP data.

Finally, we control for the effect of temperature and rainfall shocks which captures the effect of climate variability. These two variables measure the deviation of the average annual rainfall and temperature from its long-term trend (average rainfall and temperature from 1901 to 2021). The data is extracted from the Climate Research Unit (CRU) database of the University of the Orient. Following Combes et al. (2018) and Kinda and Thiombiano (2021), we control for the fact that, for example, high climate variability leads governments to tighten environmental standards which can reduce deforestation. According to Kinda and Thiombiano (2021), countries with lower levels of precipitation are often at risk of extreme weather. This is detrimental to vegetation in general, and to plants in particular, leading to a loss of forest cover.

We report the results of the propensity score in Table 4 (column [2]-[9]). The results corroborate most of our hypotheses. The public debt, public debt(t-1), demographic growth, Rich countries, Minerals reserve horizon and temperature shocks are positively correlated with resource-backed loans. However, GDP per capita and rainfall shocks are negatively affected by the probability of signing a resource-backed loan. The results of the ATT are reported in Table 6 (row [5]-[12]). The new coefficients remain qualitatively and quantitatively comparable to the results of the baseline model (see Table 5).

Table 6 – Robustness of ATTs with the use of additional control variables.

Dependent Variable :	1-Nearest Neighbor	2-Nearest Neighbor	3-Nearest Neighbor	Radius Matching			Local lineair regression	Kernel
Log forest loss		Matching		r=0.005	r=0.05	r=0.01	Matching	Matching
Baseline								
[1]ATT	1.6365***	1.5401***	1.4751***	1.5311*	1.4389***	1.6501***	1.3083***	1.4115***
	(0.5976)	(0.5547)	(0.4171)	(0.6206)	(0.3466)	(0.5059)	(0.3645)	(0.4142)
Observations	727	727	727	727	727	727	727	727
Treated	92	92	92	92	92	92	92	92
Untreated	635	635	635	635	635	635	635	635
			Excliding countries with					
[2] Forest froduct export ban	1.5163*	1.3467	1.7255***	-0.4744	0.2052	-0.7595	1.5428*	0.2513
	(0.8998)	(0.9406)	(0.6268)	(2.1421)	(0.9534)	(1.2426)	(0.6122)	(1.040)
[3] Domestic natural forest logging ban	1.3958**	1.1740**	1.1624**	0.9939	0.9482*	0.9823*	0.8148*	0.9486**
	(0.6386)	(0.4681)	(0.5081)	(0.8119)	(0.5112)	(0.5916)	(0.4469)	(0.4901)
[4] Sawnwood Export Ban	1.2576**	1.6413*	1.5225***	2.2579***	1.6960***	2.2153**	1.7433***	1.6674***
	(0.6245)	(0.6452)	(0.5010)	(0.7150)	(0.3662)	(0.5922)	(0.4863)	(0.4314)
			Adding control variables					
[5] Adding Public Debt	0.7522*	0.8738**	0.9919*	1.4455*	0.9971***	1.2347***	0.9679***	1.0243***
	(0.4326)	(0.4625)	(0.4174)	(0.5768)	(0.3391)	(0.4635)	(0.3642)	(0.3791)
[6] Adding log Gdp per capita	-0.2629	-0.1359	-0.1354	-0.4148	0.0621	-0.3985	0.0429	0.0393
	(0.3753)	(0.4243)	(0.4568)	(0.5729)	(0.3078)	(0.4357)	(0.3755)	(0.2978)
[7] Adding Public Debt (t-1)	0.8751*	1.0943*	1.2164**	1.1915*	1.3042***	1.4021*	1.1982***	1.3113***
	(0.5291)	(0.4612)	(0.5435)	(0.6629)	(0.49135)	(0.5452)	(0.3298)	(0.4933)
[8] Adding Log Demographic growth	-0.1688	-0.2306	-0.1562	-0.3219	-0.0853	-0.2879	0.0109	-0.0330
	(0.5369)	(0.4193)	(0.3909)	(0.5173)	(0.3452)	(0.5034)	(0.3680)	(0.3701)
[9] Adding Rich countries	0.5970	0.9624*	1.0041**	1.0738	1.0988***	1.2087***	1.1038***	1.1111***
	(0.5960)	(0.3989)	(0.4324)	(0.6711)	(0.3300)	(0.4137)	(0.3674)	(0.2824)
[10] Adding Minerals reserve horizon	0.9227*	0.9689*	1.2084***	1.2143**	1.0196***	1.3620*	0.8877***	1.0119***
	(0.4924)	(0.5109)	(0.3836)	(0.6098)	(0.3253)	(0.5274)	(0.3363)	(0.3785)
[11] Adding Rainfall shocks	1.3601***	1.3397*	1.3388***	1.4861*	1.5543***	1.5824***	1.4386***	1.5364***
	(0 .4200)	(0.5585)	(0.3933)	(0.5761)	(0.4351)	(0.4643)	(0.3421)	(0.3864)
[12] Adding Temperature shocks	1.1218**	1.2439***	1.1560***	1.5156*	1.3422***	1.3572***	1.2743***	1.3038***
	(0.4872)	(0.4278)	(0.3945)	(0.6313)	(0.3954)	(0.5130)	(0.3615)	(0.4022)

Bootstrapped standard errors based on 50 replications in parentheses. *** p <0.01, ** p <0.05, * p <0.1

6.3 Alternative matching method

The propensity score estimation technique may not provide robust evidence for our results. Indeed, propensity score matching has been widely criticised in the literature for producing fragile and non-robust estimates that can vary widely depending on the outcome model used (King and Nielsen, 2019). These authors believe that the PSM method may produce biased results if units that are far apart are progressively removed, the equilibrium will eventually deteriorate even if units close to each other on the propensity score remain. To test the robustness of our results and avoid interpretation bias, we use Coarsened Exact Matching as follows (King and Nielsen, 2019). This method compares each unit processed by the nearest control unit in terms of a rough exact match by first expanding the data which consists recoding indistinguishable values with the same values, and then matches the processed and unprocessed units on this expanded data (Iacus et al., 2012). Using this method, our estimated ATTs remain positive with similar magnitudes and significant (Table 7).

TABLE 7 – Robustness of the ATTs with change of matching method.

	Propensity Score	Coarsened Exact
Dependent variable : **Log forest loss**	Matching	Matching
	Baseline	**Robustness**
ATT	1.3083***	1.6072***
	(0.3645)	(0.5515)
Observations	727	960
-Treated	92	183
-Untreated	635	777
Quality of Matching		
Pseudo R2	0.010	0.050

Bootstrapped standard errors based on 50 replications in parentheses. *** p <0.01, ** p <0.05, * p <0.1

Our results are robust when we use Coarsened Exact matching. This matching is better than propensity score matching because all individuals in our sample have the same probability of being matched, so we do not lose any observations after matching. However, our results may suffer from interpretation bias due to the fact that in the regressions for both methods we were unable to control for fixed effects. For this reason, we use yet another matching method more advanced in terms of identification strategy : entropy balancing method. This method was developed by Hainmueller (2012) and implemented a few years later by Neuenkirch and Neumeier (2016), which is done in two simple steps. The first step is based on the calculation of weights that are assigned to the control units (in our case, non-resource backed loans countries). In fact, this step calibrates the unit weights so that the re-weighted treatment and control group satisfies the predefined equilibrium conditions (one advantage of entropy balancing method). In the second step, the weights obtained in the previous step are used in a regression analysis with the treatment variable (resource-backed loan country) as the explanatory variable. Thus, it becomes easy to balance resource-backed loan signatory and non-signatory countries on the basis of observable characteristics also called "twins". Therefore, the average difference in forest cover loss between treated and untreated "twins" countries should be explained by the signing of a resource-backed loan. The literature has identified several advantages of the entropy balancy method but we will not cite them here in this paper (e.g. see, Hainmueller, 2012 and Balima, 2017). However, an advantage that leads us to use this method is that it includes in the second step, individual and time fixed effects to control heterogeneity independently of the treatment (Hainmueller, 2012).

The results are reported in Table B4 in the Appendix. In column [1], we report the results of the baseline regression without adding covariates and fixed effects. Then, from columns ([2]-[4]), we report the results of time and/or individual fixed effects. From columns ([5]-[8]) we add the reference coviaraites presented in the table. Country and time fixed effects are controlled from columns ([6]-[8]).

After controlling for individual and time fixed effects, the coefficients for resource-backed loans are positive and statistically significant except for column [4] and column [8] where the coefficients remain positive but insignificant. These results confirm our baseline finding that resource-backed loans has a positive impact on forest cover loss in signatory countries.

6.4 Alternative canopy thresholds of forest

The literature has identified shortcomings in the measurement of forest cover published by Hansen et al. (2013). For example, Tropek et al. (2014) point out that the classification of high-resolution satellite data based on a single, simplistic algorithm can only provide a limited insight into real forest dynamics at the local scale. Furthermore, the authors believe that the definition of forest given by Hansen et al. (2013) includes any vegetation below 5 m that is considered forest. The inclusion of these vegetation types as forest further biases the estimates of forest cover gain and loss (Tropek et al., 2014). In addition, in the definition developed by Hansen et al. (2013), all areas deforested and converted to plantations are classified as forest before the 2000 year, which leads to an overestimation of the total forest area and biases the definition of forest canopy (Tropek et al., 2014).

For these reasons, we perform a robustness analysis following Combes et al. (2018)

that use narrower definitions of forest cover[9, 10]. We report the results of the ATT in Table 8 with the different algorithms. The observation is that the results do not change substantially, they therefore remain robust when we increase the density of the canopy.

TABLE 8 – Robustness of the ATT with alternative the forest definition

Dependent Variable :	1-Nearest Neighbor	2-Nearest Neighbor	3-Nearest Neighbor		Radius Matching		Local lineair regression	Kernel
Log forest loss		Matching		r=0.005	r=0.05	r=0.01	Matching	Matching
			Panel A : >25% canopy cover					
Baseline : ATT	1.6365***	1.5401***	1.4751***	1.5311*	1.4389***	1.6501***	1.3083***	1.4115***
	(0.5976)	(0.5547)	(0.4171)	(0.6206)	(0.3466)	(0.5059)	(0.3645)	(0.4142)
Observations	727	727	727	727	727	727	727	727
			Panel A : >30% canopy cover					
ATT	0.9011	1.2792*	1.5030***	1.5623*	1.4331***	1.7098***	1.2941***	1.3889***
	(0.6928)	(0.5461)	(0.5444)	(0.6277)	(0.4816)	(0.5980)	(0.4307)	(0.3941)
Observations	722	722	722	722	722	722	722	722
			Panel A : >75% canopy cover					
ATT	1.4538***	1.9148***	1.7643***	2.4374***	1.9863***	2.3103***	1.9090***	1.8884***
	(0.54046)	(0.5271)	(0.4429)	(0.6094)	(0.4126)	(0.6489)	(0.3730)	(0.3928)
Observations	648	648	648	648	648	648	648	648

Bootstrapped standard errors based on 50 replications in parentheses. *** p <0.01, ** p <0.05, * p <0.1

The Table 8 shows two major facts. First, we see clearly that when we increase the threshold for forest cover loss, resource-backed loans have a significant impact on deforestation. Second, the magnitude of resource-backed loans on deforestation is higher when the canopy threshold is higher than 75% (local linear regression).

6.5 Exploring heterogeneity

Many previous studies have attempted to show the negative effect of mining on the environment. For example, Cox et al. (2022) shows that the global metals and mining industry contributes about 8% of the global carbon footprint. The mining of certain minerals such as copper, nickel, lead, zinc, silver, gold, platinum, palladium, aluminium and steel etc. destroys forest cover, yet forests are essential for the sequestration of CO2. However, mining could help countries to accelerate the energy transition process in the context of low carbon apology as the minerals will be used to manufacture the electric bacteria that are much recommended for the energy transition. Therefore, the impact of mining on the environment may differ from that of oil exploitation.

We therefore test whether the impact of resource-backed loans on environmental sustainability, in particular forest cover, is heterogeneous with respect to the type of natural resource used as collateral. The results of the ATTs are reported in Table 9. We find that the impact of mineral, tobacco and cocoa-backed loans is positive and statistically

9. Combes et al. (2018) use a floss >10% in their baseline regression and floss>15% canopy cover, >20% canopy cover, >25% canopy cover, >30% canopy cover, >50% canopy cover and floss>75% canopy cover in robustness.

10. In this study, we chose two canopy densities : 30% and 75% higher thresholds, to distinguish between areas with closed forests and areas with open forests such as pineapple, soybean or tea plantations.

significant at the 1% level (local linear regression, **Panel A**), while no significant impact is found for oil-backed loans on forest cover (**Panel B**).

These results corroborate the literature suggesting that access to extractive industry rents has a heterogeneous impact on forest cover in resource-rich countries (Kinda and Thiombiano, 2021). These results suggest that, while policy makers should be cautious about the environmental impact of resource-backed loans in general, they should in particular avoid borrowing too heavily using loans secured by minerals, tobacco and cocoa. In addition, particular emphasis should be placed on the "polluter pays" principle developed by Arthur Pigou in 1920. This principle implies that pollution taxes or area taxes should be equal to the marginal damage caused (externalities). To this end, policy makers should strengthen tax systems to obtain a fair share of economic rents to improve forest protection and to promote environmental sustainability.

Table 9 – Heterogeneous impacts of resource-backed loans on deforestation by type of resource-backed loans

Dependent Variable :	1-Nearest Neighbor	2-Nearest Neighbor	3-Nearest Neighbor	Radius Matching			Local lineair regression	Kernel
Log forest loss		Matching		r=0.005	r=0.05	r=0.01	Matching	Matching
Panel A : Minerals, tobacco and cocoa backed loans								
ATT	2.4063*	2.4334***	2.4927***	3.1577 ***	3.8842***	3.4395***	2.2840***	3.9391***
	(0.95760)	(0.7331)	(0.7102)	(0.7049)	(0.7357)	(0.7184)	(0.8646)	(0.6661)
Observations	648	648	648	648	648	648	648	648
Treated	13	13	13	13	13	13	13	13
Untreated	635	635	635	635	635	635	635	635
Panel B : Oil backed loans								
ATT	0.2623	0.3202	0.2006	0.4030	0.6063	0.5405	0.5664	0.5527
	(0.6926)	(0.7958)	(0.5444)	(0.7858)	(0.6222)	(0.7408)	(0.6824)	(0.5215)
Observations	690	690	690	690	690	690	690	690
Treated	55	55	55	55	55	55	55	55
Untreated	635	635	635	635	635	635	635	635

Bootstrapped standard errors based on 50 replications in parentheses. *** p <0.01, ** p <0.05, * p <0.1

Table 10 – Heterogeneous impacts of resource-backed loans on deforestation by region

Dependent Variable :	1-Nearest Neighbor	2-Nearest Neighbor	3-Nearest Neighbor	Radius Matching			Local lineair regression	Kernel
Log forest loss		Matching		r=0.005	r=0.05	r=0.01	Matching	Matching
	Panel A : Sub-Saharan Africa							
ATT	1.3155**	0.8258	0.8930	1.0414	1.0580*	0.9849	0.9221**	1.0543**
	(0.6748)	(0.5790)	(0.5643)	(1.0045)	(0.5895)	(0.6077)	(0.5214)	(0.5479)
Observations	475	475	475	475	475	475	475	475
Treated	64	64	64	64	64	64	64	64
Untreated	411	411	411	411	411	411	411	411
	Panel B : Latin America							
ATT	-0.1422	0.4983	0.1485	-0.3283	0.0926	0.4254	0.1980	0.0543
	(1.4070)	(1.0247)	(0.7881)	(1.6414)	(0.9810)	(1.2986)	(1.4866)	(0.8781)
Observations	252	252	252	252	252	252	252	252
Treated	28	28	28	28	28	28	28	28
Untreated	224	224	224	224	224	224	224	224

Bootstrapped standard errors based on 50 replications in parentheses. *** p <0.01, ** p <0.05, * p <0.1

In Table 10, we test for potential heterogeneity that might exist between countries according to their given geographical area. Our treatment group contains three countries in the woolly Americas that have signed at least one resource-backed loan agreement compared to eleven countries in sub-Saharan Africa. Over the years, many conservation policies have been adopted in favour of Latin American countries for forest conservation and protection (e.g., conservation funds to protect the Amazon rain-forest in Brazil in 1992 by The Nature Conservancy).

When we desegregate countries by region, we find that the magnitude of resource-backed loans on forest cover increases in the sub-Saharan African region (Table 10, panel A), while no effect is found in Latin America (Table 10, panel B). Two possible explanations can be drawn from these results. First, the fact that resource-backed loans has no impact on deforestation in Latin America is due to the resources used to repay the loans. Indeed, all Latin American countries have focused their repayment on oil, which does not directly affect the forest, and not on minerals. On the other hand, most mineral-backed loans are signed by sub-Saharan African countries that are destroying forest cover considerably.

Second, all Latin American countries in our sample that have signed a resource-backed loan have benefited from several debt relief programs for nature conservation and conservation funds. With this type of **"debt-for-nature swaps"** program's, when the creditor country grants debt relief to the debtors, the debtor country is obliged to use the funds for forest conservation, protection and reforestation. The beneficiary country then feels compelled to achieve better results in terms of environmental protection and performance in order to benefit more. This would minimise the risk of deforestation (see for instance d Chamon et al., 2022 and Essers et al., 2021). We believe that the **"debt-for-nature swaps"** program's has played a crucial role in the resource-backed loan agreements for Latin American countries. Unlike sub-Saharan African countries, which benefit less from debt relief, their loans are much more heavily weighted towards tobacco and cocoa, which would explain the positive and significant impact in this region (Table 10, local linear regression).

From these results, we encourage not only non-governmental organizations that advocate for the environment to strengthen their actions, help countries in obtaining conservation funds because this allows better environmental management. As for the countries of sub-Saharan Africa, they will have to put in place a very effective mechanism of taxation in the contract of exploitation of extractive industries to compensate for the damage caused by the loans backed on the forest cover.

6.6 Endogeneity treatment

We need to address the econometric problems that can arise when estimating the baseline specification. In fact, the forest loss is likely to be endogenous, due to a forest cover measurement error since the deforestation data we used in this study are satellite estimates of global forest change imagery (Tropek et al., 2014). Furthermore, the literature has emphasised the dynamics of the forest over time such that deforestation can be interpreted as a stationary state (Combes et al., 2018). Taking this dynamic into account gives us the following equation :

$$Lnforestloss_{i_t} = \alpha 0 + \alpha_{i_t} + (1-\beta) lnforestloss_{i_t - 1} + \gamma RBL_{i_t} + X'_{i_t}\delta + \varepsilon_{i_t} \tag{4}$$

Where $Lnforestloss_{i_t}$ is the present value of forest loss in hectares in the country in the year t. α_{i_t} is a country fixed effect and ε_{i_t} is the error term. RBL_{i_t} is our variable of interest. It represents the supply of man-made capital. Indeed, the underlying assumption is that an increase in resource-backed loans leads to more deforestation as they are necessarily repaid with minerals. X'_{i_t} is a vector of control variables used in the basic model.

The presence of the lagged dependent variable among the explanatory variables in Equation 4 creates a dynamic panel bias (Nickell, 1981) because of the correlation between the lagged dependent variable and the error term. dependent variable and the error term. This bias is particularly important for the panel data set with a short time dimension in such circumstances, a panel fixed effects estimator would not be panel estimator would not be appropriate (Roodman, 2006).

We follow the literature on dynamic panel data estimation to solve these endogeneity issues using the system-GMM estimator (Blundell and Bond, 1998). Combes et al. (2018) adopt the same approach using the GMM system to estimate expenditure and credit on forest cover for 12 years of panel data from 63 developing countries over the period 2001-2012. Kinda and Thiombiano (2021) also used this estimator in their study to estimate the effect of extractive industry rents on deforestation for a panel of 52 resource-rich developing countries over the period 2001-2017.

One of the main advantages of the systemic GMM estimator lies in the fact that this estimation technique can instrument other explanatory variables that could potentially be endogenous in addition to the main regressor which is endogenous. From In addition, with the GMM system estimator, it must be ensured that the total number of instruments does not exceed the number of countries to avoid the problem of «instrument proliferation» in the system. The number of countries to avoid the problem of «instrument proliferation» in estimates (Roodman, 2006). We collapse the instruments number to avoid proliferation. We report the results of the GMM estimation in Table 11. The p-values at 5% of AR(1) and AR(2) and the Hansen tests support the validity of our results. In each specification, the lagged dependent variable is positive, significant at 1% and lower than 1 showing there are no fallacious regression. In column 1, we report the results of our basic model. Then we increase the density of our canopy in column 2 and 3 as before (see Table 8).

After endogeneity treatment, the resource-backed loan variable remains statistically significant at the 1% level with a coefficient that remains positive. Indeed, with the GMM estimator, as the canopy threshold increases, the magnitude of resource-backed loans on deforestation decreases but remains significant. Globally, all results can thus be comparable to the ATTs.

TABLE 11 – Panel two-step system GMM estimation results using different canopy cover.

Dependent Variable :	**Baseline**		
Forest loss	>25% canopy cover	>30% canopy cover	>75% canopy cover
	[1]	[2]	[3]
Log forest loss, Lagged	0.661***	0.721***	0.862***
	(0.038)	(0.028)	(0.026)
Resource-backed loans	1.977***	1.483**	0.734*
	(0.651)	(0.602)	(0.437)
Log Credit	-0.440**	-0.415*	-0.481*
	(0.205)	(0.234)	(0.280)
Oda	-0.204***	-0.195***	-0.152***
	(0.028)	(0.033)	(0.029)
Log GFC	-1.917***	-2.317***	-0.800*
	(0.442)	(0.464)	(0.414)
Expenditure	0.003	0.066**	-0.059**
	(0.021)	(0.030)	(0.026)
Natural resources rents	0.223***	0.215***	0.052*
	(0.039)	(0.042)	(0.028)
Natural resources depletion	-0.269***	-0.231***	-0.128***
	(0.050)	(0.049)	(0.034)
Constant	10.398***	10.026***	6.579***
	(1.455)	(1.505)	(0.830)
Number of observations	678	676	596
Number of countries	54	54	50
Number of instruments	39	39	39
AR(1) test, p value	0.000	0.000	0.001
AR(2) test, p value	0.218	0.283	0.183
Hansen, (p-value)	0.120	0.146	0.188

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, GMM-System - Generalized Method of Moments estimator with country fixed effects.The study period is 2004–2018. The lagged Forest Loss is endogenous ; resource-backed loans are strictly exogenous while other variables are considered

TABLE 12 – Panel two-step system GMM estimation results by of resource-backed loans.

Dependent variable : **Log forest loss**	Mineral, tobacco and cocoa backed loans	Oils backed loans
	>25% canopy cover	**>25% canopy cover**
	[1]	[2]
Log forest loss, lagged	0.694***	0.741***
	(0.028)	(0.025)
Resource-backed loans	3.738*	0.809
	(1.917)	(0.678)
Log Credit	-0.287	-0.466**
	(0.180)	(0.230)
Oda	-0.188***	-0.208***
	(0.029)	(0.028)
Log GFC	-1.657***	-2.282***
	(0.380)	(0.430)
Expenditure	0.046	0.067**
	(0.028)	(0.028)
Natural resources rents	0.187***	0.237***
	(0.042)	(0.050)
Natural resources depletion	-0.169***	-0.257***
	(0.045)	(0.058)
Constant	8.264***	10.039***
	(1.070)	(1.446)
Observations	598	640
Number of countries	52	53
Number of instruments	39	39
AR(1) test, p value	0.000	0.000
AR(2) test, p value	0.273	0.139
Hansen, (p-value)	0.186	0.249

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, GMM-System - Generalized Method of Moments estimator with country fixed effects.The study period is 2004–2018. The lagged Forest Loss is endogenous ; resource-backed loans are strictly exogenous while other variables are considered.

7 Transmission channels

7.1 The main channels through which resource-backed loans can affect forest cover

Baseline estimates have shown that resource-backed loans are associated with greater loss of forest cover. We identified two channels that could amplify the effect of resource-backed loans : Over-indebtedness and natural resource depletion. In fact, resource-backed loans are likely to exacerbate debt or even make it unsustainable. While unsustainable public debt significantly limits the government's ability to address climate change and fund environmental action. In addition, resource-backed loans may also accelerate the depletion of natural resources through an increase in material footprint, which puts great pressure on forest cover. This section tests the two identified channels by estimating the impact of resource-backed loans on public debt and natural resources depletion. we re-estimate our baseline model using a simple OLS estimator, and replacing our dependent variable with the potential channel. Results presented in Table B6 in appendix show that signing resource-backed loans increases public debt level by 0.84 percentage points and natural resource depletion by 1.34 percentage points. These results confirm our two main channels and show that the destructive effect of resource-backed loans on forest cover can be triggered by excessive debt and natural resource depletion.

In addition, another indirect channel through which resource-backed loans affects forest cover would be commodity prices. In fact, since resource-backed loans are typically denominated in U.S. dollars, a collapse in commodity prices could increase the face value of these loans and cause borrowing countries to exploit more natural resources to repay their loans (Mihalyi et al., 2020). By way of illustration, the Natural Resource Governance Institute (NRGI) report shows that of the 14 countries that signed resource-backed loans, 10 faced serious debt problems after commodity prices collapsed in 2014 (Mihalyi et al., 2020). As a result, resource-backed loans could put implicit pressure on the country's forest cover. In resource-backed loans contracts, the government can pay less money when commodity prices (or production levels or profits) are low and repay the loan more quickly when conditions are favorable. The idea is to mitigate the volatility of the loans and maintain the debt burden. Indeed, the period of rising commodity prices could lead to a strong expansion of natural resource exploitation, which would be associated with a high risk for the country's forest cover. In fact, the exploitation of natural resources is technically more profitable in times of price increase than in times of price decrease. We check this channel by increasing resource-backed loans with commodity prices from the IMF/World Bank database. Table 13 presents the results. All coefficients are positive and statistically significant (columns [1]-[3]). These results can be explained by the fact that in times of rising prices it is financially profitable to exploit natural resources in order to repay the loans signed. An activity that would cause great damage to the forest cover. In Table 14, we cross-reference desegregated resource-backed loans with commodity prices because resource-backed loans in Table 13 include oil-based loans, which in fact have no significant effect on forest cover (see Table 9). The results show that the signing of a loan backed by minerals, tobacco and cocoa, combined with increased commodity prices, leads to the destruction of forest land in the host countries.

Table 13 – Resource-backed loans, commodity prices and forest cover

	[1]	[2]	[3]
VARIABLES		**Loss forest cover**	
RBL*Commodity term of trade 1	0.0186***		
	(0.0033)		
RBL*Commodity term of trade 2		0.0211***	
		(0.0035)	
RBL*Term of trade (WDI)			0.0079***
			(0.0017)
Constant	8.9328***	8.9163***	8.9697***
	(0.1139)	(0.1139)	(0.1118)
Observations	862	862	877
R-squared	0.0355	0.0400	0.0253

Standard errors in parentheses. *** p <0.01, ** p <0.05, * p <0.1

Table 14 – Commodity prices and minerals,tobacco and cocoa backed loans

	[1]	[2]	[3]
VARIABLES		**Loss forest cover**	
Minerals, tobacco and cocoa backed loans*Term of trade (WDI)	0.0204***		
	(0.0032)		
Minerals, tobacco and cocoa backed loans*Commodity term of trade 1		0.0272***	
		(0.0048)	
Minerals, tobacco and cocoa backed loans*Commodity term of trade 2			0.0219***
			(0.0042)
Constant	4.7644***	4.7909***	4.8066***
	(0.1105)	(0.1131)	(0.1133)
Observations	890	875	875
R-squared	0.0450	0.0357	0.0299

Standard errors in parentheses. *** p <0.01, ** p <0.05, * p <0.1

7.2 Does resource-backed loans mitigate the destabilizing effect of greenhouse gases ?

In this subsection, we examine whether resource-backed loans can harm environmental sustainability by increasing greenhouse gases, or whether they can mitigate climate change by accelerating the energy transition. Resource-backed loans can accelerate the pace of production of minerals, which are essential for making batteries for the energy transition. Similarly, it is possible that tax revenues from investments made with resource-backed loans could be used to fund renewable energy sources and green projects, which can mitigate the effect of greenhouse gases and likely CO2 sequestration. On the other hand, the fact that resource-backed loans are invested in public infrastructure projects such as roads, schools, hospitals, social housing, dams, bridges, etc., may stimulate demand for energy and thus increase greenhouse gas emissions. Table B7 in appendix presents the results. Not surprisingly, the results confirm that resource-backed loans increase greenhouse gas emissions in signatory countries as opposed to non-signatory countries (columns [1]-[4]). We find the same effects when the resource-backed loans are disaggregated and country and the time fixed effects are controlled. These results could be explained by the fact that resource-backed loan borrowing countries tend to accelerate fossil fuel production to meet their resource-backed loan repayment obligations.

8 Concluding remarks

The relationship between man-made capital and natural capital has given rise to a wide-ranging debate, due to the actions to combat climate change , the increase in environmental issues and the phenomenon «curse of natural resources». The literature review, both theoretical and empirical on this topic, is divided into two streams highlighting how man-made capital impacts natural capital. A group of researchers indicates that there is a substituability relationship between artificial capital and natural capital. On the other hand, some researchers find a complementary relationship between these two types of capital. These results show that the relationship between these two types of capital is ambiguous. Building on what has been argued in the literature, this paper estimates the impact of resource-backed loans on forest cover in developing countries. The analysis focuses on the direct and indirect effects of resource-backed loans on forest cover loss, with a focus on comparing these impacts according to the nature of the resource-backed loans. Regressions are run using propensity score matching on panel data and generalized moment methods (GMM). Estimation results indicate that resource-backed loans are associated with increased forest cover loss. While resource-backed loans represent a good opportunity to finance critical development needs, they can also put pressure on borrowing countries to increase the rate of resource production in order to repay the loan, a factor that could affect environmental sustainability. So then, our estimation results support the existence of a complementary relationship between resource-backed loans and natural capital. The main recommendations of this paper suggest that resource-backed loans and especially mineral, tobacco and cocoa backed loans arrangements should combine environmental instruments with economic instruments for the implementation of sustainable development objectives. Signatory countries should include and/or improve tax instruments in resource-backed loans contracts to compensate for environmental damage because any vision of development must fit within planetary limits, in other words, resources must be mobilized to improve human well-being, but without violating the parameters of sustainability (Raworth, 2012 ; 2017). This could be interpreted as proof of Tinbergen rule that at least one policy instrument is needed for each policy objective. The issue of resource-backed loans and climate change is an emerging and topical one, as resource-rich countries have to reconcile the dual objectives of finding resources to finance development without compromising environmental sustainability for a healthy planet. There are many avenues of research to be explored on this subject. Indeed, future research could look at the impact of resource-backed loans on the sustainable development index, which measures the ecological efficiency of human development constructed by Hickel (2020). We intend to explore this avenues of research later.

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Appendix A : Data and Sample

Table A1 – List of developing countries included in the dataset

Sub-Saharan Africa : 42		Latin America and the Caribbean : 22
Angola*	Mozambique	Argentina
Benin	Namibia	**Brazil***
Botswana	**Niger***	Colombia
Cabo Verde	Nigeria	Costa Rica
Cameroon	**Republic of Congo***	Dominica
Central African Republic	Rwanda	Dominican Republic
Chad*	Senegal	**Ecuador***
Comoros	Sierra Leone	El Salvador
Côte d'Ivoire	South Africa	Grenada
Democratic Republic of the Congo*	**South Sudan***	Guyana
Equatorial Guinea	**Sudan***	Haiti
Eswatini	**São Tomé and Príncipe***	Honduras
Ethiopia	Tanzania	Jamaica
Gabon	Togo	Mexico
Ghana*	Uganda	Nicaragua
Guinea*	Zambia	Panama
Guinea-Bissau	**Zimbabwe***	Paraguay
Kenya		Peru
Lesotho		St. Lucia
Liberia		St. Vincent and the Grenadines
Madagascar		Suriname
Malawi		**Venezuela***
Mali		
Mauritania		
Mauritius		

Source : Author's construction based on information from Mihalyi et al. (2022)

Note : Countries marked with * are signatories countries of resource-backed loans (Treatment group) the other countries are non-signatories (control group)

Table A2 – List of resource-backed loans

Country	Loan year	Loans in millions of USD	Resources used	loans country	loans entity	Sectors targeted for investment
Angola	2004	2000	Oil	China	Eximbank	Infrastructure
Angola	2007	500	Oil	China	Eximbank	Infrastructure
Angola	2007	2000	Oil	China	Eximbank	Infrastructure
Angola	2009	2000	Oil	China	Eximbank	Infrastructure
Angola	2010	2500	Oil	China	ICBC	housing
Angola	2015	15000	Oil	China	CDB	Infrastructure
Brazil	2009	1000	Oil	China	CDB	Oil
Brazil	2015	3500	Oil	China	CDB	Oil
Brazil	2015	1500	Oil	China	CDB	Oil
Brazil	2016	5000	Oil	China	CDB	Budget support and debt rollover
Brazil	2017	5000	Oil	China	CDB	Oil
Chad	2013	600	Oil	International	Glencore	Budget support and debt refinancing
Chad	2014	1356	Oil	International	Glencore	Oil
RDC	2008	3000	Copper & Cobalt	China	Eximbank	Infrastructure
RDC	2011	500	Copper	Corée	Korea Exim	Infrastructure
Ecuador	2010	1000	Oil	China	CDB	Infrastructure
Ecuador	2011	2000	Oil	China	CDB	Infrastructure
Ecuador	2012	2000	Oil	China	CDB	Budget support and debt rollover
Ecuador	2015	5296	Oil	China	Eximbank	Infrastructure
Ecuador	2015	1500	Oil	China	CDB	Infrastructure
Ecuador	2016	1500	Oil	China	CDB	Infrastructure
Ecuador	2016	500	Oil	China	CDB	Budget support and debt rollover
Ghana	2011	1500	Oil	China	CDB	Infrastructure
Ghana	2011	1500*	Oil	China	CDB	Infrastructure
Ghana	2018	2000	Bauxite	China	Sinohydro	Infrastructure
Guinea	2017	20000	Bauxite	China	CCC	Infrastructure
Niger	2013	1000*	Oil	China	Eximbank	Oil
Republic of Congo	2006	1600	Oil	China	Eximbank	Infrastructure
Republic of Congo	2011	625	Oil	International	Gunvor	Oil
Republic of Congo	2012	1000	Oil	China	Eximbank	Infrastructure
Republic of Congo	2015	1000	Oil	International	Trafigura	Unknown
Republic of Congo	2015	850	Oil	International	Glencore	Unknown
Sao Tome and Principe	2010	30	Oil	Nigeria	Gouvernement	Oil
South Sudan	2015	75	Oil	International	CNPC	Unknown
South Sudan	2015	1000	Oil	China	Eximbank	Budget support
South Sudan	2016	169	Oil	China	Eximbank	Road
Sudan	2007	3000	Oil	China	Eximbank	Infrastructure
Venezuela	2006	6500	Oil	Russia	Rosneft	Infrastructure
Venezuela	2007	4000	Oil	China	CDB	Infrastructure
Venezuela	2009	4000	Oil	China	CDB	Infrastructure
Venezuela	2010	20255	Oil	China	CDB	Infrastructure
Venezuela	2011	4000	Oil	China	CDB	Infrastructure & Oil
Venezuela	2013	4000	Oil	China	CDB	Oil
Venezuela	2013	5000	Oil	China	CDB	Infrastructure
Venezuela	2014	4000	Oil	China	Eximbank	Infrastructure
Venezuela	2015	5000	Oil	China	CDB	Infrastructure
Venezuela	2016	2200	Oil	China	CDB	Oil
Zimbabwe	2004	110	Tobacco	China	CATIC	Power
Zimbabwe	2006	200	platinum	China	Eximbank	Agricultural
Zimbabwe	2011	98	Diamond	China	Eximbank	Education

Source : Author's construction based on information from Mihalyi et al. (2022)

Note : RBLs marked with * were subsequently cancelled without disbursement.

Appendix B : Data and variable definition

Table B1 – Heterogeneity analysis of the effect of RBL adoption on Forest loss

VARIABLES	[1]	[2]	[3]	[4]	[5]	[6]
RBL	0.5010***	0.5952***	0.8655***	0.8655***	0.4034**	0.8993***
	(0.1410)	(0.1532)	(0.1824)	(0.1824)	(0.1630)	(0.2914)
Pscore		0.2236	0.1794	0.1794	0.2537	0.0537
		(0.3497)	(0.3488)	(0.3488)	(0.3594)	(0.5089)
RBL*ER			-0.8991***			
			(0.3325)			
RBL*FR				-0.8991***		
				(0.3325)		
Government Stability					-0.1035***	
					(0.0245)	
Tax revenue						-0.0394**
						(0.0177)
Constant	8.8861***	9.0632***	9.0556***	9.0556***	10.5287***	9.9852***
	(0.4166)	(0.4377)	(0.4320)	(0.4320)	(0.4930)	(0.5301)
Observations	892	727	727	727	563	423

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

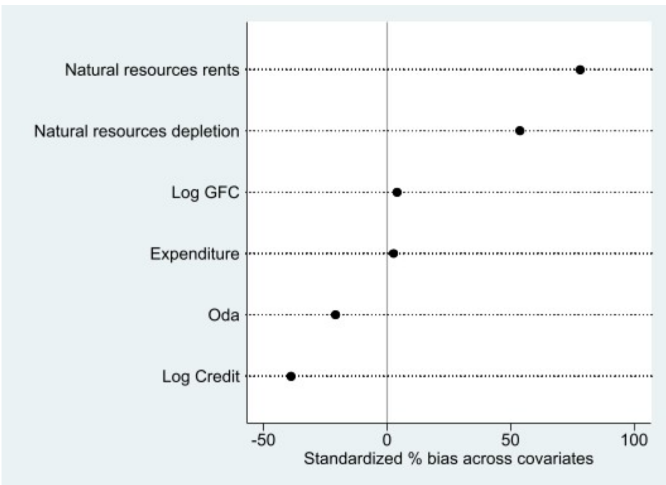

Figure B2 - Standardized percentage before and after matching.

Table B3 – Summary statistics for all variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Dependant variable					
Forest loss	945	118397.46	409805.96	0	5435241
Treatment variable					
Resource-backed loans (RBL)	960	0.139	0.346	0	1
Matching variables					
Credit	932	25.378	20.681	0.007	106.26
Oda	946	5.852	7.74	-2.313	92.141
GFC	818	23.506	9.245	0	79.401
Expenditure	800	14.135	5.975	2.047	79.169
Natural resources depletion	947	9.426	10.573	0	62.697
Natural resources rents	922	5.136	8.393	0	71.291
Control variables					
Mineral reserve horizon	915	0.082	.274	0	1
Rainfall shocks	960	118.014	66.398	7.172	414.894
Temperature shocks	960	24.483	3.082	12.309	29.376
Rich countries	960	0.5	0.5	0	1
Demographic growth	960	21703187	36068539	70387	2.095e+08
Gdp per capita	915	173.838	462.468	0.437	3139.523
ER	960	0.094	0.292	0	1
FR	960	0.156	0.363	0	1
Public Debt	948	-1.407	14.968	-165.829	154.785
Government Stability	690	7.79	1.415	4.583	11
Tax revenue	518	15.459	6.396	3.856	39.988
Brent oil price	960	75.700	23.733	38.287	112.257
Term of trade	945	130.853	48.756	21.397	458.574
Commodity term of trade 1	930	112.983	24.308	55.098	223.025
Commodity term of trade 2	930	99.886	5.053	65.479	110.784
Greenhouse gases emissions	960	74378.25	166099	100	1118100

Table B4 – Robustness : The effect of natural resource-backed loans on forest cover loss (Alternative matching : entropy balancing method).

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Dependent variable : **Log forest loss**	**Baseline**	Adding Country/FE	Adding Time/ FE	Adding Country/ Time/FE	Adding Controls	Adding Country/FE	Adding Time/ FE	Adding Country/ Time/FE
Resource-backed	1.8185***	0.4871***	1.8982***	0.1547	1.8501***	0.2428*	1.6956***	0.1974
loans Dummy	(0.3189)	(0.1844)	(0.2998)	(0.1552)	(0.2987)	(0.1331)	(0.3088)	(0.1233)
Constant	9.3341***	11.5693***	9.5304***	11.4826***	11.5429***	10.6796***	12.1181***	9.9220***
	(0.1224)	(0.2126)	(0.3379)	(0.1727)	(1.4770)	(0.5149)	(1.4296)	(0.4544)
Observations	727	727	727	727	727	727	727	727
R-squared	0.0982	0.9562	0.1089	0.9653	0.3131	0.9649	0.3358	0.9695
Covariates	**NO**	**NO**	**NO**	**NO**	**YES**	**YES**	**YES**	**YES**
Time FE	**NO**	**NO**	**YES**	**YES**	**NO**	**NO**	**YES**	**YES**
Country FE	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**

Standard errors in parentheses. *** p <0.01, ** p <0.05, * p <0.1

Table B5 – Robustness : entropy balancing method with threshold canopy>30%.

VARIABLES	[1]	[2]	[3]	[4]
Resource-backed loans	1.8309***	0.2399*	1.6817***	0.1986
	(0.3166)	(0.1345)	(0.3242)	(0.1260)
Log Credit	1.7497***	0.6451***	1.8693***	0.6230***
	(0.3214)	(0.1196)	(0.3239)	(0.1410)
Oda	0.0629*	-0.0217*	0.0615*	-0.0148
	(0.0352)	(0.0116)	(0.0366)	(0.0105)
Log GFC	-2.0568***	0.0253	-2.3103***	0.2268
	(0.5286)	(0.1686)	(0.5077)	(0.1667)
Expenditure	-0.1235***	-0.0313***	-0.1324***	-0.0270***
	(0.0347)	(0.0081)	(0.0336)	(0.0082)
Natural resources rents	0.1013***	0.0064	0.1230***	0.0050
	(0.0219)	(0.0071)	(0.0233)	(0.0059)
Natural resources depletion	-0.0310**	-0.0111	-0.0379**	-0.0057
	(0.0158)	(0.0084)	(0.0151)	(0.0083)
Constant	11.1688***	10.5534***	11.8084***	9.7848***
	(1.5384)	(0.5190)	(1.4921)	(0.4757)
Observations	725	725	725	725
R-squared	0.2967	0.9671	0.3197	0.9708
Time/FE	**NO**	**NO**	**YES**	**YES**
Country/FE	**NO**	**YES**	**NO**	**YES**

Standard errors in parentheses. *** p <0.01, ** p <0.05, * p <0.1

Table B6 – Validity of transmission channels : Resource-backed loans, public debt and natural resource depletion

	[1]	[2]	[3]	[4]	[5]	[6]
VARIABLES	Public Debt			Natural resources depletion		
Resource-backed loans dummy	0.8442***			1.3361***		
	(0.1434)			(0.1757)		
Mineral, tobacco and cocoa-backed loans dummy		0.5918**			1.4240***	
		(0.2391)			(0.2657)	
Oil resource-backed loans dummy			0.9155***			1.2938***
			(0.1532)			(0.1973)
Constant	0.8960***	0.9989***	0.9065***	1.1855***	1.2867***	1.2301***
	(0.0573)	(0.0555)	(0.0564)	(0.0646)	(0.0627)	(0.0640)
Observations	501	501	501	932	932	932
R-squared	0.0649	0.0121	0.0668	0.0586	0.0300	0.0442

Standard errors in parentheses. *** p <0.01, ** p <0.05, * p <0.1

Table B7 – Resource-backed loans and Greenhouse gases

	[1]	[2]	[3]	[4]
VARIABLES	**Greenhouse gases**			
Resource-backed loans	1.1994***	0.2166***	1.1919***	0.0638***
	(0.1707)	(0.0242)	(0.1750)	(0.0207)
Constant	9.5683***	11.0219***	9.5221***	11.0063***
	(0.0635)	(0.0441)	(0.2301)	(0.0376)
Time/FE	No	No	Yes	Yes
Country/FE	No	Yes	No	Yes
Observations	960	960	960	960
R-squared	0.0490	0.9946	0.0491	0.9965
Mineral, tabacco and cocoa RBL	1.1460***	0.1680***	1.1247***	0.0079
	(0.2646)	(0.0515)	(0.2670)	(0.0408)
Constant	9.6724***	11.0705***	9.5242***	11.0556***
	(0.0616)	(0.0642)	(0.2336)	(0.0517)
Time/FE	No	No	Yes	Yes
Country/FE	No	Yes	No	Yes
Observations	960	960	960	960
R-squared	0.0192	0.9942	0.0208	0.9965
Oil resouce-backed loans	1.2483***	0.2225***	1.2366***	0.0692***
	(0.1895)	(0.0260)	(0.1940)	(0.0220)
Constant	9.5979***	11.0160***	9.5400***	11.0006***
	(0.0627)	(0.0452)	(0.2307)	(0.0384)
Time/FE	No	No	Yes	Yes
Country/FE	No	Yes	No	Yes
Observations	960	960	960	960
R-squared	0.0433	0.9945	0.0436	0.9965

Standard errors in parentheses. *** p <0.01, ** p <0.05, * p <0.1

Table B8 – Definition and sources of variables

Variable	Source	Description
Forest loss	Hansen et al. (2013). Data available on-line from : http://earthenginepartners.appspot.com/science-2013-global-forest	Hectares of tree cover loss, by country, from 2001 to 2021 categorized by percent canopy cover, canopy cover >25%
Resource-backed loans	NRGI and Mihalyi et al. (2022)	Binary variable equal to 1 if country i in year t if the Country signed a resource-backed loans, and 0 otherwise.
Credit	WDI-World Bank	Domestic credit provided by the banking sector, percentages of GDP.
Oda	WDI-World Bank	Net ODA received per capita (current US$)
GFC	WDI-World Bank	Gross capital formation, percentages of GDP
Expenditure	WDI-World Bank	General government final consumption expenditure, percentages of GDP
Natural resources depletion	WDI-World Bank	Natural resources depletion (% of GNI)
Mineral reserve horizon	British petroleum (BP) data	The Minral reserve horizon is a dummy variable equal to 1 if a country's reserve horizon is greater than the median of all mineral-exporting countries
Natural resources rents	WDI-World Bank	Total natural resources rents (% of GDP)
Rainfall shocks	Climatic Research Unit, University of East Anglia and CERDI https://data.cerdi.org/	Deviation of the yearly average of rainfall levels (mm) from its 1901 to 2021 trend
Temperature shocks	Climatic Research Unit, University of East Anglia and CERDI https://data.cerdi.org/	Deviation of the yearly average of temperatures (°C) from its 1901 to 2021 trend
Rich countries	IMF Fiscal Rules Dataset, 2022	Dummy which equals 1 if a given country is a resource rich country and 0 otherwise. IMF Classification
Demographic growth	WDI-World Bank	Population growth (annual %)
GDP per capita	WDI-World Bank	GDP per capita, constant 2017 USD
Public Debt	WDI-World Bank	General government gross debt (% of GDP)
Tax revenue	WDI-World Bank	Tax revenue (% of GDP)
Government Stability	International Country Risk Guide (ICRG)	Government stability index from the ICRG database. It both assesses the government's ability to carry out its declared program(s), and its ability to stay in office Ranks from 0 to 12. An increase means an improvement
Fiscal rule (FR)	IMF Fiscal Rules Dataset, 2022	Dummy equal to 1 if there is a fiscal rule in place and 0 otherwise
Expenditure Rule (ER)	IMF Fiscal Rules Dataset, 2022	Dummy equal to 1 if there is an expenditure rule and 0 otherwise
Greenhouse gases	WDI-World Bank	Total greenhouse gas emissions (kt of CO2 equivalent)
Commodity term of trade 1	IMF data-WEO	Commodity export price index, individual commodities weighted by ratio of exports to GDP
Commodity term of trade 2	IMF data-WEO	Commodity export price index, individual commodities weighted by ratio of exports to total commodity exports
Term of trade	WDI-World Bank	Net barter terms of trade index (2000 = 100)