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Harouna Kinda, Noël Thiombiano

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Does transparency matter? The Effects of EITI on Deforestation in Developing Countries

Harouna Kinda¹ and Noel Thiombiano²

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Abstract:

The exploitation of extractive industries poses a serious threat to the environment. However, the exploitation of extractive industries through an equitable and transparent resource tax regime can also finance alternative livelihoods that can prevent forest loss in the short, medium, or long term. Through two main channels, this paper assesses the "treatment effect" of implementing the Extractive Industries Transparency Initiative (EITI) standard on deforestation in resource-rich developing countries. The first concerns a fair and transparent resource tax regime and environmental payments that can prevent forest loss. The second consists of improving citizens' institutions and living standards through increased government revenue. This study is the first to provide an empirical impact assessment of EITI standards on deforestation. Using a sample of 83 resource-rich developing countries from 2001–2017, we use entropy balancing methods to address the self-selection bias associated with EITI membership. Compared with the non-EITI country, the results show that implementing the EITI standard significantly reduces the loss of forest cover by approximately 300–760 ha. Additionally, the magnitudes of the effects are larger and more significant if we include institutional indicators that are more important for EITI-compliant countries. This result supports the conclusion that EITI, but not a panacea, is an effective policy program for limiting the negative impacts on forests partly caused by extractive industries. This study provides clear guidance to both the EITI Board and the EITI National Committees, and more generally, to the governments of extractive resource-rich developing countries on the vital role of the EITI in combating forest cover loss and sustainable development finance.

Keywords: *Extractive Industries (oil, mineral, and gas)–Transparency–Resource taxation–Deforestation.*

JEL Classification codes : C33 ; H23 ; Q32 ; Q5 ; H5

1. Introduction

¹ Université Clermont Auvergne, CNRS, IRD, CERDI, F-63000 Clermont-Ferrand, France. Email: hkinda40@gmail.com; harouna.kinda@doctorant.uca.fr, *Corresponding author*

² Université Thomas Sankara, CEDRES - Laboratoire d'Économie de l'Environnement et de Socio-économétrie (LEESE), 03 BP 7210 Ouagadougou, Burkina Faso. Email: thiombianoel@yahoo.fr

The United Nations Conference of the Parties on Climate Change (COP26), held in Glasgow, was marked by a firm commitment from world leaders to reduce man-made greenhouse gas emissions by halting and reversing global deforestation over the next decade as part of a multibillion-dollar package. Among the human causes of environmental degradation, mining and onshore oil and gas extraction are serious and specific threats, both directly at extraction sites and indirectly through emissions, transport infrastructure, and mechanized deforestation (Bridge, 2004; Sonter et al., 2018). Extractive industries and their associated infrastructure are among the main causes of greenhouse gas emissions, forest landscape reductions, and threats to the rights of forest communities in forested areas (Bebbington et al. 2018; A. Bebbington et al. 2018; Humphreys Bebbington et al. 2018). They are ranked the fourth most crucial driver worldwide after industrial logging, agricultural expansion, and forest fires (Potapov et al. 2017). Hosonuma et al. (2012) find that commercial agriculture is the main driver of deforestation, accounting for 40% of deforestation; local/subsistence agriculture, which is linked to 33% of deforestation, other factors, such as mining accounting for 7%, infrastructure 10% and urban expansion 10% of total forest loss in Africa, Latin America, and Asia. Kinda and Thiombiano (2021) showed that extractive industry activities affect forest landscapes at multiple spatial scales (site, local, and regional) either through a direct link (i.e., linked to the extraction activity) and/or an indirect link (public and private investment via associated infrastructure such as roads, power facilities, and hydroelectric dams).

While a direct footprint on forests can occur during all exploitation phases (exploration, exploitation, mineral processing, and closure), surface mining is today's dominant form of land-based exploitation. It is particularly damaging to forests (Hirons 2013). Thus, mining activities consume space and contribute directly to deforestation (Kinda and Thiombiano, 2021). Most research is directed at the impacts of these activities at the emergent site level and directly due to habitat degradation (Sonter, Ali, and Watson 2018). The effects on biodiversity also occur across landscapes and regions. Research at this scale has focused on the direct chemical and physical (i.e., dust and aerosols) impacts released from mining waste. Chemical emissions, including mercury or cyanide, are used to extract ores (Sader et al. 1994), and acids are released from oxidized minerals when some ores are exposed to the air. In addition to its direct impact, mining can also induce deforestation in surrounding areas (Sonter et al. 2017). This is because the development of the associated infrastructure requires the direct clearing of forests and opens up forest areas to new settlers and immigrants, who bring farming, logging, and hunting activities that further impact the forests (Finer et al. 2008; Laurance, Goosem, and Laurance 2009).

Indirect effects may also include infrastructure induced by mining, urbanization, and toxic release (Bridge, 2004). In aggregate terms, infrastructure appears to be a more significant driver of forest loss than mining or hydrocarbon extraction. Still, in practice, the two sectors are better understood as existing in a synergistic relationship (Sonter, Ali, and Watson 2018). Furthermore, overlapping economic and political incentives drive expanding investments in extractive industries affecting forested areas. While resource extraction and

infrastructure have been associated with growth, they have also been implicated in developmental underperformance (Ross 2012), a paradox widely known as the 'natural resource curse.' This paradox has several economic reasons (see & Matsuyama 1992; Sachs and Warner 1995; Sachs and Warner 2001; van der Ploeg and Venables 2013). However, the economic channel linked to the volatility of commodity prices could incur more significant environmental costs, especially in the forestry sector. In resource-rich countries, the main source of public revenue is often the extractive sector. However, fossil fuel prices can fluctuate considerably, undermining the ability of governments to effectively manage their energy rents. Macroeconomic instability resulting from volatile natural resource prices can discourage investment. The great irony is that governments are attempting to expand natural resource extraction to boost the economy by relaxing land laws and encouraging mining and commercial agriculture (A. Bebbington et al., 2018), creating the conditions for accelerated deforestation.

Furthermore, other studies have found evidence that macroeconomic factors are correlated with deforestation. These factors include the role of real exchange rate (Arcand, Guillaumont, and Jeanneney 2008), agricultural activity, access to capital, public policies et al. (Benhin and Barbier 2004; Combes Motel, Pirard, and Combes 2009), population & (Cropper and Griffiths 1994), timber harvesting, & (Damette and Delacote 2011), and the impact of plantations on forests (Heilmayr 2014). For example, Kahn and McDonald (1995) describe a significant positive association between public debt and deforestation in LDCs and defend debt relief to reduce pressure on deforestation „(S. Hansen 1989). Several countries such as Indonesia, have engaged in debt-for-nature swaps³ to prevent deforestation (Cassimon et al., 2011).

Regarding the political transmission channels of the resource curse, many economists, such as Sachs and Warner (2001) and Hodler (2006), argue that in some countries, the windfall of natural resource revenues increases the power of elites, which can increase income inequality. Elites or powerful groups capture a large part of these revenues and distribute them to benefit their immediate entourage, rather than investing in sustainable economic development. This undermines political, institutional, and social stability (Collier and Hoeffler 2004; Davis and Tilton 2005; Sala-i-Martin and Subramanian 2013). Bebbington *et al.* (2018) pointed out that corruption accelerates extractive industry expansion and is sometimes a direct driver. Extraction and infrastructure offer vast opportunities for corruption and illegal behavior involving significant private capture of resource rents, which induces additional pressure that weakens forest protection. Payments are used to obtain concessions, environmental approvals, exemptions from environmental reviews, tax exemptions, police and military security services, and others, all of which reduce the actual costs of the projects under the procedures defined by law. In this case, some entrepreneurs obtain land cheaply and can spread their activities over large areas while neglecting their social and environmental responsibilities. Several authors have established a positive link

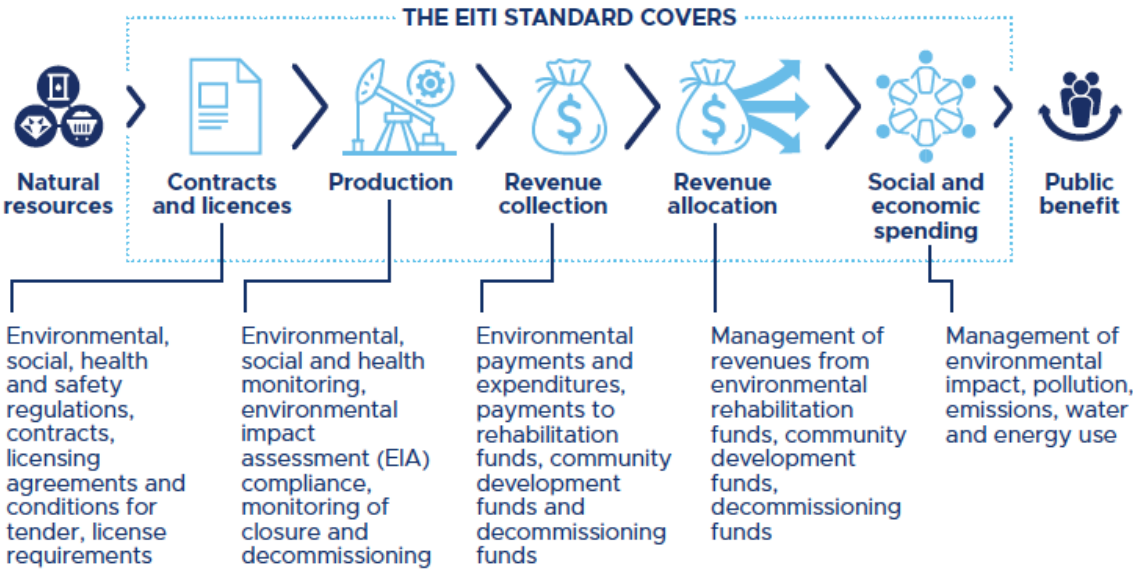
³ Debt-for-nature swaps are financial transactions aimed at reducing a country's debt in exchange for a commitment to devote part of that reduction to nature conservation. For developing countries, debt-for-nature swaps can help meet the growing dual challenge of reducing excessive public debt and combating climate change, to which they are particularly vulnerable. 39 countries benefited from debt-for-nature swaps between 1987 and 2015 (Banque de France, 2023) but the expected effect remains questionable.

between political instability, weak democracy, and poor forest governance (Bhattarai and Hammig 2001; Deacon 1994; Didia 1997; Duval and Wolff 2009). The expected public revenues from resource extraction and the growth effects of infrastructure investments are undoubtedly drivers of policies that facilitate such investments and, perhaps more importantly, legitimizing such policies (A. Bebbington *et al.* 2018).

The Extractive Industries Transparency Initiative (EITI) was launched in 2003 at the instigation of Global Witness, which conceived of the Publish What You Pay (PWYP) campaign in 2002 with other NGOs. The EITI is internationally recognized as a leading anti-corruption scheme that promotes transparency, accountability, and good governance of public oil, gas, and mining revenue. This study is motivated by the negative direct and indirect environmental impacts of extractive industries' investment champs (Kinda & Thiombiano, 2021) and the challenges resource-rich developing countries face in generating adequate revenues to finance sustainable development. Because of the environmental damage caused by extractive industries, EITI-implementing countries increasingly cover taxes, levies, and other environmental payments in their EITI reporting.

It should be noted that in practice, transparency is mainly defined in terms of the "lack" of governance emanating from Southern states (Bracking, 2009) and colonized peoples and is ultimately part of the global regulatory stranglehold of Northern states by oil and mining industry interests (Zalik, 2020). Zalik (2020) also addresses the neglect of ecological costs in the EITI regime. In June 2019, the International EITI board published its amended standards, explicitly incorporating a provision for environmental impact reports for the first time. Indeed, requirement 6.1 of the EITI standard requires that mandatory social expenditures and significant environmental payments be disclosed and reconciled to the extent possible. Thus, the EITI reinforces a scrutiny mechanism in favor of applying the polluter-pays principle. Based on *the EITI requirement 6.4*, Figure 1 shows that environmental issues are integrated throughout the Natural Resource governance decision chain. Implementing countries are encouraged to disclose information on the management and monitoring of the environmental impacts of extractive industries. Stakeholders must assess the adequacy of the regulatory framework and monitoring efforts to manage the environmental impact of extractive industries and assess extractive companies' adherence to environmental obligations.

FIGURE 1. ENVIRONMENTAL REPORTING ACROSS THE VALUE CHAIN



Source: *EITI REQUIREMENT 6.4*

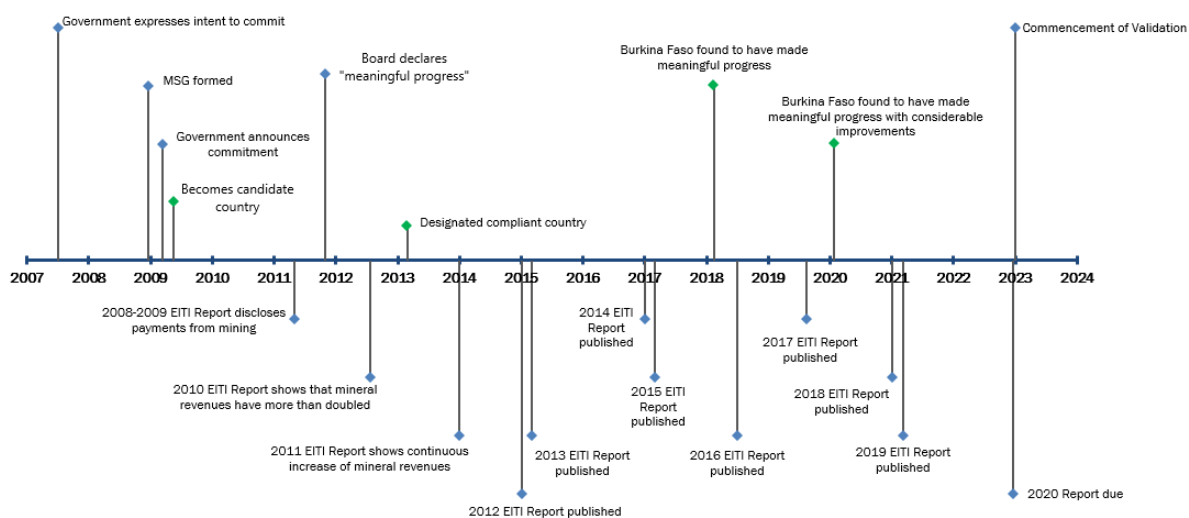
The last stage of the extractive project consists of closure and restoration, financed by financial guarantees deposited for this purpose. Long before the introduction of environmental requirements 6.1 and 6.4 in June 2019, the EITI published data on collecting surface taxes and royalties, proportional taxes related to activities governed by the mining code, and the operation of the environmental rehabilitation account from member countries. Rustad et al. (2017) concluded that any EITI evaluation must be clear regarding the type of EITI objective. This study focuses on assessing the knock-on effect of transparency (EITI) on environmental management rather than the direct impact of EITI on the environment as an objective, as described in requirements 6.1 and 6.4 of the EITI standard, introduced later. The purpose is to reinforce the political objectives of the EITI as a mechanism for controlling and protecting the environment from damage caused by the extractive activities of natural resources.

Based on EITI standards, the EITI implementation process consists of three main steps: Commitment, Candidate, and Compliance. First, the government commits to joining the EITI and implementing the EITI standards. Following the announcement of the commitment, the government, companies, and civil society must jointly commit to establishing a national EITI secretariat and a multi-stakeholder group (MSG) to oversee the implementation process. MSG requires the independent, active, and effective participation of all stakeholders. Thus, the MSG adopts a cost work plan in line with the reporting and validation deadlines of the EITI Board. This work plan sets out the country's objectives and priorities for implementing EITI. This step takes time and allows the effects of accession to be examined before acceptance as a candidate country. This demonstrates the country's intention and implies its willingness to change its transparency policies and accommodate the requirements of EITI membership. After the requirements of Commitment Status are met, the government must submit a request to the EITI Board to become a candidate country. The country becomes an EITI Candidate if the Board considers all the conditions for membership to be met. The EITI Candidate countries must publish a first EITI Report within 18 months to achieve the status of EITI compliant. It must also submit the final report for approval by the Board of Directors and the MSG's support within two years and a half. Candidate countries that have not been able to comply with the requirements of the validation process and have not submitted their final validation report by the deadline or risk suspension. Suspension can also occur if the country is politically unstable. This situation is the case for the Central African Republic in 2013 and Madagascar in 2011. After compliance, the government must submit a validation report every three years as requested by the board. Non-compliance with the latter obligation may also result in the suspension of the concerned nation (see [Figure 2](#) for more details on the EITI implementation process in Burkina Faso's example).

FIGURE 2. TIMELINE OF EITI IMPLEMENTATION

Burkina Faso

Last updated March 2021



Source: [EITI](#)

This study provides the first rigorous quantitative investigation of the impact of EITI on environmental protection and, more specifically, on deforestation in developing countries. EITI can impact environmental preservation through several transmission mechanisms. EITI membership helps to improve revenue transparency and increase public spending, thus improving the population's standard of living, which in turn will strengthen environmental policy and reduce deforestation (surface tax, local economic contribution, surface rent, surface royalty, and environmental expenses). For instance, Kinda and Thiombiano (2021) show that increasing government resource tax revenues reduces forest cover loss.

Through the transparency mechanism, EITI membership strengthens corporate commitment to social responsibility and environmentally responsible operating practices in their production processes and improves institutions and environmental regulations. Several studies established a positive link between weak institutions and poor forest governance & (Bhattarai and Hammig 2001; Deacon 1994; Didia 1997; Duval and Wolff 2009; Kishor and Belle 2004; Mak Arvin and Lew 2011).

Based on the EITI's transmission mechanisms for environmental preservation, the resulting assumptions are as follows: (i) the "extractive industries" which implement a fair and transparent resource tax regime and environmental payments can prevent forest loss; (ii) EITI reduces deforestation by improving the quality of institutions and environmental regulation.

We use the entropy balancing method to address the self-selection bias associated with EITI membership. We found that the implementation of the EITI encourages a significant decrease in annual deforestation in developing countries. This study contributes to the literature in several ways. First, this study sheds new light on the role of EITI in environmental protection. It provides material on which the national committees of EITI member countries, the EITI Board, and the financial institutions that support its operations can strengthen environmental preservation and site rehabilitation measures. Second, to the best of our knowledge, this study is the first to empirically and rigorously assess the environmental impact of EITI to address the self-selection problem. We used the entropy balancing method, which allows us to consider the factors that motivate countries to implement the EITI standard. In addition, the distinction between the three main stages of

the EITI implementation process, namely, engagement, application, and compliance, is crucial for assessing the initiative's reach. Finally, we controlled for time and country fixed effects, sensitivity to time since EITI implementation, and other governance indicators. The main results support the conclusion that EITI, but not a panacea, is an effective policy program for limiting the negative impacts on forests caused in part by extractive industries.

The remainder of this paper is organized as follows. The next section investigates the effectiveness of EITI in combating deforestation. In Section 3, the data and the empirical model are discussed. Section 4 presents and discusses the results. Finally, conclusions and policy implications are presented in Section 5.

2. Investigating the effectiveness of EITI as a scrutiny mechanism

Extractive industries play a central social and political role in at least 80 countries, where they account for a quarter of GDP. However, these deposits often involve geopolitical contestation, they often generate conflict (and even regional or civil wars), and above all, they can have considerable environmental and sustainable development impacts (Jennane and Mbarek 2020). This unfortunate correlation between natural wealth, weak institutions, and environmental costs led to the Extractive Industries Transparency Initiative (EITI). The EITI was first introduced in 2002 by then British Prime Minister Tony Blair at the World Summit on Sustainable Development in Johannesburg. With 56 members, the EITI voluntarily makes payments (royalties, taxes, bonuses, etc.) made by extractive companies on the one hand and the sums collected by public bodies on the other. Once seen as the exclusive domain of the state and ruling elites, the EITI helped establish civil society's legitimacy to intervene in the governance of natural resources, aiming for a positive impact on people and the environment. The EITI emphasizes "that enhanced transparency of natural resource revenues helps reduce corruption, and that revenues from extractive industries can transform economies, reduce poverty, and improve people's living standards in resource-rich countries" (EITI Association Constitution, Art.2.2).

The introduction of the forestry sector into the EITI in some countries also responds to the urgent need to improve public revenue collection⁴. Despite legal and institutional provisions, the forestry sector is not spared from corruption. Public access to information on the revenues generated by extractive industries represents a real opportunity to monitor the management of a sector that has long been considered opaque. Increased transparency should also help identify solutions to current challenges in forest governance. Following requirement 6.4 of the EITI standard, relating to the disclosure of information on the management and monitoring of the environmental impact of extractive industries, state institutions or entities are involved in the ecological management of extractive activities. For example, in the case of Senegal, the Ministry of the Environment is responsible for implementing policies adopted by Senegal in terms of environmental monitoring, pollution control, and the protection of nature, fauna, and flora (Rapport ITIE 2020, 2021).

⁴ Formally, the forestry sector is not yet considered in the EITI standard applied to the mining, oil, and gas industries. For instance, the forestry sector was included for the first time at the initiative of Liberia, while the EITI presidency and secretariat were generally opposed to its more systematic inclusion.

The Extractive Industries Transparency Initiative (EITI) is a global standard for the good governance of oil, gas, and mineral resources. It seeks to address the key governance issues in the extractive sector. Thus, studies analyzing the impact of democracy on deforestation have highlighted three important factors: (i) informal politics, (ii) property rights regimes (e.g., property risk), and (iii) political institutions that include both informal politics and property rights regimes (e.g., the rule of law and political stability) and power inequalities.

Some studies suggest that EITI membership has not reduced corruption. Kasekende et al. (2016) rescaled the Worldwide Governance Indicators (WGI) Corruption Control Index from 0 to 5 with a panel of 76 countries over the period 2002-2012 and find that EITI membership is positively associated with poorer governance through enhanced perceived corruption. Sovacool et al. (2016) analyze the performance of the first 16 countries to attain EITI compliance status from 1996 to 2014 and find that in most metrics EITI countries do not perform better during EITI compliance than before it. Sovacool et al. (2016) conclude that EITI is not a panacea for good resource governance or sustainable development.

Following the logic of Rustad et al. (2017), we postulate that an evaluation should consider something other than the EITI in general as a success or failure based on the evaluation of only a few aspects. Kasekende et al. (2016) use the OLS method, which obviously does not control for selection bias, and a treatment effect method that compares individuals with heterogeneous characteristics since the t-test shows a significant difference in the means of the covariates. A more advanced impact evaluation method would have compared EITI and non-EITI individuals based on similar characteristics. The re-scaling of the control of corruption variable would also have impacted the result, and the authors could robustly test an unre-scaled control of the corruption variable. Concerning the study of Sovacool et al. (2016), the post-treatment period seems relatively limited compared to the pre-treatment period. Although the study retains all of its quality, a certain balance between the pre-treatment and post-treatment periods would have enabled us to better identify the impact of the EITI. Second, it is not surprising that there is no significant additional effect between the commitment and compliance phases, given that the application phase seems to be more decisive in the EITI implementation process. Papyrakis et al. (2016) argue that the EITI is most effective in the fight against corruption during the implementation phase when countries receive candidate status. Indeed, during this phase, candidate countries must implement a series of important changes, including the timely publication of EITI reports and the public disclosure of all financial flows related to the extractive sector, to be fully compliant. Corrigan (2014) and Papyrakis et al. (2016) suggest that intervention effects can occur before a country achieves compliance. For example, Papyrakis et al. (2016) argue that the effects of the EITI are strongest when a country is in the commitment phase (i.e., in preparation for compliance validation).

In contrast, more recent studies using advanced evaluation methods prove that the EITI improves institutions, particularly the control of corruption. Using a case-comparison approach called the Synthetic Control Method (SCM), Villar and Papyrakis (2017) find that the implementation of EITI provoked a significant decrease in corruption in Zambia (with the corruption-reducing effect of EITI being, though, much stronger at earlier stages of implementation). Villar (2021) finds that corruption scores improved significantly among the EITI member countries. The evidence is strongest when examining a subgroup of EITI

members designated as fully compliant with the initiative's transparency standards. While some studies established a positive link between weak institutions and poor forest governance (Bhattarai and Hammig 2001; Deacon 1994; Didia 1997; Duval and Wolff 2009; Kishor and Belle 2004; Mak Arvin and Lew 2011). These are mainly the quality of the rule of law, political stability, the extent of political and civil rights, and power inequalities (Sader *et al.* 1994). However, extractive industry exploitation can also finance alternative livelihoods that can prevent forest loss in the short-, medium-, or long-term. Some studies suggest a trade-off between revenues from forest resources and access to alternative state funding sources. Mainardi (1998) showed in a case study that a high dependence on mineral exports allowed some countries, notably Gabon, to maintain a lower rate of deforestation during the 1980s compared to the least developed non-mineral countries. Therefore, EITI contributes to preserving the forest by improving the quality of institutions and increasing tax revenues (Kinda & Thiombiano, 2021), improving the investment climate (Sovacool 2020), economic development (Corrigan 2017), governance reform (Arond, Bebbington, and Dammert 2019), mitigating corruption (Villar 2021) and building accountability (Fenton Villar 2020) in the governance of extractive resources.

Even so, with so much empirical evidence pointing to the economic and political impact of the EITI, some of the initiative's expectations might seem ambitious, given the goals it set itself at the outset. In this vein, Rustad et al. (2017) questioned the success of the EITI based on a systematic identification of the various objectives associated with the initiative and a review of empirical evidence. The authors find that the EITI has been successful in achieving its institutional objectives, including becoming a recognized brand and consolidating transparency as a global standard, as well as some of its operational objectives, such as setting standards for auditing, reporting, and involving civil society in multi-stakeholder groups. However, the authors remain reserved on the question of whether the EITI has had an impact on development goals because of the limitations of identifying the correct measures of impact and find that many of the evaluations focus on goals that are exaggerated in relation to what the initiative officially seeks to achieve. Although the particular environmental aspect was not introduced as a requirement of the EITI standard until later, it is nevertheless framed by the challenge of transparency and accountability across the entire value chain of EITI requirements for a given extractive project. The lifecycle stages of extractive projects first require a preliminary economic assessment, a pre-feasibility study, and a feasibility study, followed by an environmental and social impact assessment and review, leading to a site rehabilitation and restoration plan validated by all parties. The third stage consists of construction and operation, intending to minimize the environmental footprint and respect local communities. The fourth stage consists of closure and restoration financed by the financial guarantees deposited for this purpose (see Von Below, 1993; Zhengfu et al., 2010; Asr et al., 2019). Long before the introduction of environmental requirements 6.1 and 6.4 in 2019, the EITI published data from member countries on collecting surface taxes, royalties, and proportional taxes related to activities governed by the mining code and operation of the environmental rehabilitation account. This study focuses on assessing the knock-on effect of transparency (EITI) on environmental management rather than the direct impact of EITI on the environment as an objective, as described in

requirements 6.1 and 6.4 of the EITI standard. The objective is to reinforce the political objectives of the EITI as a mechanism for controlling and protecting the environment from the damage caused by the extractive activities of natural resources.

3. Data and empirical model

3.1. Data

We use a panel of 83 developing countries rich in extractive resources for the period 2001–2017. The main variables concern extractive rents (minerals, oils, and natural gas rents), EITI implementation status, and deforestation. The choice of this panel data sample is based primarily on our extractive resource dependence indicator and the availability of data on forest cover loss. Extractive-dependent countries are defined as those that depend on minerals for at least 25% of their tangible exports (Haglund, 2011). The sample includes 46 EITI countries (*treated*) and 37 non-EITI members (*controls*).

Treatment variable. The variable of interest is a dummy for *EITI implementation* based on the information available on the EITI website (World Bank Group, 2016). The *EITI* dummy takes the value of 1 starting from when a country becomes an EITI member and 0 for the years in which the government is not an EITI member. This study used EITI commitment status as the primary treatment variable. However, we also analyzed the heterogeneity of the outcome concerning candidates and compliance status. As of January 2017, in a sample of 46 countries committed to implementing the EITI, 43 had achieved candidate status, and 24 had achieved compliance status (see Appendix A1 for the data sources and definitions of the different variables and A2 for the list of countries and their various stages of EITI implementation). Note that the countries joined the EITI on different dates. Thus, countries that joined later may also constitute controls for those that joined earlier. This means that the number of EITI countries exceeding that of non-EITI countries is not a problem.

Outcome variable. This study used annual deforestation or forest cover loss (*forest loss years*) from Hansen et al. (2013). It is available in the Global Forest Change dataset at the Earth Engine as the outcome variable (<http://earthenginepartners.appspot.com/science-2013-global-foreston>). Following Kinda and Thiombiano (2021), the dataset is based on Landsat satellite images from 2000 to 2019 and are available at a spatial resolution of 20 m. The "loss of forest cover" is the change from a forested to a non-forested state over time.

Conversely, "forest cover gain" reflects a complete shift from a non-forest to a forest state. The "forest loss year" disaggregates the total forest loss at the annual scale. The dataset comes primarily from the University of Maryland and was recently published and made freely available by Hansen *et al.* (2013). This dataset remains a potentially valuable source of forest cover information, although it has been criticized for its inaccuracies in distinguishing between forests and plantations at the local level (Tropek et al. 2014)). This study considered any area with more than 20% trees in 2000 as a forest, thus excluding all areas with a lower percentage of trees.

Controls or matching variables. Lujala (2018) argues that examining the factors that influence a country's decision to join and implement the standard is crucial to understanding whether and how adherence to the EITI Standard can affect resource governance and development. We estimated PS using a probit model with the binary variable EITI as the dependent variable. The aim is to measure the correlation between the control variables and the probability of implementing the EITI standard. The control variables comprised structural and institutional indicators. These factors will likely explain the choice to implement EITI and deforestation for a given country. Therefore, we monitor the endogeneity of the following factors: total extractive rents in percent of GDP (oil, gas, mineral), GDP per capita growth, commodity prices, foreign direct investment (FDI), population density, climate shocks, industry value-added, forest rents, governance indicators such as control of corruption, government effectiveness, rule of law, voice and accountability, political stability, and non-violence. It is impossible to control for unobserved factors that may affect the likelihood of joining EITI. However, the control variables allow us to consider known sources of bias. These data come mainly from the datasets of the World Development Indicators (WDI), the International Monetary Fund (IMF), and World Governance Indicators (WGI).

Following Lujala (2018), our primary selection equation consists of three structural factors influencing EITI implementation and deforestation: internal motivation, internal capacities, and external pressure, such as from development agencies and organizations (Lujala, 2018).

The internal motivation to implement the EITI Standard will likely depend on the extent to which a country believes that the EITI process can support its goals of improving extractive sector management. Leaders of resource-rich developing countries joined the EITI to consolidate their international prestige as enthusiastic reformers, allowing them to maintain and attract FDI (Öge, 2016). Natural resource wealth is one of the main internal motivations of a country to join the EITI standard. *Extractive rents, forest rents, and commodity prices* are expected to positively affect the likelihood of implementing EITI (Pitlik et al., 2010; O'ge,2016; Kasekende et al., 2016; David-Barrett & Okamura, 2016; Lujala, 2018). These later studies also find that countries that are relatively poorer are more likely to join the EITI, as well as those that are more corrupt. However, wealthy countries with strong *industry value-added (% GDP)* will be less motivated to implement the EITI. We use *GDP per capita (growth)* to approximate the country's level of development.

A high per capita income negatively affects the likelihood of implementing EITI. GDP per capita growth captures the effect of national wealth on forest loss. Foster and Rosenzweig (2003) show that neither agricultural productivity nor wages have increased local forest cover. Depending on a country's level of development, the expected impact of GDP growth on deforestation may vary. Resource rent measures the sustainability of extractive industries in the new millennium. As explained above, this variable represents the profit from the extraction of natural resources. It takes the form of economic rent because it is not produced. We use this value because it captures the importance of the extractive sector in the national economy in terms of monetary value. Thus, it depends on the size of the operation, production volume, general price level, and other institutional factors. We use the share of rent from extractive industries as a percentage of the GDP (RENTS). Specifically, we consider mining, oil, and natural gas rents (% GDP). Following the evidence of David-Barrett and Okamura (2016) and Lujala (2018), we assume that a higher level of *FDI flows (% GDP)* is positively associated with the likelihood of implementing EITI.

Kasekende et al. (2016) show that, on average, corrupt countries and countries attracting a higher share of FDI, as well as countries with a lower GDP per capita, are more likely to sign up for the EITI. Based on the country sample in this study, most resource-rich countries are poor desert countries, which could possibly explain the negative impact of high rainfall (*average precipitation*) on EITI membership.

Internal capacity refers to countries with strong capabilities and greater openness. Thus, countries with better institutions may already have some of the procedures and information required by the EITI standards and are likely to have a more active civil society with more rights and political influence than other countries, which should facilitate and accelerate the implementation of the EITI standard (Pitlik et al., 2010; Lujala, 2018). This development can affect a country's decision to implement the EITI. Following Lujala (2018), more developed countries can finance the reforms required by the EITI standard, and the greater capacity of state bureaucracies while implementing the EITI also offers considerable symbolic value, enabling them to attract other resource-rich countries to join the EITI initiative. Thus, this study includes the control of corruption and the rule of law. Population density is an important determinant of deforestation. Population density is lower in resource-rich developing countries than in developed countries. An increase in population density positively affects the likelihood of EITI implementation.

External pressure. Although the EITI is a voluntary program, some countries that receive international assistance may be encouraged to join. In countries that have recently experienced major armed conflict, the influence of international organizations and agencies can help promote extractive sector reforms (Lujala & Rustad, 2012; Sovacool & Andrews, 2015; Lujala et al., 2016). However, a very low or non-existent risk of *internal conflict* could be negatively correlated with the likelihood of joining the EITI.

To provide greater robustness in our econometric results, we introduced other control variables likely to influence deforestation, such as *population density* and *rainfall (average precipitation)*. Population growth is a mid-year estimate for all country residents regardless of legal status or citizenship. This variable can affect natural resource availability, habitat size, and agricultural holdings. An increase in population fuels the demand for arable land, fuelwood, and charcoal, as basic needs such as food, energy, water, social services, and infrastructure can drive deforestation (Cropper and Griffiths 1994). Foster and Rosenzweig (2003) find that the demand for forest products associated with population and income growth leads to forest growth. Therefore, the expected impact on the population growth is ambiguous.

Internal conflict is a significant institutional shock associated with extractive activities due to the infrastructure footprint of forests. An analysis exploring these issues in Mexico, Central America, the Brazilian and Western Amazon, and Indonesia indicates that resource extraction has induced more mobilization and protests from local communities than road, rail, or waterway construction projects (Bebbington et al. 2018). We consider an internal conflict index to measure the influence of political institutions. It is an assessment of political violence in a country and its actual or potential impact on governance. A score of 4 points is

equivalent to a shallow risk and 0 points to a very high risk. Internal conflicts can generate high or low levels of deforestation et al.(Larcom, van Gevelt, and Zabala 2016)). Mean rainfall shock, which is defined as the deviation of the mean annual rainfall from its long-term trend (mean rainfall from 1901 to 2016), is a data point extracted from the University of East Anglia's Climate Research Unit (CRU) database. This climate variable is thought to control the profitability of agriculture and natural determinants of forest cover loss. Countries with low precipitation levels tend to experience extreme temperatures. This can be detrimental to plants and lead to the loss of forest cover. High climate variability may also lead policymakers to tighten environmental standards and reduce deforestation. Thus, an ambiguous effect of rainfall shock on deforestation can be expected.

3.2. Descriptive statistics and stylized facts

Table A1 (Appendix) shows that the variables do not have the same number of observations; however, we consider this in our estimation. We notice that the standard deviation of the dependent variable is very high compared to that of the explanatory variables.

Figure 3 shows the negative relationship between total extractive rents (oil, mining, and gas rents), government resource revenues, and deforestation before and after the EITI membership. Specifically, for extraction rents, the slope of the adjustment line is steeper during the EITI period than during the non-EITI period. This means that implementing EITI standards through the transparency mechanism strengthens the collection of financial funds for restoration and rehabilitation as well as companies' commitment to social responsibility and environmentally responsible operating practices in their production processes. Although the final stages of an extractive contract are closure and reclamation, there has been an increase in resource rent-sharing objectives since the 1990s. For example, in the mining sector, expectations of taxation go beyond mere revenue collection and extend to the environment (Sinkala, 2009; Collier & Venables, 2014) to the impact on economic development in its broadest sense (Bird, 2014). For resource government revenues, the slopes of the adjustment lines remain slightly identical before and after the EITI membership. This latter relationship is unsurprising, since the EITI thus far has no particular requirement on the share of government revenues in green spending. For instance, Kinda and Thiombiano (2021) show that increasing government resource tax revenues reduces forest cover loss. EITI membership helps to improve revenue transparency and increase public spending, thus improving the population's standard of living, which in turn will strengthen environmental policy and reduce deforestation. The Mustache box diagram (Figure 4) shows the distribution of deforestation before and after EITI membership. Median deforestation decreases with the stages of EITI implementation (non-EITI, commitment, candidate, and compliance).

Our statistical analysis suggests that EITI implementation contributes to reducing deforestation in resource-rich, developing countries. Before concluding these results, we conduct econometric verification because the stylized representation of economic variables does not consider specific endogenous factors. Likewise, the periods before and after EITI are possibly different. We began the analysis using propensity score matching on two more comparable groups.

FIGURE 3. RELATIONSHIP BETWEEN EXTRACTIVE REVENUES AND FOREST LOSS

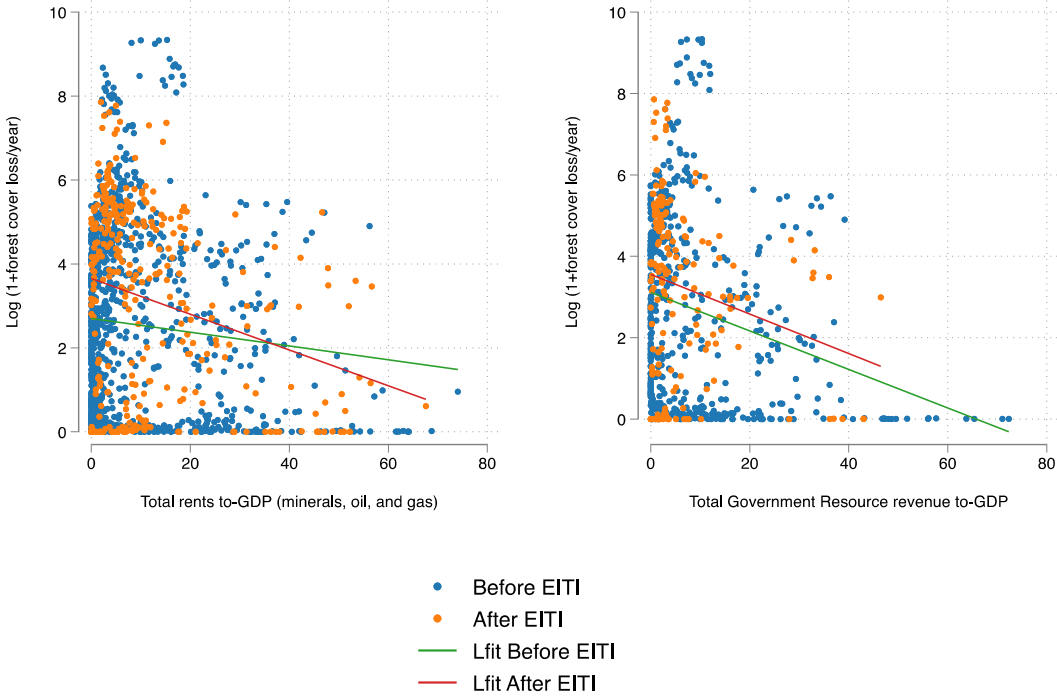
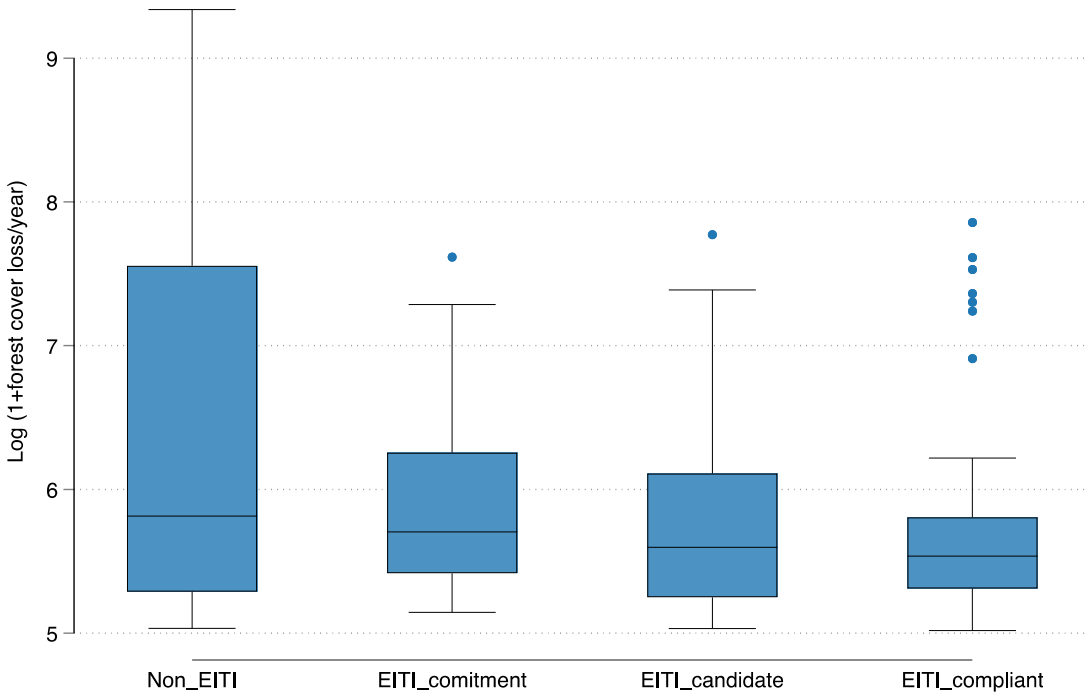


FIGURE 4. DISTRIBUTION OF FOREST COVER LOSS BY EITI IMPLEMENTATION STAGE



4. Empirical strategy: Entropy balancing

We primarily estimated the EITI treatment effect using the entropy balancing method developed by Hainmueller (2012) and implemented by Neuenkirch and Neumeier (2016). Entropy balancing comprises two main steps. The first requires the computation of weights assigned to the control units (non-EITI countries). In the second step, the weights obtained in the first step are used in a regression analysis with the treatment variable (EITI countries) as the control variable. We then balance the EITI and non-EITI countries based on observable characteristics. Thus, the average difference in deforestation between EITI countries and the "closest" non-EITI countries should be explained by EITI implementation. Entropy balancing has several advantages over other treatment effect estimators because it combines matching and regression analyses. It outperforms the classical regression-based approach and matching on propensity score methods, given that it is non-parametric (there are no concerns regarding misspecification of the model's functional form, which could bias the results). It also rules out multicollinearity issues, as the reweighting mechanism makes the treatment variable orthogonal to the covariates.

Entropy balancing is more effective than the other matching methods in balancing the covariates of the treatment and control groups. For example, in propensity score matching methods, the control group comprises only a subset of units that are not subject to treatment (Diamond and Sekhon 2013; Hainmueller 2012; Neuenkirch and Neumeier 2016). Each untreated unit receives a weight equal to 0 if it does not represent the best match for a treated unit or 1 if it represents the best match for one treated unit (Neuenkirch & Neumeier, 2016). Thus, a low covariate balance could bias the estimates of the treatment effects. However, in the case of entropy balancing, the vector of weights assigned to units not exposed to treatment can contain any non-negative values. In the latter situation, the constructed control group adequately reflected the treatment group.

In summary, entropy balancing addresses the panel structure of our data by combining a reweighting scheme with regression analysis (Neuenkirch & Neumeier, 2016). Controlling for both country-fixed effects and time-fixed effects in the regression analysis is also possible. Including country-fixed effects helps account for potential unobserved heterogeneity across non-EITI and EITI countries. Indeed, EITI and non-EITI countries may differ (beyond the set of factors used to balance them) in their specific structural characteristics. Including country-fixed effects allows us to account for country-specific time-invariant factors that explain differences in deforestation in developing countries.

Our analysis is based on the idea that EITI implementation represents a treatment and forest cover loss is the outcome variable. The units of analysis are country-year observations. Observations with EITI implementation in place comprised the treatment group, and

observations without EITI implementation constituted a potential control group. Our outcome is the so-called average treatment effect on the treated (ATT), which is defined as follows:

$$ATT = E[(Y^1 - Y^0) | EITI = 1] = E[Y^1 | EITI = 1] - E[Y^0 | EITI = 1]. \quad (1)$$

where Y is the outcome variable measuring the forest cover loss. EITI indicates whether the observation unit is subject to EITI membership, ($EITI = 1$) or not ($EITI = 0$). $E[Y^0 | EITI = 1]$ is the level of forest loss that would have occurred for country i if country i had not adhered to the EITI standard, and $E[Y^1 | EITI = 1]$ is the level of forest loss observed for country i .

The issue is that $[Y^0 | EITI = 1]$ is not observable because of the non-random nature of EITI adoption. If this were the case, ATT could easily be identified by comparing deforestation in EITI countries with non-EITI countries. Identifying ATT requires a good proxy for $[Y^0 | EITI = 1]$. To do so, we matched EITI units with non-EITI units that are as close as possible to observable characteristics that meet two criteria: correlated with EITI adoption and deforestation. Under the condition that non-EITI units are fairly close to EITI units, any difference in deforestation is attributable to EITI adoption. Based on these elements, we can rewrite Equation (1) as follows:

$$ATT = E[Y^1 | EITI = 1, X = x] - E[Y^0 | EITI = 1, X = x] \quad (2)$$

where $X = x$ is a vector of observable covariates that may affect the decision to adopt EITI and deforestation and $E[Y^1 | EITI = 1, X = x]$ is the expected outcome for the synthetic control units. The estimation of ATT using entropy balancing involves two steps. The first step is to compute the weights for the control group. These weights may satisfy the pre-specified balanced constraints involving sample moments of observable characteristics (X). Following Neuenkirch and Neumeier (2016), we choose balance constraints that impose equal covariate means on the treatment and control groups. In doing so, we want to ensure that the control group, on average, has non-treatment units that are as similar as possible to treated units⁵. The second uses the weights from the first step of the regression analysis, where deforestation is the dependent variable. In the second step, we controlled for the covariates employed in the first step. This is equivalent to including the control variables in a randomized experiment and increases estimation efficiency. In addition, time- and country-specific effects are included in the second step to account for time-specific effects, such as country-specific heterogeneity arising from differences in the control of corruption and the rule of law.

⁵ This procedure ensures that once the weights are generated, EITI countries exhibit similar trends in their outcome variable over the pre-treatment period (see Ogrokhina & Rodriguez, 2019)

Moreover, unlike other matching methods, entropy balancing ensures a high degree of covariate balance between the treatment and control groups, even with small sample sizes. With "conventional" matching methods such as, for example, nearest neighbor matching or propensity score matching, each treated unit, in the simplest case, is matched with the untreated unit closest to the metric balancing score. As a result, the control group consists of only a subset of units that are not subject to treatment (Hainmueller, 2012; Diamond & Sekhon, 2013). In other words, with conventional matching methods, each untreated unit is given a weight equal to 0 if it does not represent the best match for a treated unit, or equal to 1 if it represents the best match for a treated unit. However, when the number of untreated units is limited, and the number of pretreatment features is large, this procedure does not ensure a sufficient balance between the pretreatment features of the treatment and control groups. This is a serious problem, as a poor covariate balance can lead to biased estimates of the treatment effect. By contrast, with entropy balancing, the vector of weights assigned to units not exposed to treatment can contain any non-negative values. Thus, the synthetic control group is designed to represent a virtually perfect image of the treatment group. Thus, entropy balancing can be interpreted as a generalization of the conventional matching approaches⁶. Furthermore, entropy balancing uses more flexible reweighting schemes than conventional matching, in which control units are either eliminated or matched. It reweights units with the goal of achieving a balance between processed and unprocessed units while keeping the weights as close to the base weights as possible to avoid information loss. Despite the various advantages presented in this section, it is essential to note that this approach has some limitations. Indeed, entropy balancing may fail to control for potential endogeneity biases resulting from unobserved temporal factors that may affect both EITI and deforestation, as well as the reverse causality problem that may exist between the treatment variable and the outcome variable, on the one hand, and the other hand, to successfully deal with the inertia of deforestation. To test the robustness of our findings, we supplement entropy balancing with alternative estimation methods such as propensity score matching (PSM).

Table 1 shows the sample means of all matching variables for both the EITI and non-EITI groups and the differences in means between the two groups according to the stage of EITI implementation. Given these descriptive statistics, selecting an adequate control group is crucial before estimating the treatment effect using a matching approach. Otherwise, the estimated treatment effect of EITI implementation on deforestation may be biased. After weighting, we find that the differences in the means and variances between the treatment and synthetic control groups are statistically insignificant. Entropy balancing allowed us to obtain a perfect control group for the treated units.

⁶ Hainmueller, 2012, using Monte Carlo simulations as well as empirical applications, demonstrates that entropy balancing outperforms other matching techniques, such as propensity score matching, nearest neighbor matching, and genetic matching, in terms of estimation bias and mean square error.

5. Baseline results

5.1. Descriptive statistics and covariate balancing

Table 1 shows the sample means and variance of all matching variables for both the EITI (columns 1 and 2) and non-EITI groups (columns 3 and 4). The differences in the means and variances between these two groups are shown in Columns 5 and 6. Given these descriptive statistics, selecting an adequate control group before estimating the treatment effect using a matching approach is crucial. Otherwise, the estimated treatment effect of EITI implementation on deforestation may be biased. After weighting, we remark that the differences in means and variances between the treatment and synthetic control groups are statistically insignificant. Entropy balancing allowed us to obtain a perfect control group for the treated units.

TABLE 1. DESCRIPTIVE STATISTICS AND COVARIATE BALANCING

	Before weighting								
	Commitment			Candidate			Compliance		
	Treated [1]	control [2]	Diff. [2]-[1]	Treated [1]	control [2]	Diff. [2]-[1]	Treated [1]	control [2]	Diff. [2]-[1]
Total_extactive rents	10.04	9.247	-0.79	10.27	9.247	-1.02	11.85	9.192	-2.66
Forest_rents	4.546	2.497	-2.05	4.385	2.497	-1.89	4.006	3.1	-0.91
GDP growth	5.005	4.514	-0.49	4.964	4.514	-0.45	5.15	4.619	-0.53
Internal Conflict	8.473	8.778	0.31	8.434	8.778	0.34	8.227	8.735	0.51
Commodity	99.67	98.11	-1.56	99.75	98.11	-1.64	98.98	98.61	-0.37
Av. Precipitation	109.7	92.58	-17.12	107.1	92.58	-14.52	91.62	99.54	7.92
FDI	6.223	3.416	-2.81	6.833	3.416	-3.42	5.925	4.179	-1.75
Population density	66.38	72.13	5.75	65.98	72.13	6.15	63.45	71.07	7.62
Industry_value added	27.59	31.5	3.91	27.79	31.5	3.71	28.87	30.32	1.45
Rule of law	-0.7048	-0.5695	0.14	-0.6956	-0.5695	0.13	-0.3483	-0.4936	-0.15
N. Obs.	342	637	-	277	637	-	122	857	-
	After weighting : Covariate balancing								
	Commitment			Candidate			Compliance		
	Treated [1]	control [2]	Diff. [2]-[1]	Treated [1]	control [2]	Diff. [2]-[1]	Treated [1]	control [2]	Diff. [2]-[1]
Total_extactive rents	10.04	10.04	0.00	10.27	10.27	0.00	11.85	11.85	0.00
Forest_rents	4.546	4.546	0.00	4.385	4.385	0.00	4.006	4.005	0.00
GDP growth	5.005	5.005	0.00	4.964	4.964	0.00	5.15	5.15	0.00
Internal Conflict	8.473	8.473	0.00	8.434	8.434	0.00	8.227	8.227	0.00
Commodity	99.67	99.67	0.00	99.75	99.75	0.00	98.98	98.97	-0.01
Av. Precipitation	109.7	109.7	0.00	107.1	107.1	0.00	91.62	91.62	0.00
FDI	6.223	6.222	0.00	6.833	6.833	0.00	5.925	5.925	0.00
Population density	66.38	66.38	0.00	65.98	65.98	0.00	63.45	63.45	0.00
Industry_value added	27.59	27.59	0.00	27.79	27.79	0.00	28.87	28.88	0.01
Rule of law	-0.7047	-0.7047	0.00	-0.6956	-0.6956	0.00	-0.3483	-0.3484	0.00
N. Obs.	342	342	-	277	227	-	122	122	-

Notes: This Table presents the sample means matching covariates after weighting across the treated and synthetic control groups obtained from entropy balancing in columns 5 and 6.

5.2. Results from entropy balancing

Based on the synthetic control group in [Table 1](#), we estimated the impact of EITI implementation on deforestation (forest cover loss) using weighted least squares regressions. We provide ten sets of treatment effect estimates based on different treatment indicators, with and without the controls, according to the stages of EITI implementation (*Commitment, Candidacy, and Compliance*). In our primary approach, considering the year of commitment as the beginning of treatment, the control group comprises non-EITI countries. Considering the year of candidacy as the beginning of treatment, the control group comprised non-EITI countries and countries with only committed status. With the compliance year as the start of treatment, the control group comprised non-EITI countries and countries with commitment and/or candidate status. In our sample of EITI countries, there is an average two-year gap between commitment to the EITI and achieving candidate country status. This would explain the smaller effect when considering the EITI candidacy date as the start of treatment, keeping the commitment observations in the pretreatment periods. The countries in which EITI candidates and EITI-compliant countries have essentially the same characteristics. This would explain the less pronounced effect when considering the date of EITI compliance as the start of treatment and keeping the commitment and candidacy observations in the pretreatment periods.

[Table 2](#) presents the results for a baseline model assessing the impact of EITI implementation on deforestation, using a binary variable taking the value of 1 if EITI is implemented and 0 otherwise. These results indicate that deforestation is less important in EITI countries than in non-EITI countries. For each treatment level, we first estimate without covariates (columns [1-3-5-7-9]) and then with covariates (columns [2-4-6-8-10]) in the specification. The results show that EITI commitment, candidacy, and compliance significantly contribute to the reduction of deforestation. The estimated ATTs remained robust with the inclusion of covariates. With covariates, the Average Treatment Effect on Treated (ATT) is about -337 ha if treatment is started in the EITI commitment year, about -400 ha if treatment is started in the candidacy year, and about 640 ha if treatment is started in the compliance year. We note that if we consider the treatment at the candidacy and compliance dates by removing the observations from the previous steps (i.e., the period corresponding to the commitment on the one hand, and on the other hand, the two periods corresponding to the commitment and the candidacy, respectively), the ATTs are more important for commitment than for candidacy (see columns [5-6] and [9-10] compared to columns [3-4] and [7-8]). These results suggest that the effects of different implementation steps add to each other. In other words, forest cover loss is less important in EITI-committed countries than in non-committed ones, higher in EITI candidate countries than in "only" committed countries, and higher in EITI compliant countries than in "only" candidate countries. Our results are robust and similar to those of the PSM.

TABLE 2. THE IMPACT OF EITI MEMBERSHIP ON FOREST LOSS OF THE BASIC MODEL

Dep. Variable: Forest loss year (ha)	EITI commitment.		EITI candidate.				EITI compliant.			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
EITI (Baseline ATT)	-352.7*** (113.6)	-337.1*** (109.2)	-333.8*** (120.5)	-313.7*** (116.0)	-426.9*** (145.7)	-398.9*** (140.4)	-332.3*** (124.1)	-334.3*** (121.5)	-690.2*** (246.3)	-639.5*** (235.1)
Observations	1,037	1,037	1,037	1,037	972	972	1,037	1,037	817	817
R-squared	0.032	0.073	0.028	0.068	0.038	0.078	0.020	0.063	0.049	0.093
Including Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Including Commitment period Obs.	Yes	Yes	0*	0*	No*	No*	0*	0*	No	No*
Including Candidate period Obs.	Yes	Yes	Yes	yes	Yes	Yes	0*	0*	No	No*
Including Compliance period Obs.	Yes	Yes	Yes	yes	Yes	Yes	Yes	Yes	yes	Yes
Country-fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; 0* indicates that we keep the observations of the said period (commitment and/or candidate) in the pre-EITI adoption period. No* indicates that we delete the observations of the period prior to the considered EITI implementation stage.

5.3. Sensitivity to institutional variables

Tables 3 and 4 include two important governance indicators separately (control of corruption and the rule of law) to check their sensitivity to the impact of the EITI implementation on deforestation (ATT). Although the results remain consistent for all specifications, there is a clear improvement in the magnitude of the estimated coefficients (ATTs). These results are consistent with our theoretical assumptions and evidence from some studies that have established a positive link between weak institutions and poor forest governance (Bhattarai and Hammig, 2001; Deacon, 1994; Dida, 1997; Duval and Wolff, 2009). In other words, we demonstrate that better institutional qualities are positively associated with better forest governance, reducing forest cover loss.

TABLE 3. THE IMPACT OF EITI MEMBERSHIP ON FOREST LOSS OF THE BASIC MODEL

Dep. Variable: Forest loss year (ha)	EITI commitment.		EITI candidate.				EITI compliant.			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Inc. Control corruption (ATT)	-401.9*** (131.1)	-382.5*** (123.7)	-387.7*** (139.8)	-368.6*** (133.9)	-486.4*** (167.2)	-457.4*** (158.6)	-365.1*** (135.0)	-365.9*** (132.8)	-761.7*** (272.7)	-713.2*** (258.0)
Observations	979	979	979	979	914	914	979	979	759	759
R-squared	0.037	0.085	0.032	0.081	0.043	0.093	0.021	0.069	0.054	0.113
Including Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Including Commitment period Obs.	Yes	Yes	0*	0*	No*	No*	0*	0*	No	No*
Including Candidate period Obs.	Yes	Yes	Yes	yes	Yes	Yes	0*	0*	No	No*
Including Compliance period Obs.	Yes	Yes	Yes	yes	Yes	Yes	Yes	Yes	yes	Yes
Country-fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; 0* indicates that we keep the observations of the said periods (commitment and/or candidate) in the pre-EITI adoption period. No* indicates that we delete the observations of the period prior to the considered EITI implementation stage.

TABLE 4. THE IMPACT OF EITI MEMBERSHIP ON FOREST LOSS OF THE BASIC MODEL

Dep. Variable: Forest loss year (ha)	EITI commitment.		EITI candidate.				EITI compliant.			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Inc. Rule of Law (ATT)	-378.6*** (123.3)	-360.3*** (117.8)	-361.0*** (131.3)	-342.0*** (127.1)	-458.2*** (158.2)	-431.1*** (152.2)	-331.1*** (121.5)	-330.5*** (119.3)	-690.0*** (244.0)	-640.5*** (231.5)
Observations	979	979	979	979	914	914	979	979	759	759

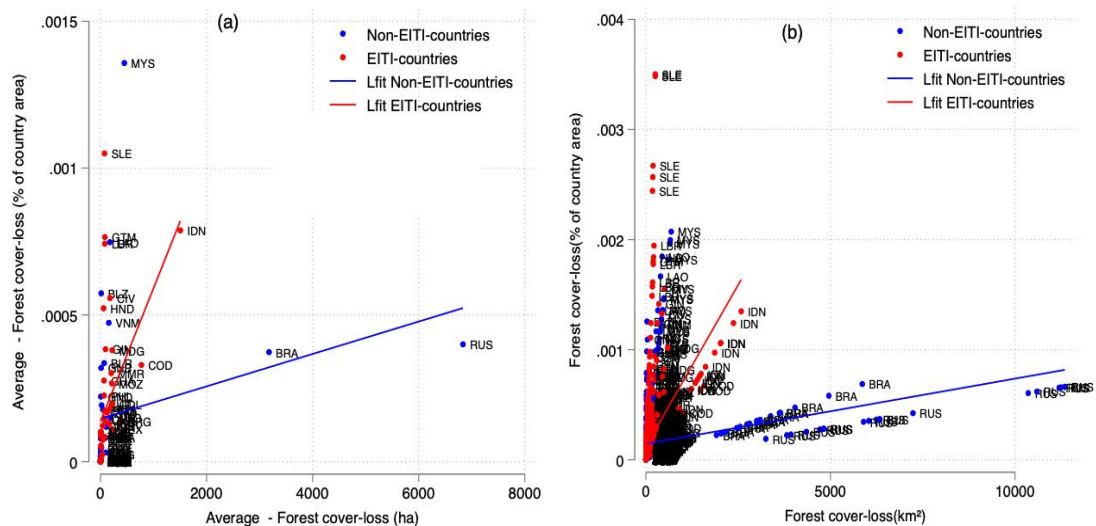
R-squared	0.034	0.077	0.030	0.071	0.040	0.083	0.020	0.064	0.049	0.098
Including Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Including Commitment period Obs.	Yes	Yes	0*	0*	No*	No*	0*	0*	No	No*
Including Candidate period Obs.	Yes	Yes	Yes	yes	Yes	Yes	0*	0*	No	No*
Including Compliance period Obs.	Yes	Yes	Yes	yes	Yes	Yes	Yes	Yes	yes	Yes
Country-fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; 0* indicates that we keep the observations of the said period (commitment and/or candidate) in the pre-EITI adoption period. No* indicates that we delete the observations of the period prior to the considered EITI implementation stage.

5.4. Sensitivity to outliers

Figure 5 shows the correlation between average forest cover in hectares and average forest cover (km²) relative to the country area (km²) for the period studied (a) for both the EITI (treated) and non-EITI (controlled) groups of countries, as well as the correlation between forest cover in hectares and forest cover (km²) relative to the country area (km²) (b). While this representation shows a strong positive correlation between the two variables (substitutable to some extent), it also enables us to identify values that would appear to be outliers to assess their relevance and deal with them appropriately. Outliers influence the current estimates of the mean and variance. The literature presents several methods for detecting outliers⁷, each of which has its advantages and limitations, drawing the attention of researchers to the need to avoid incorrectly considering values as outliers. The graph shows very high deforestation values (based on distance) for some countries that are also rich in forest resources so that we can rule out the hypothesis of measurement errors.

FIGURE 5. CORRELATION BETWEEN AVERAGE FOREST COVER (IN HA) AND FOREST COVER TO-COUNTRY AREA (IN %)



We apply two methods to rule out any concerns about biased estimates caused by outliers. The first is to remove observations (country-year) from the values that appear to be outliers. However, it should be noted that this method of dealing with outliers is not encouraged by many researchers because attrition is not random, which could cause a selection bias, and we lose information. Table 5 shows the

⁷ In general, outlier detection techniques can be classified into 7 major groups, each based on (i) distribution, (ii) density, (iii) distance, (iv) depth, (v) classification, (vi) clustering and (vii) spectral decomposition or projection of the data. <https://www.aspexit.com/outliers-donnees-aberrantes-on-fait-le-point/>.

estimated coefficients, which remain consistent in significance with decreasing magnitudes. The second method used by Asatryan et al. (2018) seems more appropriate. We estimate the equations by reducing the outliers of the dependent variable (forest cover loss in ha) to 1%. For example, our sample's maximum value (99 percentiles) of forest loss is approximately 11350 ha. The outliers of the dependent variables are trimmed at the top and bottom percentiles of the distribution. Table 6 presents the robustness tests by winsorizing outliers. Several exercises ensure that the main results are independent of influential outliers.

TABLE 5. THE IMPACT OF EITI MEMBERSHIP ON FOREST LOSS OF THE BASIC MODEL

Dep. Variable: Forest loss year (ha)	EITI commitment.		EITI candidate.				EITI compliant.			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
EITI(ATT) Inc. Control corruption	-203.7**	-188.2**	-235.7**	-211.6**	-177.2**	-159.6*	-100.4*	-99.36*	-280.2**	-246.4**
	(81.84)	(78.02)	(103.9)	(100.2)	(87.31)	(84.73)	(57.53)	(57.54)	(129.2)	(125.2)
Observations	974	974	909	909	974	974	974	974	754	754
R-squared	0.024	0.073	0.026	0.076	0.019	0.069	0.009	0.067	0.032	0.091
Including Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Including Commitment period Obs.	Yes	Yes	0*	0*	No*	No*	0*	0*	No	No*
Including Candidate period Obs.	Yes	Yes	Yes	yes	Yes	Yes	0*	0*	No	No*
Including Compliance period Obs.	Yes	Yes	Yes	yes	Yes	Yes	Yes	Yes	yes	Yes
Country-fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; 0* indicates that we keep the observations of the said periods (commitment and/or candidate) in the pre-EITI adoption period. No* indicates that we delete the observations of the period prior to the considered EITI implementation stage.

TABLE 6. THE IMPACT OF EITI MEMBERSHIP ON FOREST LOSS OF THE BASIC MODEL

Dep. Variable: Forest loss year (ha)	EITI commitment.		EITI candidate.				EITI compliant.			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
EITI(ATT) Inc. Control corruption	-335.6***	-319.7***	-320.2***	-304.0**	-402.2***	-377.7***	-304.9**	-307.2**	-616.9***	-578.7**
	(113.8)	(108.4)	(123.0)	(119.1)	(145.6)	(139.9)	(121.3)	(120.4)	(235.5)	(226.3)
Observations	978	978	978	978	913	913	978	978	758	758
R-squared	0.033	0.080	0.029	0.076	0.038	0.086	0.021	0.068	0.048	0.104
Including Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Including Commitment period Obs.	Yes	Yes	0*	0*	No*	No*	0*	0*	No	No*
Including Candidate period Obs.	Yes	Yes	Yes	yes	Yes	Yes	0*	0*	No	No*
Including Compliance period Obs.	Yes	Yes	Yes	yes	Yes	Yes	Yes	Yes	yes	Yes
Country-fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; 0* indicates that we keep the observations of the said periods (commitment and/or candidate) in the pre-EITI adoption period. No* indicates that we delete the observations of the period prior to the considered EITI implementation stage.

6. Robustness to estimation techniques

We use **propensity score matching** (PSM) to estimate the effect of EITI implementation on forest cover loss. This corrects for selection bias related to the choice of implementation of the standard in some countries.

The PSM method compares EITI and non-EITI countries with similar observed characteristics so that the difference in the value of the outcome variables between the two groups can be attributed to the effect of EITI membership. In other words, to determine

treatment effects, it is essential that the two groups are as comparable as possible before the experimental treatment is implemented.

The first assumption necessary to apply the PSM method is "conditional independence." This requires that conditional on the observables (X) not affected by the treatment, the results are independent of the EITI implementation dummy variable.

The equation for the estimated average treatment effect on treated individuals (ATT) is expressed as follows:

$$ATT = E[(Y^1 - Y^0)|EITI = 1] = E[Y^1|EITI = 1] - E[Y^0|EITI = 1] \quad (1)$$

Where EITI is the dummy variable for EITI implementation, and Y is the outcome indicator (level of forest cover loss). $Y^0|EITI = 1$ is the level of forest loss that would have occurred for country i if it had not adhered to the EITI standard and $Y^1|EITI = 1$ is the level of forest loss observed for country i . Equation (1) indicates that a simple comparison between the level of observed forest loss for country i in the treatment group and the level of observed forest loss for the same country i if it had not joined the EITI would provide an unbiased ATT estimate. However, the main difficulty in estimating the ATT is that the second term ($E[Y^0|EITI = 1]$) is not observable. One cannot observe the level of forest loss in an EITI country if it has not joined the EITI. This creates an identification problem, which is often the case in experimental studies. A commonly used approach to circumvent this difficulty is to compare the sample mean of the treatment group (EITI) with that of the control group (non-EITI), if and only if the country's choice of EITI implementation is random. This method produces biased estimates if the decision to implement EITI is not random. However, the implementation of EITI may not be random because the choice of whether to implement EITI may be correlated with a set of observables that also affect the level of forest loss. This will lead to the problem of "selection on observables," which makes traditional linear regression an unreliable method (see Dehejia and Wahba 2002; Heckman *et al.* 1998).

Matching on propensity scores

To determine the treatment effects, it is essential that before the experimental treatment is implemented, the two groups of countries (EITI and non-EITI) are as comparable as possible. The key assumption necessary to apply the matching method is "**conditional independence**" ($Y^0, Y^1 \perp EITI|X$). This requires that conditional on the observables (X) not affected by the treatment, the results are independent of the EITI implementation dummy variable. This implies that the researcher must account for all factors influencing treatment and outcomes. Under this assumption, the original equation can be rewritten as

$$ATT = E[Y_i^1|EITI = 1, X_i] - E[Y_i^0|EITI = 0, X_i]$$

where is replaced $E[Y_i^0|EITI_i = 1, X_i]$ by $E[Y_i^0|EITI_i = 0, X_i]$ which is observable. The PSM method would involve matching the treated units with control units with similar values of X . As the number of covariates in X increases, matching X becomes difficult to implement in practice. To overcome this important problem, we follow Rosenbaum and Rubin (1983), who propose matching the treated and control units on their propensity scores. The propensity score (PS) is the probability of adhering to the EITI conditional on observable covariates (X) and can be estimated using simple probit or logit models.

$$p(X_i) = E[EITI_i|X_i] = Pr(EITI_i = 1|X_i)$$

A **second assumption** necessary to apply propensity score matching is the "common support," that is, the existence of comparable control units for each treated unit (countries in our case). The equation $p(X_i) < 1$ indicates the existence of comparable control units for each treated unit (the countries in the case).

This condition ensures that each country implementing the EITI standard will have a counterfactual effect in the non-EITI country group. Using SHP, the ATT estimation equation is as follows:

$$ATT = E[Y_i^1 | EITI = 1, p(X_i)] - E[Y_i^0 | EITI = 0, p(X_i)]$$

6.1. Estimating the Propensity score

Table 7 reports the probit estimates of propensity scores for the full sample, which includes only developing resource-rich countries, based on the starting dates of EITI implementation (to the date of commitment and date of the candidate, respectively). Recall that EITI implementation is a binary variable. It takes the value of 1 during the period in which a given country implements EITI, and zero otherwise. Most of the coefficients are significant and have the expected signs of EITI commitment, in light of the literature. Almost all explanatory variables are also significant for EITI candidates and compliance with the EITI. Total extractive rents, commodity prices, FDI, Population density, and quality of governance are positively correlated with the likelihood of EITI implementation. However, GDP per capita growth, internal conflict, climate shock, forest rents, and industry value-added are negatively associated with the likelihood of EITI implementation. After estimating the propensity score for the sample, it is essential to ensure that for each EITI member, there is at least one non-EITI member with the same propensity score.

According to Heckman *et al.* (1999:31), common support is an area of overlap between treated and untreated individuals in the set of propensity score values. This ensured that for each of the treated individuals, there is at least one individual in the control group with simulated observed characteristics (Bryson et al. 2002). The two main techniques for determining common support are the comparison of the minima and maxima between two groups of individuals (R. H. Dehejia and Wahba 1999) and the comparison of trimming distributions (R. Dehejia 2005). The first is to retain all treated and untreated individuals except those with no counterfactual. The propensity score of the latter is lower than the minimum (higher than the maximum) score of individuals in the control group. A disadvantage of this method is that observations within the limits are discarded, even if they are close to the limits. We used the second method, which estimates the density of the distribution in the two groups (trimming). We exclude untreated individuals for whom the proportion of potential counterfactuals is lower, that is, treated individuals with a propensity score very close to the propensity score of the untreated individuals under consideration.

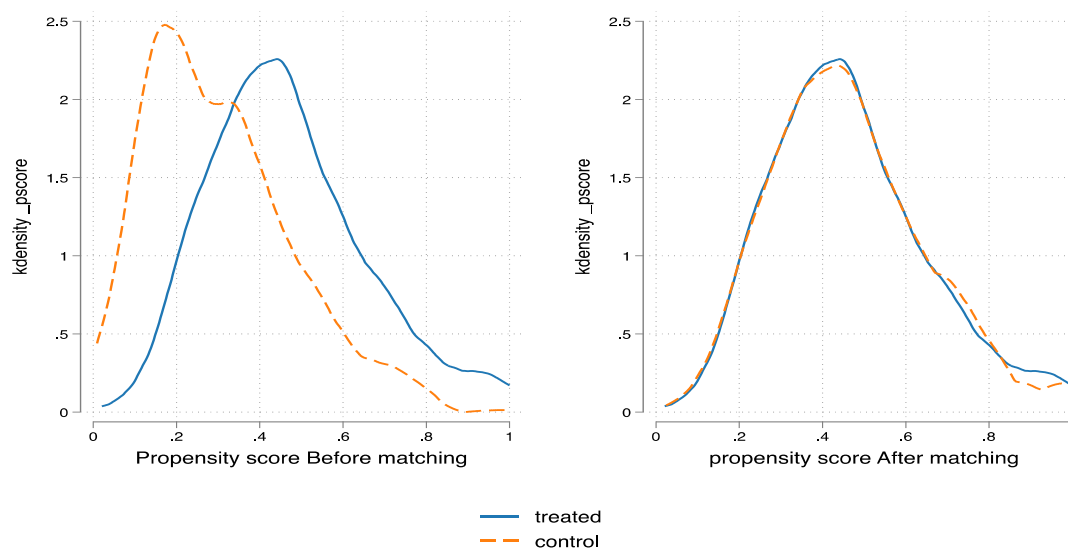
Figure 6 shows a fictitious situation in which the propensity score distribution supports that the treatment and control groups largely overlap, which is a good case for allowing matches. This indicates common support between EITI members and non-EITI members and verifies the second assumption when applying propensity score matching.

TABLE 7. PROPENSITY SCORE

VARIABLES	Treatment starts EITI-commitment year			Treatment starts EITI-candidate year		
	[1]	[2]	[3]	[4]	[5]	[6]
Total_extactive rents	0.0950*** (0.0228)	0.0986*** (0.0227)	0.106*** (0.0229)	0.0728*** (0.0240)	0.0940*** (0.0262)	0.0840*** (0.0227)
GDP/capita growth	-0.0450** (0.0192)	-0.0367* (0.0188)	-0.0345* (0.0182)	-0.0503** (0.0206)	-0.0483** (0.0216)	-0.0283 (0.0190)
Internal Conflict	-0.0557 (0.0894)	-0.0789 (0.0871)	-0.104 (0.0856)	-0.226** (0.0965)	-0.275*** (0.101)	-0.261*** (0.0856)
Commodity prices	0.105*** (0.0224)	0.102*** (0.0224)	0.0935*** (0.0221)	0.0994*** (0.0212)	0.107*** (0.0234)	0.0874*** (0.0201)
Climate shocks	-0.00687 (0.00434)	-0.00913*** (0.00354)	-0.00588* (0.00331)	-0.0165** (0.00654)	-0.0197*** (0.00525)	-0.0122*** (0.00330)
FDI	0.0496*** (0.0171)	0.0508*** (0.0166)	0.0532*** (0.0162)	0.0571*** (0.0168)	0.0529*** (0.0171)	0.0615*** (0.0157)
Forest_rents	-0.110* (0.0591)	-0.112* (0.0581)	-0.0891* (0.0516)	-0.190*** (0.0730)	-0.131 (0.0808)	-0.0852 (0.0626)
Population density	0.188*** (0.00781)	0.123*** (0.00351)	0.0960*** (0.00344)	0.225*** (0.0153)	0.257*** (0.00863)	0.0971*** (0.00371)
Industry_value add	-0.0401 (0.0252)	-0.0576** (0.0258)	-0.0593** (0.0257)	-0.0588** (0.0279)	-0.0905*** (0.0289)	-0.0660*** (0.0241)
Control of corruption		0.966** (0.419)			1.798*** (0.532)	
Rule of Law			1.615*** (0.474)			2.255*** (0.484)
Constant	-28.00*** (2.611)	-21.62*** (2.586)	-15.78*** (2.538)	-25.98*** (2.315)	-23.99*** (2.562)	-12.98*** (2.257)
Observations	1,037	979	979	1,037	979	979
Countries	64	64	64	64	64	64

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

FIGURE 6. COMMON SUPPORT BEFORE MATCHING



6.2. Treatment Effects by Propensity Score Matching

We used four PSM algorithms commonly used in the literature to match each EITI member with non-EITI members, given the closeness of their propensity scores ⁸. Tables 8, 9, and 10 report the results from matching presented by the ATT (Average Treatment effect Treated). Recall that the treatment here consists of implementing the EITI. Considering that the treatment starts from the date of the country's commitment or candidacy, the control group included non-EITI countries.

The first three columns show the results of n-nearest neighbor matching (n-NNM) with $n = 1, 2, 3$ (LaLonde, 1986). This technique is subject to the risk of inaccurate matching when the nearest neighbor is numerically distant. The following three columns show the results of r-Radius matching (r-RM), which matches a treated unit to the control units with estimated propensity scores falling within a radius (or caliper) of length r (we consider a small radius $r=0.005$, medium radius $r=0.01$, and large radius $r=0.05$). In other words, each EITI member is associated only with a non-EITI member whose propensity score falls within a predefined neighborhood of that of the EITI member country (Dehejia and Wahba, 2002). This approach is advantageous because it uses only the number of matching units available within a predefined radius. A possible drawback is that it is difficult to determine a reasonable radius a priori. We also consider kernel matching (KM), in which a treated unit (EITI members) is matched to a weighted average of all control units (non-EITI members). All non-EITI members are used but weighted by their propensity score closeness to EITI members.

Moreover, all control units contribute to the weights; thus, the variance is reduced. The further the control unit is from the treated unit, and the lower is the weight (Dehejia & Wahba, 2002). Finally, we consider regression-adjusted local linear matching (LLRM) in the last column. This method, developed by Heckman et al. (1998), is similar to kernel matching, but includes a linear term in the weighting function instead of a kernel. Each of these methods has advantages and disadvantages. The contrast between the most straightforward method (nearest neighbor matching) and the most complex method (kernel matching) reflects the classic dilemma between bias and variance. In practice, it is recommended that the sensitivity of the results be tested according to the method used. We follow Dehejia and Wahba (2002) and compute standard errors using bootstrapping because the matching estimator has no analytical variance.

Tables 8, 9, and 10 indicate that the estimated ATT remains positive and statistically significant for all matching algorithms. Regardless of the stage considered (commitment or candidate) or the date on which the country started to implement EITI standards, we noticed a significant improvement in the estimated ATT.

First, EITI-committed and EITI-candidate countries are more effective in reducing deforestation than non-EITI countries. According to our estimations, EITI members increase deforestation by an average value of approximately 300 to 600 ha compared to non-EITI members. Suppose that EITI implementation starts from the commitment date or the

⁸ While matching EITI members with non-EITI members, we limit the analyses to "common support." This restriction allows us to exclude treated countries whose propensity score is above the maximum or below the minimum of non-treaties. This is a sine qua non condition to avoid structural confusion bias when estimating treatment effects with the propensity score (R. H. Dehejia and Wahba 1999; Lucotte 2012).

candidacy date; it turns out that the treatment effects are slightly identical. We also controlled for the sensitivity of some indicators of governance, such as the control of corruption and the rule of law. These variables alternately focus on governance in the natural resource sector (Kaufmann, Kraay, and Mastruzzi 2010). The estimated ATT is more significant by controlling corruption and the rule of law. Nevertheless, the analysis of stylized facts suggests that the median of deforestation is less for a country at the candidate stage than at the commitment stage.

Our results support the theoretical hypothesis and confirm the stylized fact that EITI implementation has encouraged resource-rich developing countries to protect forest cover. In addition to the graphic evidence of common support, we also checked the matching quality using the other three main diagnostic tests. First, pseudo-R2 shows that our control variables significantly explain the probability of implementing the EITI, given that its values after matching are 'fairly low' (see, for instance, [Caliendo and Kopeinig 2008](#); [Sianesi 2004](#)). Second, the diagnostic test based on standardized bias evaluates the balancing score (e.g., [Caliendo and Kopeinig 2008](#); [Lechner 2001](#); [Sianesi 2004](#)). According to Rosenbaum and Rubin (1985), the p-value associated with standardized bias should be above the critical value of 10%. These results satisfy the conditional independence assumption. This indicates no significant difference between the EITI- and non-EITI-observable characteristics within the selected common support. Third, the Rosenbaum bounds sensitivity test shows whether unobserved variables simultaneously affect treatment (EITI adoption) and the outcome variable ([Paul R. Rosenbaum 2002](#)). These results suggest that there is no hidden bias⁹.

TABLE 8. THE IMPACT OF EITI COMMITMENT ON FOREST LOSS

	Treatment: EITI Commitment date (EITI 1)			Dependant var.: Forest loss (ha)				
	n-Nearest neighbors matching			r-Radius matching			KM	LLRM
	n=1	n=2	n=3	r=0.005	r=0.01	r=0.05		
[1] ATT basic	-267.0** (131.6)	-315.4** (135.8)	-261.4** (110.0)	-256.5*** (98.94)	-268.4*** (88.82)	-281.0*** (76.91)	-274.3*** (76.33)	-271.6*** (81.62)
N. Obs.	1037	1037	1037	1037	1037	1037	1037	1037
Treated/control	349/ 688	349/ 688	349/ 688	349/ 688	349/ 688	349/ 688	349/ 688	349/ 688
psedo R2	0.021	0.010	0.005	0.010	0.012	0.005	0.004	0.021
Standardized bias (p-value)	0.12	0.337	0.790	0.367	0.119	0.828	0.882	0.12
Rosenbaum sensitivity	1.1	1.1	1.1	2.2	3.1	4.3	4.3	5.1

⁹ In order not to clutter the tables, we do not display the diagnostic tests of the control of governance indicators, but it should be noted that the results of the diagnostic tests are even better with the introduction of these indicators.

[3] Control of corruption	-488.0*** (160.9)	-317.6** (139.0)	-345.0*** (130.6)	-339.0*** (125.0)	-343.9*** (102.6)	-328.5*** (92.91)	-328.4*** (90.92)	-317.7*** (87.87)
[5] Rule of Law	-425.6*** (158.6)	-387.8*** (147.3)	-328.2*** (122.9)	-342.0*** (119.4)	-299.2*** (103.1)	-313.7*** (86.40)	-308.7*** (89.90)	-312.4*** (81.94)
N	979	979	979	979	979	979	979	979

The standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap replications = 500. All the control variables estimating the propensity score are included beforehand, and then we use Governance Indicators estimated one by one to test their specific influence on the outcome.

TABLE 9. THE IMPACT OF EITI CANDIDACY ON FOREST LOSS

	Treatment: EITI Candidacy date (EITI 2)						Dependant var.: Forest loss (ha)	
	n-Nearest neighbors matching			r-Radius matching			KM	LLRM
	n=1	n=2	n=3	r=0.005	r=0.01	r=0.05		
[1] ATT basic	-253.5* (149.7)	-255.3* (131.5)	-206.2* (123.0)	-235.1** (104.1)	-242.9*** (86.47)	-230.7*** (75.81)	-227.6*** (73.66)	-221.1*** (70.90)
N. Obs.	1037	1037	1037	1037	1037	1037	1037	1037
Treated/control	287/ 750	287/ 750	287/ 750	287/ 750	287/ 750	287/ 750	287/ 750	287/ 750
psedo R2	0.009	0.006	0.008	0.010	0.010	0.007	0.008	0.009
Standardized bias (p-value)	0.559	0.789	0.634	0.526	0.512	0.714	0.669	0.559
Rosenbaum sensitivity	1.4	1.1	1.1	2.3	2.8	3.7	3.6	4.3
[2] Control of corruption	-341.4** (157.8)	-457.9*** (151.6)	-373.0*** (135.8)	-306.1*** (112.2)	-272.6*** (99.22)	-269.2*** (86.97)	-267.2*** (88.34)	-252.8*** (77.85)
[4] Rule of Law	-153.1 (165.4)	-204.5 (147.9)	-232.9* (127.2)	-251.1** (114.9)	-253.3** (99.03)	-258.4*** (82.83)	-258.2*** (86.21)	-250.3*** (83.08)
N	979	979	979	979	979	979	979	979

The standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap replications = 500. All the control variables estimating the propensity score are included beforehand, and then we use Governance Indicators estimated one by one to test their specific influence on the outcome.

TABLE 10. THE IMPACT OF EITI CANDIDACY (2) ON FOREST LOSS EXCLUDING COMMITMENT PERIODS

	Treatment: EITI Candidacy date (EITI 2)						Dependant var.: Forest loss (ha)	
	n-Nearest neighbors matching			r-Radius matching			KM	LLRM
	n=1	n=2	n=3	r=0.005	r=0.01	r=0.05		
[1] ATT basic	-338.2** (151.7)	-293.9** (140.4)	-228.4* (135.9)	-248.8** (113.6)	-251.7*** (95.59)	-261.7*** (83.09)	-257.4*** (80.98)	-257.8*** (78.74)
N. Obs.	967	967	967	967	967	967	967	967
Treated/control	272/695	272/695	272/695	272/695	272/695	272/695	272/695	272/695
psedo R2	0.008	0.004	0.007	0.016	0.010	0.006	0.004	0.008
Standardized bias (p-value)	0.607	0.944	0.723	0.179	0.539	0.823	0.939	0.607
Rosenbaum sensitivity	1.1	1.1	1.1	2.3	2.7	4.1	3.9	5.1
[2] Control of	-225.7	-423.1**	-342.7**	-342.3**	-326.3***	-309.5***	-309.1***	-305.2***

corruption	(178.0)	(167.4)	(152.9)	(134.8)	(109.2)	(97.11)	(88.42)	(90.90)
[4] Rule of Law	-317.7*	-250.0	-226.0	-275.6**	-276.4**	-292.1***	-289.6***	-296.3***
	(173.3)	(152.4)	(143.9)	(124.2)	(108.6)	(94.39)	(91.08)	(93.65)
N	909	909	909	909	909	909	909	909

The standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap replications = 500. All the control variables estimating the propensity score are included beforehand, and then we use Governance Indicators estimated one by one to test their specific influence on the outcome.

7. Conclusion

This study aimed to assess the environmental impacts of EITI implementation in a panel of 83 developing countries from 2001 to 2017. The intuition is that EITI implementation would boost the quality of governance in resource-rich countries and thus improve environmental policies and payments to prevent forest loss. Second, EITI reduces deforestation by enhancing the quality of institutions and the living standards of citizens because of increased government revenues.

Our empirical strategy focuses on the entropy-balancing method. We highlight various matching algorithms that allow us to control the self-selection of choice to implement the EITI. We find that ATT is negative and robust to EITI implementation stages. In other words, there is a significant difference between EITI and non-EITI members in terms of reducing deforestation. All else being equal, EITI membership reduces deforestation by approximately 150–600 ha for a given country. In other words, EITI members are more effective than non-EITI members in reducing deforestation. ATTs are more significant if the EITI implementation starts from the candidacy date rather than the commitment date. Furthermore, ATTs are more important if governance indicators are considered.

Resource-rich countries could improve their environmental policies by implementing the EITI according to the requirements. Most importantly, the implementation of the EITI reduces the environmental resource curse. Countries already implementing EITI need to build good institutions. This study draws the attention of policymakers (EITI Board, EITI National Committees, and governments) to the potential role of the EITI in combating forest cover loss and financing sustainable development. Further studies should examine the management of property rights, the standard of living of forest communities, and the role of the EITI in green spending.

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Appendix

TABLE A 1. DESCRIPTIVE STATISTICS AND DATA SOURCES

Variable	Obs	Mean	Std.dev.	Min	Max	Source	Description
Forest cover loss (ha)	1,411	199.8476	896.1247	0	11350.24	Hansen et al. (2013). http://earthenginepartners.appspot.com/science-2013-global-forest	Hectares of tree cover loss, by country, from 2001 to 2018, categorized by percentage of canopy cover, canopy cover > 20%
Total_extactive rents	1,385	9.442419	12.89975	0	74.03297	WDI-World Bank	Mineral rents + Oil rents + Gas rents (% GDP)
Forest_rents	1,394	3.061847	4.569089	0	36.06835	WDI-World Bank	Forest rents (% GDP)
GDP growth	1,398	4.828063	6.987497	-62.07592	123.1396	WDI-World Bank	GDP per capita growth (annual %)
Internal Conflict	1,113	8.625509	1.479958	2.916667	11.91667	International Country Risk Guide (ICRG)	Internal Conflict index from the ICRG database. This is an assessment of political violence in the country and its actual or potential impact on governance. A score of 4 points equates to very low risk and a score of 0 indicates very high risk.
Commodity prices	1,394	98.70003	7.053785	56.30123	117.7615	IMF, https://www.imf.org/en/Research/commodity-prices	Comm. Terms of Trade Index (xj-mj weighted by GDP; defl.; 2012m6=100)
Av, Precipitation	1,411	95.2218	70.44941	1.977812	308.7322	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 2019 trend
FDI	1,373	4.47441	7.503551	-37.15476	103.3374	WDI-World Bank	Foreign direct investment, net inflows (% of GDP)
Population density	1,394	69.38187	77.9308	1.557447	485.648	WDI-World Bank	Population density (people per sq. km of land area)
Industry_value added	1,359	29.57727	13.63291	2.073173	87.79689	WDI-World Bank	Industry (including construction), value added (% of GDP)
Control of corruption	1,328	-.63538	0.5510653	-1.826361	1.568294	Kaufmann et al. (2011). Worldwide Governance Indicators. Estimate of governance in standard normal units ranging from approximately -2.5 (weak) to 2.5 (strong) governance performance. Percentile rank among all countries, ranging from 0 (lowest) to 100 (highest) rank. www.govindicators.org	capturing perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests."
Rule of Law	1,328	-.6928969	0.5518954	-2.255286	.7305223		capturing perceptions of the extent to which agents have confidence in and abide by the rules of society and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence."

TABLE A 2. LIST OF EITI MEMBERS, EVENT DATES, AND STATUS IN FEBRUARY 2018

EITI members	Commitment	MSG	Candidate	First Report	Valid. Report	Compliant	Suspended	Status Feb. 2018	Non-EITI members
1 Afghanistan	March-09	oct-09	Feb-10	Aug-12	Feb-13	Aug-11	Jan-19 -	Candidate	Algeria
2 Albania	Jan-09	March-09	May-09	March-11	Aug-11	May-13		Compliant	Angola
3 Argentina	Dec-17	Dec-18	March-19					Committed	Azerbaijan
4 Armenia	Jan-17		March-17					Candidate	Belarus
5 Burkina Faso	June-07	Dec-08	May-09	Apr-11	Sept-11	Feb-13		Compliant	Belize
6 Cameroon	Feb-05	May-05	Sept-07	Oct-06	July-10	Oct-13		Compliant	Bhutan
7 Central African Republic	Sept-07	July-08	Nov-08	Feb-09	Nov-10	March-11	April-13 -	Suspended	Bosnia and Herzegovina
8 Chad	Sept-07	Feb-10	Apr-10	Oct-12	May-13	Oct-14		Compliant	Botswana
9 Colombia	May-13	Feb-14	Oct-14					Candidate	Brazil
10 Co ^{te} d'Ivoire	May-07	Feb-08	May-08	Jan-10	Nov-10	May-13		Compliant	Bulgaria
11 Ethiopia	July-09	June-09	March-14	May-15				Candidate	Cuba
12 Gabon	2007		2008				2013-2019	Candidate	Ecuador
13 Ghana	May-03	Jan-05	Sept-07	Sept-07	June-10	Oct-10		Compliant	Egypt
14 Guatemala	June-10	May-12	March-11	Apr-13	Nov-13	March-14	Feb - may-15	Compliant	Equatorial Guinea
15 Guinea	March-05	Apr-05	Sept-07	July-07	Aug-12	July-14	Jan-Nov-11	Compliant	Gabon
16 Guyana	May-10	Apr-10	Oct-17					Candidate	Gambia
17 Honduras	Nov-12	Dec-12	May-13	May-15				Candidate	Georgia
18 Indonesia	Dec-08	June-10	Oct-10	May-13	July-13	Oct-14	Feb - Dec-15	Compliant	Guinea-Bissau
19 Iraq	March-09	Aug-10	Feb-10	Nov-11	Aug-12	Dec-12		Compliant	India
20 Kazakhstan	June-05	Apr-05	Sept-07	Nov-07	Aug-10	Oct-13		Compliant	Iran
21 Kyrgyzstan	Apr-04	June-08	Sept-07	Nov-09	Apr-10	March-11		Compliant	Jordan
22 Liberia	May-07	Apr-07	Sept-08	Jan-09	July-09			Candidate	Lao PDR
23 Madagascar	March-07	Jan-08	Feb-08	May-11	Sept-11		Oct-12 - Jan-14	Candidate	Lesotho
24 Malawi	June-14	March-15	Oct-15					Candidate	Libya
25 Mali	Aug-06	June-07	Sept-07	Nov-09	Sept-10	Aug-11		Compliant	Malaysia
26 Mauritania	Oct-05	Dec-06	Sept-07	Feb-07	Sept-10	Feb-12	March - May-13	Compliant	Morocco
27 Mexico	Jan-15	Nov-17	Oct-18	Dec-19				Candidate	Namibia
28 Mongolia	March-06	Jan-06	Sept-07	Dec-07	Feb-10	Oct-10		Compliant	Russian Federation
29 Mozambique	May-08	Apr-09	May-09	Jan-11	May-11	Oct-12		Compliant	Rwanda
30 Myanmar	Dec-12	Jan-14	July-14	Dec-15				Candidate	South Africa
31 Niger	March-05	Jul-05	Aug-07			March-11	Oct-17-March-18	Compliant	Sudan
32 Nigeria	Nov-03	Dec-03	Sept-07	Oct-06	June-10	March-11		Compliant	Syrian Arab Republic
33 Papua New Guinea	Apr-13	Nov-13	March-14	Feb-16				Candidate	Tunisia
34 Peru	Apr-05	May-06	Sept-07	Oct-09	Sept-10	Feb-12		Compliant	Uzbekistan
35 Philippines	July-12	Jan-13	May-13	Dec-14				Candidate	Venezuela
36 Republic of the Congo	June-04	Sept-06	Sept-07	Aug-08	Sept-10	Feb-13		Compliant	Vietnam
37 Sao Tome and Principe	Dec-05	Dec-07	Feb-08	July-14	June-16		Feb - March-10	Candidate	Yemen
38 Senegal	Feb-12	Feb-13	Oct-13	Dec-15				Candidate	Zimbabwe
39 Sierra Leone	May-06	June-07	Feb-08	Feb-10	July-10	Apr-14		Compliant	
40 Suriname	Feb-16	Nov-17	Apr-18				Feb-19 -	Committed	
41 Tajikistan	Aug-12	Aug-12	Feb-13	Oct-15				Candidate	
42 Tanzania	Nov-08	Feb-09	Nov-09	Jan-11	May-11	Dec-12	Nov - Dec-15	Compliant	
43 Timor-Leste	Apr-07	Apr-07	Feb-08	Oct-09	March-10	July-10	March - June-17	Compliant	
44 Togo	Dec-09	Apr-10	Oct-10	Feb-12	Apr-13	May-13		Compliant	
45 Ukraine	Oct-09	Oct-12	Oct-13	Nov-15				Candidate	
46 Zambia	July-08	July-08	May-09	Jan-11	May-11	Sept-12		Compliant	

Precept 5 (NRGI). Governments should seek opportunities to generate benefits for local communities and address, mitigate, and compensate for extractive projects' environmental and social costs.