Ecole Doctorale des Sciences Economiques, Juridiques, Politiques et de Gestion
Laboratoire d'Economie d'Orléans, Université Clermont Auvergne (LEO-UCA)
Université Clermont Auvergne, Université d'Orléans, LEO, 45067, Orléans, France

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FOUR ESSAYS ON MINING, FOREST AND WELFARE IN DEVELOPING COUNTRIES

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Par

Manegdo Ulrich DOAMBA

sous la direction de:

Pr. Pascale Combes Motel

Composition du jury:

Cécile COUHARDE	Professeure, Université Paris Nanterre, EconomiX	Rapporteure
Luc Désiré OMGBA	Professeur, Université de Lorraine, BETA	Rapporteur
Kimm GNANGNON	Sr Economist, World Bank Group	Suffragant
Sampawende Jules TAPSOBA	Deputy Chief Economist/Director of Data Management and Model Development (Afreximbank Group), Senior Fellow (FERDI)	Suffragant
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Pascale COMBES MOTEL	Professeure, Université Clermont Auvergne, LEO-UCA	Directrice

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À ma famille, À mes amis,

Au peuple Burkinabè!

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Résumé

Les populations des pays en développement aspirent à de meilleures conditions de vie. Les revenus tirés de l'exploitation des ressources naturelles peuvent améliorer leur bien-être s'ils sont gérés de manière appropriée. En effet, les revenus tirés de l'exploitation des ressources naturelles peuvent soutenir des politiques et des projets de développement durable. Cependant, les pays riches en ressources naturelles peuvent avoir des résultats économiques médiocres. Ce paradoxe a été largement traité dans la littérature. Le terme « syndrome hollandais » a été inventé par The Economist (1977). Il explique le déclin du secteur industriel à la suite de l'essor des matières premières et les performances plus médiocres des pays riches en ressources naturelles. Sachs and Warner (1995) ont mis en lumière théoriquement et économétriquement les effets négatifs de l'abondance des ressources naturelles sur la croissance, à savoir la « malédiction des ressources ».

Cette thèse s'inscrit dans ce courant de littérature en se concentrant sur les activités minières et forestières. Elle tire parti de la quantité et de la qualité croissantes des données disponibles au niveau mondial sur le secteur minier et les combine aux bases de données existantes au niveau des entreprises et des pays. Le manuscrit est structuré en cinq chapitres. Le chapitre 1 est l'introduction générale, suivi de quatre chapitres originaux. Les chapitres 2 et 3 portent sur les ressources forestières. Le chapitre 2 explore les conséquences environnementales (perte de forêts) des activités minières et le rôle atténuateur des aires protégées, tandis que le chapitre 3 s'interroge sur la présence de cycles électoraux au niveau des rentes forestières. Les deux derniers chapitres explorent les impacts socio-économiques des activités minières. Le chapitre 4 traite de l'effet des activités minières sur la participation et le positionnement des pays dans la chaîne de valeur mondiale. En revanche, le chapitre 5 adopte une perspective microéconomique et évalue dans quelle mesure les activités minières dans les pays affectent les performances des entreprises dans le contexte des pays en développement.

Le chapitre 2 de la thèse étudie l'efficacité des aires protégées face à la déforestation induite par l'exploitation minière dans les pays d'Afrique subsaharienne (ASS). Les activités minières peuvent être un levier de développement et contribuer au bien-être des populations africaines qui aspirent légitimement à de meilleures perspectives. Cependant, leurs conséquences environnementales peuvent compromettre ces promesses de développement durable. Dans ce chapitre coécrit, nous examinons les impacts environnementaux des activités minières sur les forêts, qui constituent une partie essentielle du capital naturel des pays d'Afrique subsaharienne. Ces forêts sont multifonctionnelles et contribuent largement au bien-être des populations locales. Notre contribution est double. Premièrement, nous estimons dans quelle mesure les activités minières contribuent à la déforestation. Deuxièmement, nous évaluons si les aires protégées (AP) peuvent efficacement contrecarrer les effets néfastes des activités minières sur les forêts. Nous construisons une base de données originale combinant des données à petite échelle sur la perte de forêts provenant de la base de données de Hansen et al. (2013), des activités minières provenant de la base de données Minex, et des aires protégées provenant de la base de données mondiale sur les aires protégées (UNEP-WCMC, 2019). L'ensemble de données comprend 2.207 polygones d'une taille moyenne d'environ 12.000 kilomètres carrés. Neuf cent vingt-six polygones (926) étaient boisés en 2001, dont 198 abritaient des mines industrielles. Un modèle spatial autorégressif (SAR) permet de prendre en compte la dépendance entre les décisions de déforestation au niveau des polygones. Les résultats économétriques montrent qu'une mine supplémentaire augmente la déforestation d'environ 155 kilomètres carrés. Les aires protégées atténuent peu la déforestation. Cent kilomètres carrés de aires protégées ne permettent qu'une réduction de 9,7 kilomètres carrés de la perte de forêt. Il faudrait plus que doubler les aires protégées pour compenser la perte de forêt due à l'exploitation minière. Les aires protégées ne peuvent donc à elles seules atténuer les effets négatifs de l'exploitation minière sur les forêts et l'environnement en général. En outre, l'efficacité des aires protégées disparaît dans les régions connaissant des conflits. Il est donc essentiel d'améliorer la qualité de la gestion des aires protégées pour les rendre plus efficaces et promouvoir des pratiques minières plus vertueuses.

Le chapitre 3 examine la relation entre les rentes forestières et la qualité institutionnelle. Plus précisément, il met en lumière les cycles politiques au niveau des rentes forestières dans les pays en développement. Ce chapitre enrichit la littérature puisque les études existantes se sont principalement concentrées sur les rentes liées aux combustibles fossiles et à l'exploitation minière. En outre, les études existantes portent sur des pays ayant une bonne qualité institutionnelle, ce qui peut conduire à une moindre attention portée aux pays en développement. La présence de rentes peut être une motivation supplémentaire pour rester au pouvoir, et ces rentes peuvent financer des dépenses supplémentaires sans risque de déficit budgétaire ni d'augmentation d'impôts. Les forêts étant des ressources ponctuelles, nous émettons l'hypothèse qu'elles sont plus susceptibles de faire l'objet de manipulations électorales. La mauvaise qualité des institutions dans les pays en développement peut également favoriser la manipulation électorale, en incitant les politiciens à utiliser les rentes pour rester au pouvoir. Nous testons notre hypothèse sur un ensemble de données de panel de 83 pays en développement entre 1990 et 2018. La méthode des moindres carrés ordinaires corrigée du biais de Nickell permet de prendre en compte la convergence conditionnelle des rentes forestières. Nous constatons que les cycles politiques n'apparaissent que lorsque l'on tient compte de la compétitivité des élections. Nous mettons en évidence deux types de cycles politiques. Nous avons trouvé des cycles « positifs » dans le cas d'élections compétitives et des cycles « négatifs » dans le cas d'élections non compétitives. Ainsi, dans les pays où la compétitivité électorale est élevée, les rentes forestières augmentent pendant la période électorale, alors qu'elles diminuent dans les pays où la compétitivité électorale est faible. Ces résultats sont relativement robustes aux différents tests. Les résultats de l'analyse de l'hétérogénéité montrent que les cycles ne se produisent que lorsque le candidat au pouvoir se représente aux élections et seulement si les élections ont été reportées. Les cycles se produisent également dans les pays où la corruption est moindre et où la liberté individuelle est plus grande. Ces cycles montrent qu'il est essentiel d'établir des structures indépendantes pour gérer les rentes tout en encourageant les initiatives de transparence nationales et internationales.

Dans le chapitre 4, nous étudions les effets de l'exploitation minière sur la participation et le positionnement des pays dans la chaîne de valeur mondiale (CVM). L'ouverture commerciale affecte les moyens de subsistance de diverses manières. Elle élargit la gamme des produits disponibles sur le marché local. Elle stimule l'activité économique, ce qui se traduit par une augmentation des revenus en moyenne. Ce chapitre contribue à la littérature sur la manière dont les activités minières affectent la chaîne de valeur mondiale. À notre connaissance, le rôle de l'industrie minière dans la participation à la chaine mondiale des valeurs n'a pas encore fait l'objet d'une étude approfondie et les effets des activités minières sur la chaîne de valeur mondiale ne sont pas clairs. D'une part, l'exploitation minière favorise la participation des pays à la chaîne de valeur mondiale. D'autre part, la spécialisation dans les activités extractives peut maintenir les pays riches en ressources au bas de la chaîne de valeur mondiale et compromettre leur avantage concurrentiel. Ce chapitre s'appuie sur une base de données originale qui combine des indices de participation et de positionnement dans la chaîne mondiale de valeur construits à l'aide de la base de données EORA à une variable d'activité minière tirée de la base de données Minex. Nous nous appuyons sur une méthodologie d'étude d'événements où les cinq années suivant l'activation de la mine est la variable d'intérêt. L'ensemble de données comprend soixante-quatorze (74) pays en développement de 1995 à 2018. Nous constatons que l'activité minière n'affecte pas la participation des pays à la chaîne de valeur mondiale, mais nuit à leur positionnement, en contrôlant par le type de minerai extrait, la taille de la mine et la position géographique du pays. L'analyse explore également les canaux de transmission relatifs au capital humain, à la productivité totale des facteurs et au syndrome hollandais. Nos résultats soutiennent les recommandations politiques visant à protéger les autres secteurs en cas de choc par le biais d'investissements ou d'aides destinés aux secteurs affectés. Les décideurs devraient concevoir des politiques industrielles favorisant la transformation locale des minéraux afin d'améliorer leur positionnement dans la chaîne de valeur mondiale.

Enfin, dans le chapitre 5, nous adoptons une perspective microéconomique en examinant les effets des activités minières sur les performances des entreprises. Nous partons de l'idée que la transition énergétique accroît la demande de minerais et pourrait améliorer les performances des entreprises à travers la disponibilité de ces ressources. Cependant, la littérature sur la malédiction des ressources met en évidence les effets néfastes de l'abondance des ressources naturelles sur la compétitivité des pays. Ce chapitre contribue à la littérature à plusieurs égards. Premièrement, alors que la littérature sur le syn-

drome hollandais et la malédiction des ressources naturelles se concentre généralement sur les indicateurs macroéconomiques, nous fusionnons les données au niveau de l'entreprise provenant des enquêtes sur les entreprises de la Banque mondiale (WBES) avec des données minières à petite échelle provenant de la base de données Minex. L'ensemble des données couvre 15 642 entreprises dans 44 pays en développement entre 2006 et 2020. Nous nous appuyons sur un modèle économétrique multiniveau pour prendre en compte les facteurs de performance au niveau de l'entreprise et à l'échelle nationale. Deuxièmement, nous explorons plusieurs canaux par lesquels les activités minières affectent la performance des entreprises. Il s'agit de l'appréciation du taux de change, de la mauvaise qualité des institutions et des déplacements de la main-d'œuvre. D'après nos résultats, l'activation des mines nuit à la performance des entreprises. Les pertes de compétitivité causées par l'appréciation du taux de change, la mauvaise qualité des institutions et le déplacement de la main-d'œuvre expliquent ces résultats. Nos résultats mettent en évidence le conflit potentiel entre la transition énergétique et la performance des entreprises lorsque la transition énergétique stimule les activités minières.

Mots-clés : Booms des ressources · Ressources naturelles · Pays en développement · Cycles politiques · Aires protégées · Syndrome hollandais · Comportement de recherche de rente · Malédiction des ressources naturelles · Chaine mondiale des valeurs · Performance des firmes

Codes JEL : C21 · D22 · D24 · D72 · E62 · 72 · F14 · F15 · L70 · Q23 · Q33 · Q32 · O0

Abstract

Developing countries' populations aspire to better living conditions. The revenues from exploiting natural resources can improve their well-being if appropriately managed. Indeed, revenues from exploiting natural resources can support sound development policies and projects. However, countries rich in natural resources may perform poorly. The literature has dealt extensively with this paradox. The "Dutch disease" was coined by The Economist (1977). It explains the decline of the industrial sector following natural resource commodity booms and the poorer performance of natural resource-rich countries. Sachs and Warner (1995) theoretically and econometrically evidenced the adverse effects of natural resource abundance on growth, namely the "Resource curse." This thesis adds to this stream of literature while focusing on mining and forest-related activities. It takes advantage of the growing quantity and quality availability of data on the world's mining sector and combines them with existing firm-level and country-level databases. The manuscript is structured in five chapters. Chapter 1 is the general introduction, followed by four original chapters. Chapters 2 and 3 are related to forest resources. Chapter 2 explores the environmental (forest loss) consequences of mining activities, while Chapter 3 questions the presence of electoral cycles in forest rents. The last two chapters further explore the socio-economic impacts of mining activities. Chapter 4 addresses the effect of mining activities on the participation and positioning of countries in the global value chain. In contrast, Chapter 5 takes a micro perspective and assesses how far mining activities in the countries affect the firm's performance in developing countries.

Chapter 2 of the thesis studies the effectiveness of protected areas in the face of mining-induced deforestation in Sub-Saharan African (SSA) countries. Mining activities can be a lever for development and contribute to the well-being of African populations, who legitimately aspire to better prospects. However, their environmental consequences can undermine

sustainable development. In this co-authored chapter, we look at the environmental impacts of mining activities on the forests, which are an essential part of the natural capital in SSA countries. These forests are multifunctional and widely contribute to the well-being of local populations. Our contribution is two-fold. First, we estimate how far mining activities contribute to deforestation. Second, we assess whether protected areas (PAs) can effectively counteract the harmful effects of mining activities on the forests. We construct an original dataset combining fine-scale data on forest loss from the Hansen et al. (2013) database, mining activities from the Minex database, and PAs from the World Database on Protected Areas (UNEP-WCMC, 2019). The dataset entails 2,207 polygons with an average size of about 12,000 square kilometres. Nine hundred twenty-six polygons (926) were forested in 2001, of which 198 hosted industrial mines. A spatial autoregressive model (SAR) allows dependence between deforestation decisions at the polygon level. The econometric results show that an additional mine increases deforestation by about 155 square kilometres. Protected areas mitigate deforestation poorly. One hundred square kilometres under protected areas enable only a 9.7 square kilometres reduction in forest loss. More than doubling protected areas would be necessary to offset mining-driven forest loss. Protected areas cannot alone mitigate the adverse effects of mining on forest loss and other environmental consequences. Moreover, the effectiveness of protected areas vanishes in highly conflicted regions. It is, therefore, essential to improve the quality of protected area management to make them more effective and promote less harmful mining practices.

Chapter 3 examines the relationship between forest rents and institutional quality. More precisely, it sheds light on political cycles in forest rents in developing countries. This chapter adds to the literature since existing studies have mainly focused on fossil fuel and mining rents. Moreover, existing studies cover countries with good institutional quality, which may lead to lower attention paid to developing countries. The presence of rents can be an additional motivation to stay in power, and these rents can finance additional expenses without running a deficit or increasing taxes. Since forests are point resources, we hypothesise that they are more likely to electoral manipulation. Poor institutional quality in developing countries can also foster electoral manipulation, incentivising politicians to use the rents to stay in office. We test our hypothesis on a panel dataset of 83 developing countries from 1990 to 2018. The Nickell bias-corrected ordinary least squares method allows for catching conditional convergence in forest rents. We find that political cycles appear only when considering the elections' competitiveness. We evidence two types of political cycles. We found "positive" cycles in the case of competitive elections and "negative" cycles in the case of non-competitive elections. So, for countries with greater electoral competitivity, forest rents increased during the electoral period, while they decreased in countries with low electoral competitivity. These results are relatively robust to various tests. The heterogeneity analysis results show that the cycles only occur when the ruling candidate stands for re-election and only if the elections have been postponed. Cycles also happen in countries with less corruption and greater individual freedom. These cycles show that it is essential to establish independent structures to manage rents while encouraging national and international transparency initiatives.

In Chapter 4, we study the effects of mining on the involvement and positioning of countries in the global value chain (GVC). Trade openness affects livelihoods in diverse ways. It widens the range of products available on the local market. It triggers economic activity, which translates into higher incomes on average. The chapter contributes to the literature on how mining activities affect the global value chain. To the best of our knowledge, the role of the mining industry has not yet been extensively studied, and the effects of mining activities on the GVC are unclear. On the one hand, mining promotes countries' participation in the GVC. On the other hand, specialisation in extractive activities can stick resource-rich countries at the bottom of the global value chain and undermine their competitive advantage. This chapter relies on an original database that combines indices of participation and positioning in the GVC constructed using the EORA database to a mining activity variable from the Minex database. We rely on an event study methodology where the activation of a mine within a five-year horizon is the interest variable. The dataset includes seventy-four (74) developing countries from 1995 to 2018. We find that mining activity does not affect countries' participation in the global value chain but hurts their positioning, controlling for the ore extracted, the size of the mine, and the country's geographical position. The analysis also explores channels of transmission that pertain to human capital, total factor productivity, and the Dutch disease. Our results support policy recommendations to protect other sectors in the event of a shock through investment or aid intended for affected sectors. Decision makers should design industrial policies favouring the local processing of minerals to improve their positioning in the GVC.

In Chapter 5, we take a microeconomic perspective while considering the effects of mining activities on firm performance. We depart from the idea that the energy transition fosters the demand for ores and could improve firm performance. However, the resource curse literature highlights the effects of natural resource abundance on countries' competitiveness. This chapter contributes to the literature in several respects. Firstly, while the Dutch disease and the natural resource curse literature usually focus on macroeconomic indicators, we merge firm-level data from the World Bank Enterprise Surveys (WBES) with fine-scale mining data from the Minex database. The dataset covers 15,642 firms in 44 developing countries from 2006 to 2020. We rely on a mixed multilevel econometric model to account for firm-level and nationwide drivers of firm performance. Secondly, we explore several channels through which mining activities affect firm performance. These are the exchange rate appreciation, poor institutional quality, and labour force shifts. According to our results, mine activation hurts firm performance. Competitiveness losses caused by exchange rate appreciation, poor institutional quality, and labour displacement explain the results. Our results highlight the potential conflict between energy transition and corporate performance when energy transition boosts mining activities.

Keywords : Resources booms · Natural resources · Developing countries · Political cycles · Protected Areas · Dutch disease · Rent-seeking behavior · Natural resources curse · Global Value Chain · Firms performance

JEL Codes : C21 · D22 · D24 · D72 · E62 · 72 · F14 · F15 · L70 · Q23 · Q33 · Q32 · O0

Contents

List of Figures

List of Tables

Chapter 1

Introduction: Mining, forest and welfare in developing countries

Developing countries have been facing many challenges. The most important of which is improving the living conditions of populations sustainably in the context of climate change. Natural resources, such as minerals and forests, can constitute a source of financing for improving the welfare of populations. On a global scale, natural resource rents fell from 2011 before starting to rise again in 2020, as we see in Figure 1.1. However, there is a heterogeneity since mineral rents exploded after 2020 while forest rents continued falling (see Figures 1.6 and 1.7). Also, there is a difference in the dynamic of rents between developing and developed countries, as we can see in Figures 1.8 and 1.9. The level and the post-2020 growth of natural resource rents are much higher in developing countries.

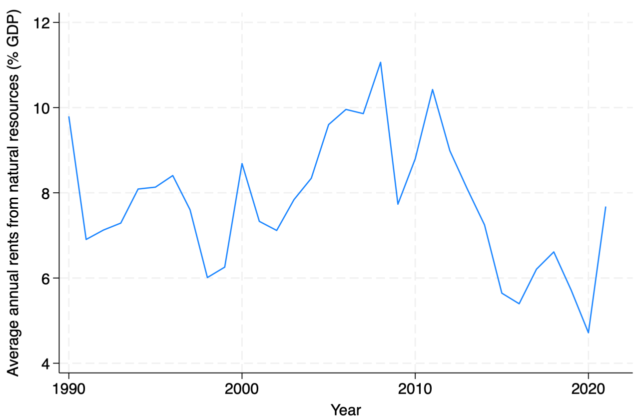


Figure 1.1: Evolution of average level of rents of natural resources
Sources : Author from World Development Indicators

Exploiting minerals and forest resources directly impacts climate change. Indeed, minerals and forest mining lead to environmental change (deforestation, for instance), which impacts climate change. Also, minerals are needed more and more for less polluting goods production and energy transition. So, the heterogeneity in these resource effects between developing and developed countries and their essential role in climate change mitigation motivate our focus on developing countries and mining and forest resources.

Over the period from 1990 to 2022, almost all countries in the world have benefited from minerals and forest rents, especially developing countries, as Figures 1.2 and 1.3 show. This raises the question of using these rents to improve the population's welfare through improved living conditions. These living conditions can refer to revenues, environment, and institutional quality.

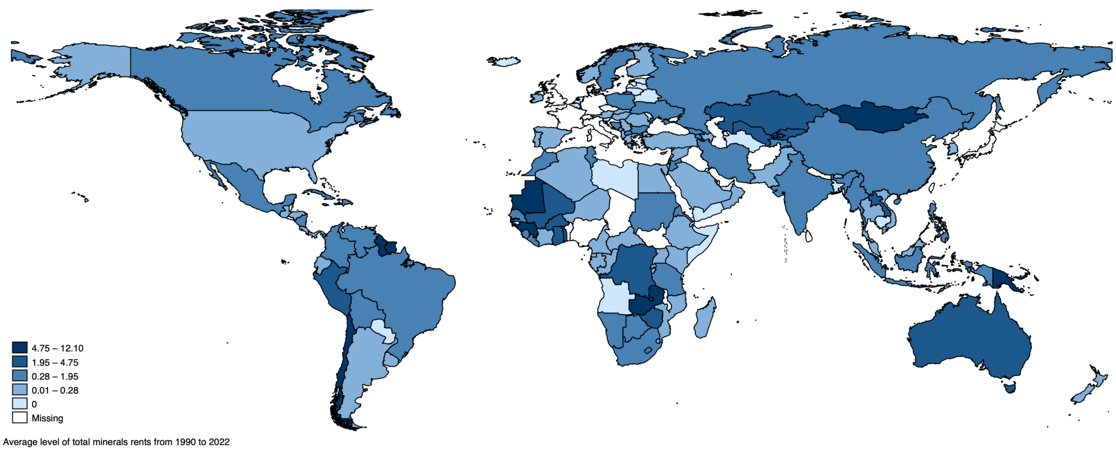


Figure 1.2: Map showing the average level of minerals rents between 1990 and 2022

Sources : Author from World Development Indicators

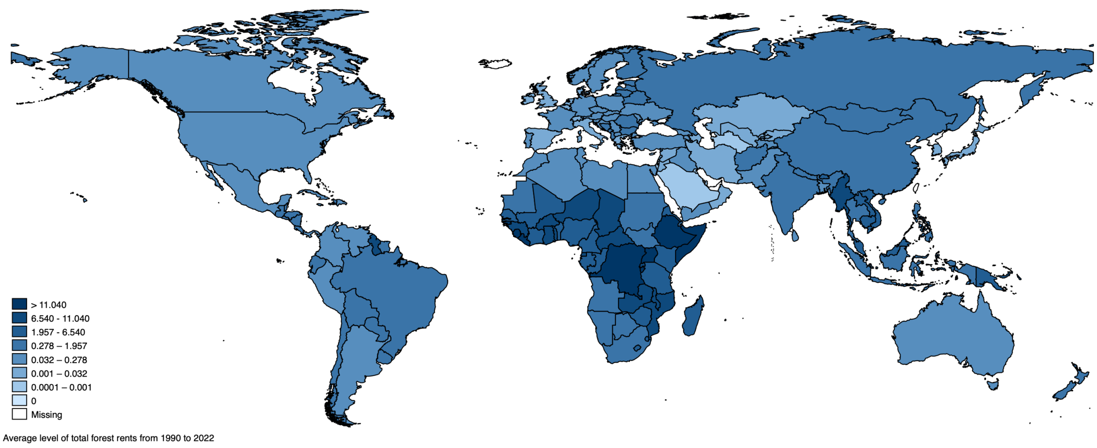


Figure 1.3: Map showing the average level of forest rents between 1990 and 2022

Sources : Author from World Development Indicators

Studying the relationship between mining, forest, and welfare in developing countries amounts to studying the relationship between mining, forest rents, and several facets of the economy affecting the living conditions in these countries. Minerals and forest mining affect populations' living conditions through different channels, and these effects can often be contradictory. Mining and forest exploitation can impact the level of economic activity both positively and negatively, impacting the income level per capita. Also, the degradation or the improvement of institutional quality due to mining and forest exploitation impacts welfare through increased or decreased inequalities, conflicts, or corruption. Moreover, mining and forest exploitation, through their impact on the environment, impact the welfare of populations. Indeed, the environmental reorganization and pollution due to the exploitation of minerals or forests also impact the health of populations, directly impacting the well-being of populations (Von der Goltz and Barnwal, 2019; Hajkowicz et al., 2011). Finally, through inflation caused by the appreciation of the real exchange rate, mining or forest rents reduce the local population's welfare.

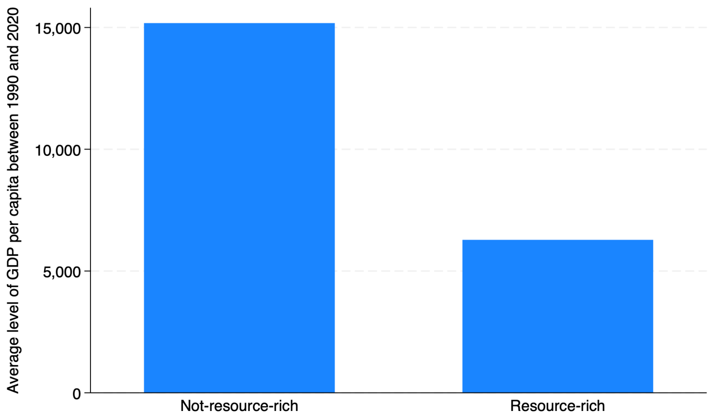


Figure 1.4: Average GDP per capita for dependent countries versus other countries based on IMF classification
Sources : World Development Indicators
We rely on the classification on the IMF to distinguish resource-rich from other countries. According to IMF, a country is resource-rich if its exports of non-renewable natural resources (oil, minerals, and metals) account for more than 25% of the value of the country's total exports

The experiences of different countries have highlighted that natural resources and, mining and forests, as far as we are concerned, are a double-edged sword. Indeed, these resources have been a blessing for some countries such as Botswana, Indonesia, Malaysia, and Thailand (Van der Ploeg, 2011), while they have been a curse for other ones such as Democratic Republic of Congo, and Ghana (Gylfason, 2001). These different examples highlighted the complex relationship between minerals and forest mining and different determinants of welfare, and a large body of literature

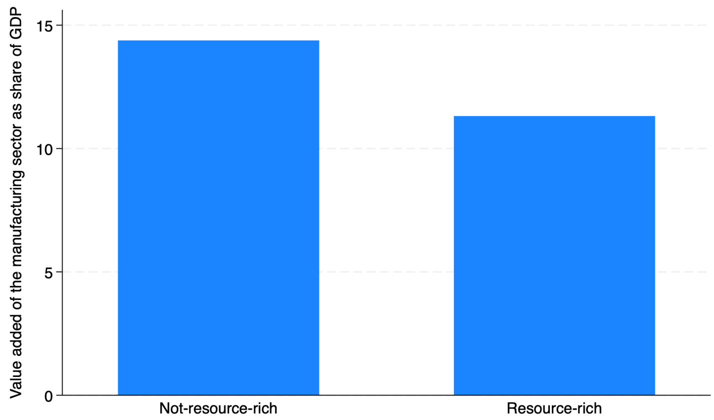


Figure 1.5: Average manufacture sector VA for dependent countries versus other countries based on IMF classification

Sources : World Development Indicators

We rely on the classification on the IMF to distinguish resource-rich from other countries. According to IMF, a country is resource-rich if its exports of non-renewable natural resources (oil, minerals, and metals) account for more than 25% of the value of the country's total exports

has focused on it (Sachs and Warner, 1995, 1999, 2001; Van der Ploeg, 2011). These papers show that countries dependent on natural resource rents, including forests and minerals, have poor economic performance compared to other countries, as shown in Figures 1.4, 1.12 and 1.13. Figure 1.4 represents the average GDP per capita for resource-dependent countries versus other countries based on IMF classification. Figures 1.12 and 1.13 focus on mineral and forest resources, respectively. This economic weakness can be explained by the Dutch Disease (Corden and Neary, 1982) and the natural resource curse (Sachs and Warner, 1995, 1999, 2001; Auty, 2002; Van der Ploeg, 2011). Dutch disease predicts a fall in the manufacturing sector due to shocks in the minerals and forest mining sectors, as we can see in Figures 1.5, 1.18, and 1.19. These two mechanisms explaining the delay of resource-rich countries can be seen through the difference in the Human Development Index (Figures 1.15, 1.14 and 1.16), which is a synthetic index summing all the factors affecting populations living conditions.

Faced with this ambiguous effect of mineral and forest mining on living conditions, solutions exist in the form of challenges in the extractive sector to allow natural resources to impact populations' welfare positively. The extractive industry must overcome these challenges to fully participate in developing communities and countries. For instance, McPhail (2010) has highlighted many factors determining the positive effect of mining, and these factors can be applied to all extractive industries. The first concerns the establishment of a consultation framework involving local communities, firms, states, and extractive companies to reduce the harmful consequences for each of these actors. The second, and one of the most important, is the need for transparency and freedom from corruption. In this sense, the Extractive Industry Transparency Initiative (EITI) is already a considerable effort in the right direction (Corrigan, 2014; Aaronson, 2011). Also, local non-governmental organizations can, together with local populations, discuss how resources from mining can be equitably distributed. The establishment of sovereign funds can also allow extractive activity to improve populations' living conditions. In effect, these funds limit the massive influx of revenues from the mining sector into the economy by promoting investments for future generations.

For the remainder of this introductory chapter, we will present the literature on forest resources management in Section 1.1. This literature will connect us with the question of political-budgetary cycles in forest rents on the one hand and the question of the effectiveness of environmental protection in the presence of mines on the other hand. Then, Section 1.2 will be devoted to mineral resources, reviewing the literature on the socio-economic impact of mineral mining. We will study the literature on the relationship between mining booms and participation in international trade on the one hand and the performance of firms on the other hand. In Section 1.3, we will present the different research questions that will motivate the different chapters of this thesis, highlighting the different contributions.

1.1 Forest management in developing countries

Forest resources provide goods and financing means in developing countries, leading to their misuse as the financing of incumbents' reelection. Also, minerals in the forests' underground often lead to their destruction. However, in the context of global warming, it is urgent to find ways of using these resources sustainably to protect the forests. To this end, protected areas play a crucial role in protecting forest resources from overexploitation.

1.1.1 Mining effects on forests

Environmental effects of mining

Mining alters the landscape. This change in the landscape leads to a positive or a negative impact of this activity on the environment, including forest (Down et al., 1977; Agboola et al., 2020). Indeed, mining requires deforestation, the movement of enormous amounts of earth, the use of polluting chemicals, and enormous amounts of water and energy. It also requires the construction of new infrastructure, the growth of cities, or even the birth of new cities, affecting the environment. All these environmental impacts can be grouped into direct and indirect effects of mining. The direct impact of mining on the environment refers to the effects directly linked to the activity itself. These include the disturbance of the earth and the pollution of water due to the discharge of toxic products in these funds, air pollution due to emissions, and mainly deforestation (Douglas and Lawson, 2002; Schwantes, 2000; Spitz and Trudinger, 2019; Sonter et al., 2017; Gonzalez, 2000; Azomahou and Ouédraogo, 2021; Weisse and Naughton-Treves, 2016). Indirect effects refer to the repercussions of mining but do not result directly from this activity. These include biodiversity loss, climate change participation, and changes within societies close to mines (Spitz and Trudinger, 2019).

Several scholars carried out works to highlight and quantify the environmental effects of mining. This is how Spitz and Trudinger (2019) revisit all the essential questions about the mining-environment relationship. This study reviews the history of mining, the process of mining, and the repercussions of this on local communities, the environment, and biodiversity. Other works have also studied the environmental effects of mining, but by focusing on the pollution issue (Douglas and Lawson, 2002; Schwantes, 2000). The mining-induced deforestation was also at the heart of the work to quantify it. However, a large part of this work is focused on the Amazon (Sonter et al., 2017; Gonzalez, 2000; Azomahou and Ouédraogo, 2021; Weisse and Naughton-Treves, 2016).

Various studies have shown that each mining activity stage has an environmental impact (Eggert, 2010; Asr et al., 2019; Spitz and Trudinger, 2019). Thus, the exploration phase is associated with drilling, blasting, creating landfills, and creating access roads. The phase of putting the mine into operation consists of constructing the different components of the mine, transporting the different machines, and drilling the mines. The exploitation phase consists of the extraction and transportation of the ore. Finally, the mine closure phase corresponds to the period of deconstruction of the infrastructure used for the activity. Each of these stages of mining contributes to forest destruction.

The environment changes quickly once the mining activity is over and the mine is closed. However, using toxic products leads to long-term soil contamination that is detrimental to forest recovery. Also, specific infrastructures that are carried out remain in place for a long time. These include roads and developed cities also remain so (Asr et al., 2019; Cao, 2017; McHaina, 2001; Maczkowiack et al., 2012).

Mining and forests conservation

Implementing environmental policies can be motivated by safeguarding people's well-being (Bonnieux and Desaigues, 1998). Faced with the multitude of human activities (including mining) having negative repercussions on the forests in developing countries, environmental protection policies have been implemented for those countries, particularly given their vulnerability to climate change. There are several types of environmental protection policies, depending on the sources of pollution and the protection object. Above all, several environmental policy instruments, including command and control, market-based, and voluntary approaches, can be promoted in a multilateral and/or national framework (Blowers, 1993; Fiorino, 2023; Jörgens, 2012; Runhaar, 2016).

Despite the desire to protect the environment of which the forests from human activity and mining activity particularly, the various policies have limits, thus limiting their effectiveness (Warhurst, 2013; Eggert, 2013). Regardless of existing protection, the literature highlights the harmful effects of mining activity on the forest. For example, Sonter et al. (2017) highlight the presence of deforestation beyond mining concessions due to mining activity despite environmental protection mechanisms.

These papers lead us to question the interaction between mining activity and environmental protection policies. One of the most concrete examples is the capacity of environmental policies to reduce deforestation induced by mining activity. Protected areas represent the quintessence of forest protection policy. A protected area is "a geographically defined area, recognized, dedicated and managed, by legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values." [1]. The conservation of "at least 17% of

[1]Source: IUCN available at https://www.iucn.org/theme/protected-areas/about.

terrestrial and inland water areas and 10% of coastal and marine areas" is mandated by Aichi Biodiversity Target 11 [2]. According to Bingham et al. (2021), at least 22.5 million km2 (16.64%) of the land surface and inland waters and 28.1 million km2 (7.74%) of the coastal and ocean surfaces are located in protected areas and Other Effective Conservation Measures (OECM). Several studies have attempted to analyze the effectiveness of protected areas globally. It appears that protected areas help reduce deforestation. However, this result is highly heterogeneous and, therefore, varies depending on the protection category and the protected area's location, for example (Pfaff et al., 2015; Nolte et al., 2013; Kere et al., 2017).

1.1.2 Forest and institutions

One of the explanations for the delay in the development of countries exploiting natural resources, including forest resources, is the natural resource curse. It highlights the role of institutional quality, which has been discussed extensively in the literature. Among the potential institutional effects of the exploitation of forest resources are electoral cycles in state budgets. So, we will first talk about the resource curse and then review the literature on how forest resources affect politics.

Natural resources curse

Until the 1980s, mainstream economics considered the presence and abundance of natural resources to promote economic growth. Indeed, natural resources, inclusive of forest resources, allow natural resource-rich countries to increase their wealth and purchasing power on imports. It results in increased investment and economic growth. Also, exploiting the forest can lead to the development of infrastructures and industries and the development and transfer of technologies. However, countries rich in natural resources had, on average, lower growth and poor institutional quality compared to countries with no or few natural resources (Sachs and Warner, 1995, 1999, 2001; Van der Ploeg, 2011) (see Figures 1.4 and 1.5). We had to wait until 1993, and the work of Auty (2002) to put a name to this paradox of plenty. It is the natural resource curse.

Many works have been carried out to explain the curse. It appears from the literature that six main factors can explain this phenomenon (Frankel, 2012). The first factor is the downward trend in raw material prices, confirming the Singer-Prebisch thesis. The second factor is the volatility of the prices of these raw

[2] https://www.informea.org/en/goals/aichi-targets

materials. The third factor is the macroeconomic instability of the country dependent on natural resources. The fifth factor is increased armed conflicts to monopolize natural resource deposits. Finally, the last factor is the poorer institutional quality in these countries. Torvik (2002) groups these factors into two broad groups: Dutch disease and rent-seeking behavior.

Furthermore, studies have focused on the particular case of developing countries, given their particular economic and institutional situation (Henri, 2019; Kronenberg, 2004). Henri (2019) is interested in the particular case of African countries. It seeks to highlight the indicators affected by the exploitation of natural resources. It emerges from his work that the institutional problems caused by the exploitation of natural resources come mainly from corruption and low quality of public service. Kronenberg (2004), for his part, is interested in emerging economies in his study of the curse of human resources. In these countries, the main sources of this curse are corruption and neglect of the education sector.

Forests affect politics

One particular example of the effect of the exploitation of natural resources, including forest resources, on institutions, is the presence of electoral cycles. These are political-budgetary cycles. A political budget cycle is an increase or decrease in a specific component of the government budget due to the electoral cycle. This simply means that a political-budgetary cycle is an increase or decrease in one of the components of the budget, whether taxation or expenditure.

Several theoretical works have tried to explain these cycles. The first were Nordhaus (1975); MacRae (1977). However, the first models developed were "result models." Nordhaus (1975); MacRae (1977) have developed models in which the candidate in power creates inflation during an election period to take advantage of the Philips curve in the short term to get elected again. These first models were improved by Rogoff and Sibert (1988); Rogoff (1990), who developed new ones in which the candidate in power tries to signal his competence by manipulating macroeconomic variables. However, all of these models have the limitation of being results models in which the hypothesis is made that the candidate in power can manipulate macroeconomic quantities, which is different in reality.

To overcome this limitation of the first theoretical models, a new series of models in which political cycles are explained by moral hazard or information asymmetry have been developed (Brender, 2003; Brender and Drazen, 2005; Shi and

Svensson, 2006). In these models, the asymmetry of information explains the size of political cycles. The more voters are informed, the less the powerful candidate is interested in manipulation.

Following these theoretical models, papers have empirically tested the presence of political cycles. The first work is that of Tufte (1978), which highlighted these cycles in the eve of the American presidential elections. Following this first work, several other works were carried out to corroborate the developed theoretical models (Iddrisu and Bokpin, 2018; Boly et al., 2023). Many factors seem to condition the presence of political-budgetary cycles from an empirical point of view. It is, on the one hand, the institutional quality (press freedom, check, and balance) (Nordhaus, 1975; Tufte, 1978; Block, 2002; Klomp and de Haan, 2016) and, on the other hand, the age of the democracy (experience of voters) (Shi and Svensson, 2006; Klomp and de Haan, 2016).

Since the first works dealing with the existence of political cycles, the results remain mixed. As Akhmedov and Zhuravskaya (2004) pointed out, the results relating to developing economies still need to be more conclusive. This can be attributed to two main factors. The first factor is the conformity of the assumptions of theoretical models to the reality of many developing countries. Indeed, according to theoretical models, elections take place competitively. This is not necessarily the case in most elections in developing countries, especially African ones. This difference must, therefore, be taken into account during studies by taking into account the level of competition in elections and the level of institutional quality. Then the second problem, which is very recurrent in studies on developing countries, is the availability of data on the different countries. To overcome the first issue, the authors attempt to consider the level of electoral competition by considering the level of democracy in the countries. This is how Gonzalez (2000) and Shi and Svensson (2002) highlight the important role of institutional quality in these counterintuitive results concerning developing countries. Thus, studies focusing on groups of largely democratic countries make it possible to corroborate the results of theoretical work. Other studies attempt to go to the sub-national level, such as Akhmedov and Zhuravskaya (2004), which studies political cycles during regional elections in Russia based on monthly data. Sáez and Sinha (2010) also studied a single country, India. Some papers focused exclusively on the case of developing countries (Block, 2002; Block et al., 2003; Mosley and Chiripanhura, 2016; Iddrisu and Bokpin, 2018).

Pailler (2018) highlighted deforestation cycles due to incumbent mayor representation to elections in Brazil, showing that forests resources are used to finance elections. These results raise the question of the use of forests' resources for re-elections in developing countries. Such cycles can be observed through forests rents dynamics. In the face of climate emergencies, particular interest should be focused on forest resources, which directly impact climate change, to assess how far elections can impact climate change through forest rents.

1.2 Mining and economic performance

In addition to the relationship between mining activity and deforestation, the literature has also focused on the relationship between mining and economic activity. Indeed, the mining sector can trigger structural change perceptible at both the macroeconomic and microeconomic levels.

1.2.1 Mining and macroeconomic performance

Structural change induced by mining

Mining is one of the oldest industries worldwide, including diverse activities from exploration to production and processing. It plays a vital role in economic growth and improving living conditions for over a century (McMahon and Moreira, 2014). Mining has structuring effects on the economies, including structural change and the energy transition. First, mining is essential to other industries, especially transitioning to lower carbon intensity. The energy transition depends on the ability of the mining sector to deliver critical minerals sustainably (Azevedo et al., 2022).

Second, mining leads to structural change in economies where it takes place. Matsuyama (2008) describes structural change as a somewhat complex phenomenon impacting the process of growth of the economy. From the different definitions in the literature (McMillan and Rodrik, 2011; Matsuyama, 2008; Syrquin, 1988), it appears that the structural change of an economy refers to a change in the functioning of a country's industries and markets. This change in functioning follows a complementary change at several levels of the economy, such as the composition of the workforce, which migrates from one sector to another, or the composition of the sectors' production.

The Dutch disease is a concept introduced by The Economist (1977). It explains the decline of the industrial sector in several countries following commodity booms. Hence, the Dutch disease exemplifies mining as one of the drivers of structural change. This phenomenon appeared for the first time in the Netherlands, hence the name Dutch disease. In 1960, the Netherlands experienced the discovery of large gas deposits. This phenomenon has resulted in a loss of competitiveness in the non-oil sectors. We can ask ourselves why the increase in wealth translates into a loss of competitiveness in specific sectors of the economy.

The economic literature has highlighted the mechanism explaining this loss of competitiveness. Corden and Neary (1982) shows that following a boom in a sector, the booming and non-tradable goods sectors crowd out the tradable goods sectors. The discovery of mining deposits and their activation increases exports, which creates an influx of foreign currencies into the country. However, this impact depends on the exchange rate regime. In both cases, we have an appreciation of the real exchange rate, which harms the economy's competitiveness. This mechanism is called the spending effect (Kojo, 2015).

Alongside the spending effect is the resource movement effect, which results in a movement of productive resources from the sectors of tradable goods towards the sectors of non-tradable goods and the sector that has experienced the boom: the mining sector, in our case. The concept of Dutch disease has evolved to encompass any shock that results in a substantial influx of foreign currencies, leading to a rise in the real exchange rate and subsequently a loss in the economy's competitiveness. These shocks can manifest in various forms, including foreign direct investment, migrant remittances, and public development assistance.

These shocks, even temporary, can affect economic development due to the irreversibility of the consequences of the shock and the loss of positive external effects generated by the mining sector.

Mining effects on countries' participation to global economy

Structural change can be understood in several ways, notably through changes in sector production. This change in production structure is reflected through changes in trade with other countries. There are many determinants of participation in the global value chain. In their article, Kowalski et al. (2015) summarizes these different factors, which are, among others, the size of the country's market, the level of development of the country, the structure of the industry, the location of the country, the level of foreign direct investment, the quality of infrastructure in the country and finally commercial regulation in the country concerned. Each country participates in international trade (Freund et al., 2020), and depending on these factors, each country participates differently in GVC and positions itself differently in the chain. Thus, developing countries participate in the global value chain. Nevertheless, efforts must be made in specific sectors for the latter to participate fully and occupy a prominent place. These include, among other things, the human capital sector, infrastructure, and institutional quality to have a good business climate (Bamber et al., 2014; Publishing, 2013).

We saw above that mining activity can be a source of structural change in the economy. Indeed, booms in this sector and price shocks for raw materials can shift labor from manufacturing to mining, leading to a change in the production structure of countries. Work in the literature highlights this relationship between structural changes and participation in the global value chain (Stöllinger, 2016).

Thus, this structural change can be captured through participation in the global value chain. This change is achieved on the one hand through simple exports of natural resources. This is, therefore, a comparative advantage that mining countries have in participating in the global value chain (Ruta and Venables, 2012). In addition to influencing countries' participation in the global value chain by giving them a comparative advantage, mining activity can also be a source of Dutch disease, which changes the structure of production of economies. This Dutch disease can, in turn, be a mechanism through which mining activity influences countries' participation in the global value chain. So, through the change in the economy's structure, production also changes and consists mainly of raw materials. The aim of this is to specialize countries towards lower chain industries. Mining, therefore, impacts participation and positioning in the global value chain. This change induced by mining can be better comprehended by looking at the effects of mining on manufacturing firms' behavior since these firms are the main actors of countries' integration in the global economy.

1.2.2 Mining and firms behaviour

Mining effect at the local level

Just as environmental changes arise due to economic activity, changes arise among local populations near mining sites. Indeed, on the one hand, the establishment of extraction sites requires the displacement of the population, the requisition of areas used for agriculture or livestock breeding, or, finally, the degradation of the quality of life due to the pollution generated. On the other hand, this activity is a source of economic boom at the local level. Whether at the industrial or artisanal level, mining activity is a source of employment for local populations. Also, local investments and the population's income boost economic activity.

Scientific works need help confirming the thesis that mining activity can be a source of development locally. This is how Al Rawashdeh et al. (2016) shows that in Jordan, mining regions are more prosperous than other regions using socio-economic indicators such as unemployment, the Human Development Index, poverty, education, health, and education. Meanwhile, in Australia, local development was not automatically achieved due to the employment of non-residents in the mines and the flight of capital to large urban centers (Sincovich et al., 2018; Chuhan-Pole et al., 2017; Veiga et al., 2001). Wall and Pelon (2011) in a more global approach, show how some initiatives like foundations, trusts, and funds can help share mining benefits. Madagascar and Senegal put these initiatives in place to better redistribute mining benefits. They also show that mining projects can contribute to local development through employment, tax payments to local authorities, and community investment projects.

As the example of Jordan has shown, mining activity can be a source of local development. Recent work explains a mechanism behind good local economic performance due to mining activity. Indeed, in the United States, mining activity has contributed to the local development of communities. The authors showed the presence of an agglomeration phenomenon explaining this positive effect at the local level. They found that wage levels positively affect economic activity (Allcott and Keniston, 2018). This is explained firstly by the fact that mining booms in certain localities increase wages, population, and employment, increasing income. This increase in income can lead to growth in the manufacturing industry due to the presence of a sub-sector subject to local trade or linked to the mining sector. This subsector is, therefore, not negatively affected like the exportable goods subsectors, but rather positively. Thus, these sub-sectors of goods traded locally or linked to the mining sector experience a boom during mining booms due to increased income and employment. The exportable goods subsector, of course, contracts during mining booms; however, their total factor productivity does not decline. Thus, in a temporary boom, the positive effects outweigh the adverse effects, and the Dutch disease mechanism disappears in favor of the agglomeration effect (Allcott and Keniston, 2018). In other words, labor mobility within the country neutralizes the appreciation of the Real Exchange Rate: supply responds to the increase in demand.

Mining and manufacturing firm performance

According to Taouab and Issor (2019), a firm's performance has many definitions. Initially, it referred to organizational effectiveness (Bartoli and Blatrix, 2015). Then, performance refers to the firm's ability to be effective and efficient (Georgopoulos and Tannenbaum, 1957). Finally, the last definition given to the notion of performance is growth, profitability, productivity, and efficiency (Siminică et al., 2008), but again, it refers to several notions.

The factors explaining a firm's performance level can be internal and external, and empirical models have also been developed to explain performance (Hansen and Wernerfelt, 1989; Sosnick, 1970). Empirical articles have also sought to understand the sources of firm performance. It emerges that factors such as the geographical location of the firm, its size, its age, the ethnicity of the manager, his/her sex, his/her level of education, his/her place of study and his/her orientation are factors explaining the level of performance (Bigsten et al., 2000; Fafchamps, 2001; Mazumdar and Mazaheri, 2003; Söderbom and Teal, 2004; Van Biesebroeck, 2005; Smith et al., 2006; Bhagat et al., 2010).

Mining activity affects the competitiveness of firms in several ways. Already, the loss of competitiveness of the economy following the Dutch disease also makes firms less competitive. Then, the migration of production factors towards the mining sector also leads to firms losing competitiveness. Also, the evolution of the business environment due to mining activity significantly impacts local firms' competitiveness. Indeed, the literature shows a negative effect of natural resource wealth on institutions that are supposed to promote a good business climate. This effect on firms can be understood through the decline in firm performance due to mining activity. Finally, the mining workforce will acquire a lower level of training than those working in other industries. This will result in lower spillovers, reducing the effect mining booms could have on economies (Choi and Pyun, 2020; Yasar et al., 2011; Aron, 2000; Loayza et al., 2005; Dixit, 2009; North, 1990; Wright et al., 2005).

1.3 Thesis objectives and results

The literature review presented previously gave a view of the specific effects of natural resource extraction on developing countries. Although the literature is quite well-stocked, questions still need to be answered and addressed. This thesis gathers four essays on two critical drivers of people's well-being in developing countries: the quality of institutions and economic activity. Thus, Chapter 2 deals with the effectiveness of institutions and policies in the face of the effects of mining activity and, more precisely, deforestation induced by mining activity. Chapter 3 refers to rent-seeking behavior and political-fiscal cycles. Indeed, the presence of rents and, in our case, forest rents can give rise to political-budgetary cycles. Chapter 4 deals with the relationship between mining activity and economic structure, focusing on participation and positioning in the global value chain. Moreover, Chapter 5, which still deals with the relationship between mining and economic activity, goes to a more disaggregated level. Indeed, in this chapter, we discuss the relationship between mining activity and firm performance.

1.3.1 How effective are protected areas in face of deforestation caused by mining activity?

While previous studies have explored the positive correlation between mining and deforestation and the effectiveness of protected areas in reducing deforestation separately, our research takes a novel approach. We delve into the specific relationship between mining, the deforestation it causes, and the role of protected areas in mitigating this deforestation.

Indeed, mining activity positively correlates with deforestation. Likewise, protected areas have proven effective in protecting forests. A question that could emerge from the literature results is: How effective are protected areas in the face of deforestation induced by mining activity?

Answering this question allows us to contribute to the literature in two ways. First, we estimate how far mining activities contribute to deforestation. Second, we assess whether protected areas (PAs) can effectively counteract the deleterious effects of mining activities on forests.

We use an identification strategy based on spatial econometrics, namely the Spatial Autoregressive Model (SAR), taking as study units square polygons covering our study area. Thanks to the different databases, we went to a very fine level in this study. Indeed, the variable of interest comes to us from Hansen's database on deforestation. The variable of interest, namely the presence of an active mine at the level of a polygon, is given to us by the [3] geolocalized database. Finally, the conditional variable, the surface of the protected area, comes from the global database on protected areas (WDPA). The other control variables come from various sources, allowing us to analyze them at a fine level.

Our findings show that, both directly and indirectly, an extra mine in a polygon causes deforestation to increase by roughly 155 square kilometers. In contrast, a reduction in forest loss of 9.7 square kilometers can be achieved by protecting 100 square kilometers of land. So, doubling these protected areas could counteract the adverse effects of mining on the loss of forests. In other words, the adverse effects of mining on the loss of forests and other environmental repercussions cannot be entirely offset by protected areas. It is, therefore, vital to strengthen the quality of management of protected areas to make them more effective and promote mining practices such as smart mining that are less dangerous for the environment.

1.3.2 Are there political cycles in forest rents in developing countries?

A long literature has developed around political cycles within countries' economic policy components. Part of this literature has also focused on the possible presence of political cycles in government revenues, especially at the level of natural resource rents. The rents would allow the government to finance its re-election without running a deficit, which the voters punish.

However, many models developed to explain political-budgetary cycles assume a well-established democracy at the country level, thus limiting econometric studies to samples of developed countries with democracies in place. In this third chapter, we seek to highlight the presence of political cycles in forest rents in developing countries. The question we want to answer is: Is there an increase or a decrease in the forest rents in the pre-electoral period?

The answer to this question presented in this chapter adds to the literature since existing studies have mainly focused on fossil fuel and mining rents. Moreover, existing studies cover countries with good institutional quality, which may lead to lower attention paid to developing countries. The presence of rents can be an additional motivation to stay in power, and these rents can be used to finance

[3] https://consulting.com

additional expenses without running a deficit or increasing taxes.

We opt for a dynamic specification highlighting possible pre-electoral cycles, forcing us to opt for Nickell's bias-corrected least squares methodology. The variable of interest, the level of forest rents, and many control variables are extracted from the World Development Indicators (WDI) database. The electoral period variable, one of the variables of interest, was constructed following a methodology recommended in the literature based on the National Elections Database[4] (NELDA). Finally, the electoral competition variable, the other variable of interest, comes from the Political Constraint Index[5] database (POLCON).

The results show that there are indeed political cycles regarding forest revenue in developing countries. We tested the robustness of our results through a series of robustness tests. The level of electoral competition, the level of corruption, and finally, the representation of the candidate in power influence the appearance of these cycles. It is, therefore, essential to set up independent rent management structures while encouraging the establishment of national and international transparency initiatives to manage these rents.

1.3.3 What does mining effect on the economy mean in terms of participation and positioning in the global value chain?

Booms from the mining sector influence the structure of the economy. This structural change in the economy can be felt through a change in the products exchanged with the rest of the world. With the manufacturing sector collapsing due to the shock, so are the goods imported and exported by the affected countries. This change in the trade balance corresponds to a change in participation in international trade. In this logic, we studied the relationship between mining activity and participation and positioning in the global value chain in the fourth chapter. Faced with the various elements provided by the literature, we can legitimately ask the following question: What is the effect of these mining booms on the participation and positioning of countries in the global value chain?

Numerous studies have been carried out to demonstrate the link between

[4] https://nelda.co

[5] https://mgmt.wharton.upenn.edu/faculty/heniszpolcon/polcondataset/

shocks originating in the natural resources sector and structural changes in the economy. However, little focus has been made on the effects of commodity booms. Firms in countries affected by these shocks can lose their competitive edge. Also, this chapter is the first to shed light on mining booms as determinants of participation in the global value chain by combining indices of participation and positioning in the global value chain (constructed using the EORA database) to a mining activity variable.

The methodology we have meticulously chosen to answer this question is that of an event study with a five-year study horizon. This approach allows observing, year after year, the ripple effects of the activation of mines on participation and positioning in the Global Value Chain. In other words, it enables us to capture the dynamic effects of mining on participation and positioning in the Global Value Chain. We have constructed three dependent variables in this study, using the UNCTAD-Eora database to measure participation and positioning in the global value chain. The variable of interest, the activation of a mine, comes from the database. The other variables come from the World Development Indicators database.

The main results, which are robust to a series of rigorous tests, reveal that activating mines negatively impacts a country's positioning in the global value chain. Thus, mining activity hampers positioning in the global value chain through specialization towards start-of-the-chain industries. These findings, which demonstrate significant heterogeneity, are influenced by factors such as the ore extraction method and the country's geographical position.

Therefore, countries dependent on natural resources must protect other sectors in the event of shocks through investments or aid for reconversion. This protection can also be done through the local processing of minerals, increasing the positive effect of mining activity on economies.

1.3.4 How do the effects of mining booms on the economy translate at a more disaggregated level; firm performance?

The structural change induced by mining booms can be observed at a more disaggregated level, that is to say, at the firm level. Given that the collapse of the manufacturing sector characterizes this shift, we expect to see a fall in the performance of manufacturing firms following booms in the mining sector. Indeed, following the literature, positive shocks to natural resources could result in a loss of competitiveness in the economy and a deterioration of institutional quality, all things which have repercussions on firm performance. Labor migration from manufacturing to mining is another channel through which these shocks can influence manufacturing firms.

In this logic, we seek to highlight and quantify the effect of mining booms on the firm's performance in the fifth chapter. This answers the question: How do booms affect firm performance in the manufacturing sector?

This chapter, constituting an answer to this question, contributes to the literature in several respects. Firstly, while the Dutch disease and natural resource curse literature usually focus on macroeconomic indicators, we merge firm-level data from the World Bank Enterprise Surveys (WBES) with fine-scale mining data provided by the database to explore these mechanisms at the firm level. Secondly, we explore several channels through which mining booms affect firm performance. These are the exchange rate appreciation, poor institutional quality, and labor force shifts.

To answer this question, we constructed a measure of firm performance following the literature, especially using the World Bank Enterprise Survey (WBES) database[6]. The methodology used is the multilevel mixed model. Once again, mine activation variable and mine characteristics come from the [7] database. Macroeconomic control variables from the WDI database were added to our analysis.

Results suggest a decline in the performance of manufacturing firms following mining booms, which is consistent with the literature on Dutch disease. The mechanism explaining this result is the loss of competitiveness following the appreciation of the exchange rate and the drop in institutional quality due to rent-seeking behavior.

[6] https://www.enterprisesurveys.org/en/data

[7] https://consulting.com

1.4 Appendix

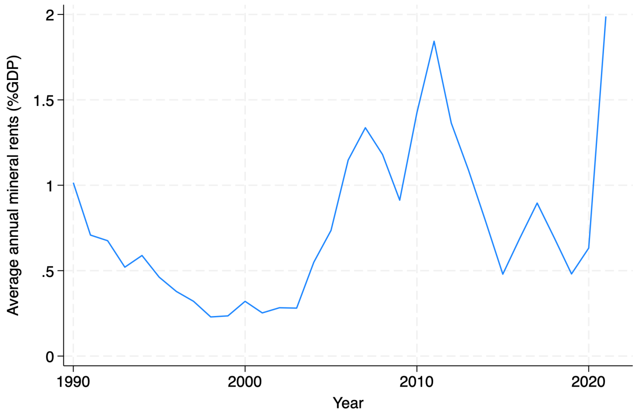


Figure 1.6: Evolution of average level of mineral rents
Sources : World Development Indicators

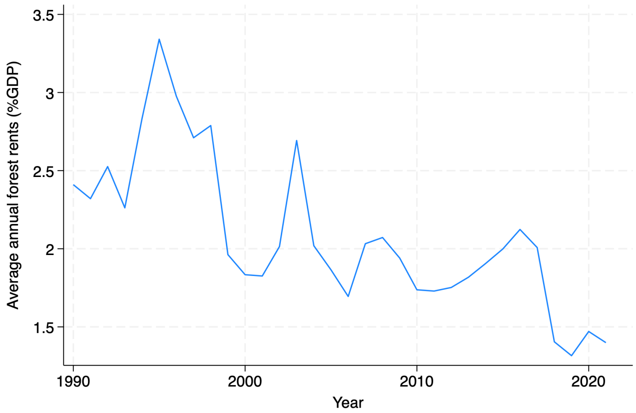


Figure 1.7: Evolution of average level of forest rents
Sources : World Development Indicators

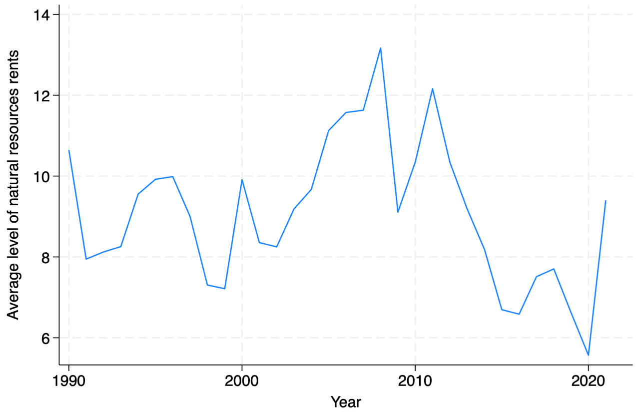


Figure 1.8: Evolution of average level of rents of natural resources for developing countries

Sources : Author from World Development Indicators

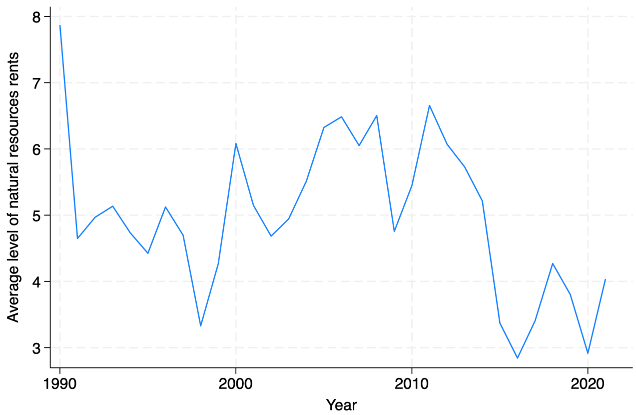


Figure 1.9: Evolution of average level of rents of natural resources for developed countries

Sources : Author from World Development Indicators

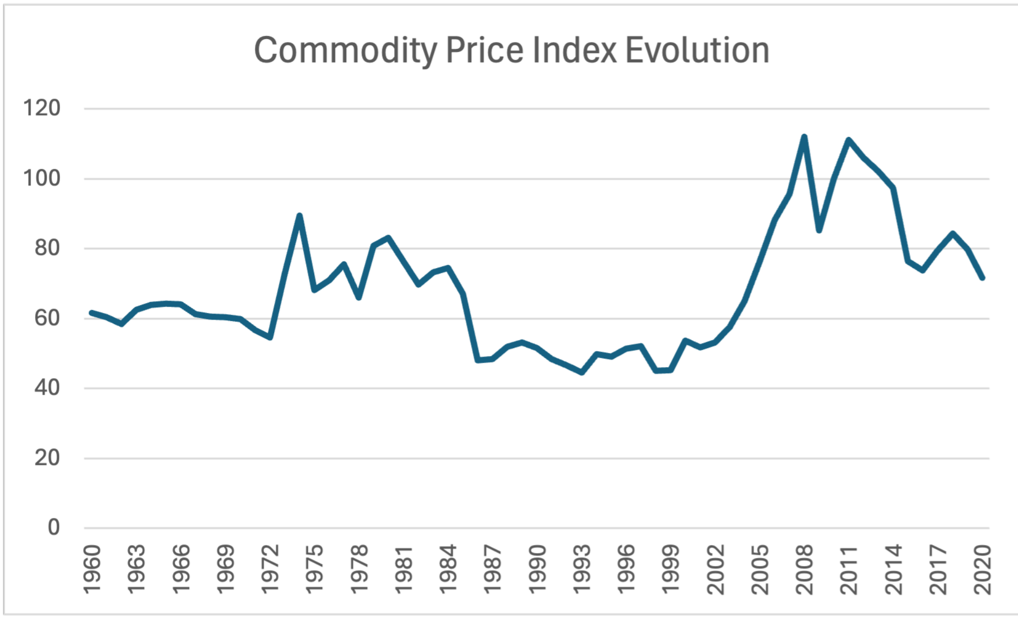


Figure 1.10: Evolution of the Commodity Price Index from 1990 to 2020
Sources : Author from World Development Indicators and Our World in Data

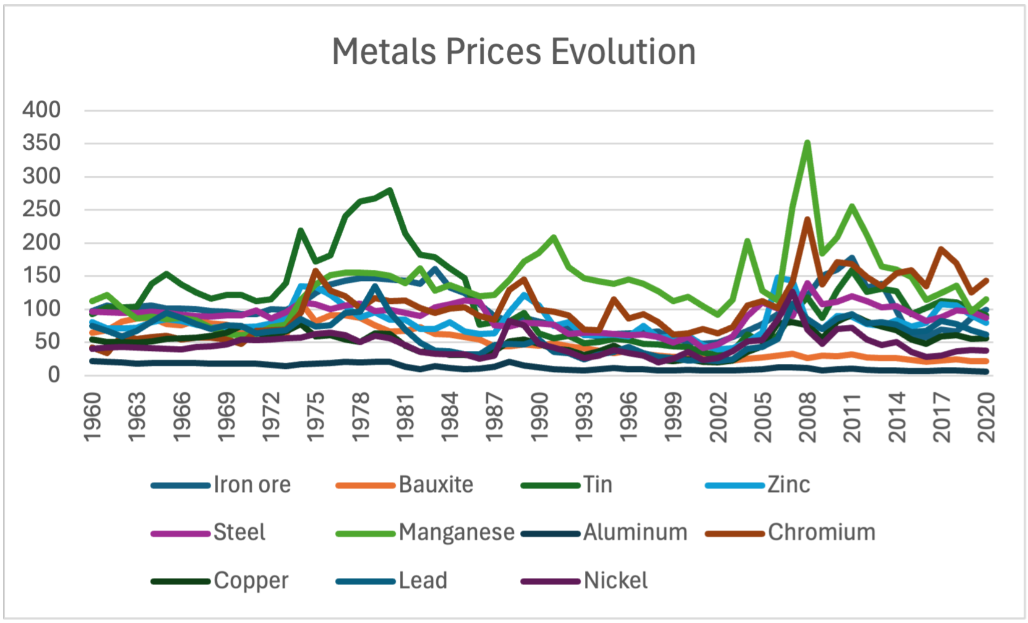


Figure 1.11: Evolution of the Metal Prices from 1990 to 2020
Sources : World Development Indicators and Our World in Data

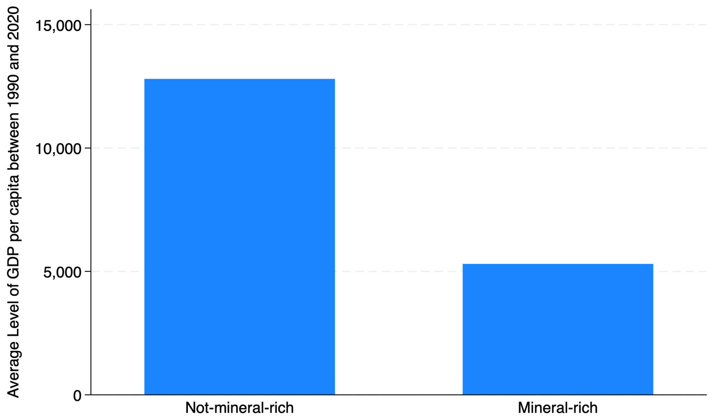


Figure 1.12: Average GDP per capita for minerals-dependent countries versus other countries
Sources : World Development Indicators

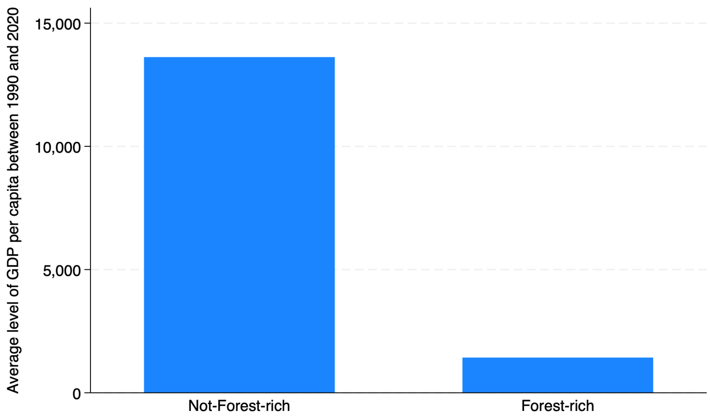


Figure 1.13: Average GDP per capita for forest-dependent countries versus other countries
Sources : World Development Indicators

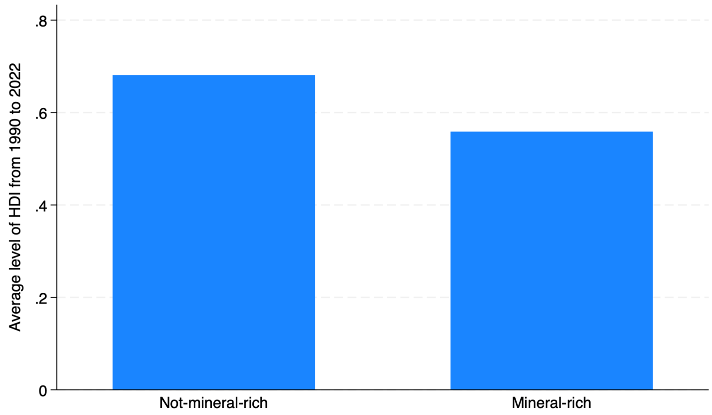


Figure 1.14: Average HDI for mineral-dependent countries versus other countries
Sources : Our World inData

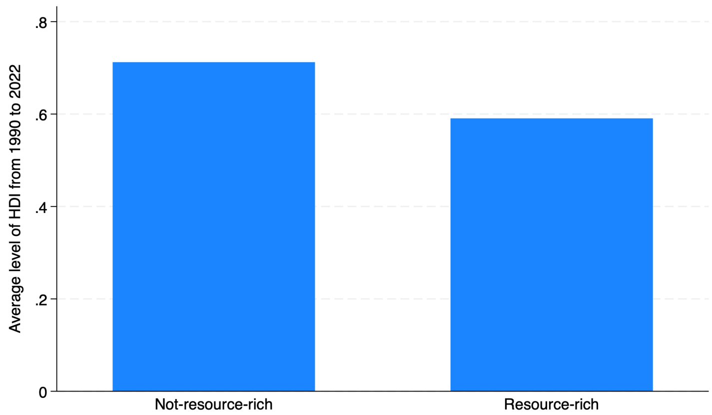


Figure 1.15: Average HDI for resources-dependent countries versus other countries based on IMF classification
Sources : Our World in Data

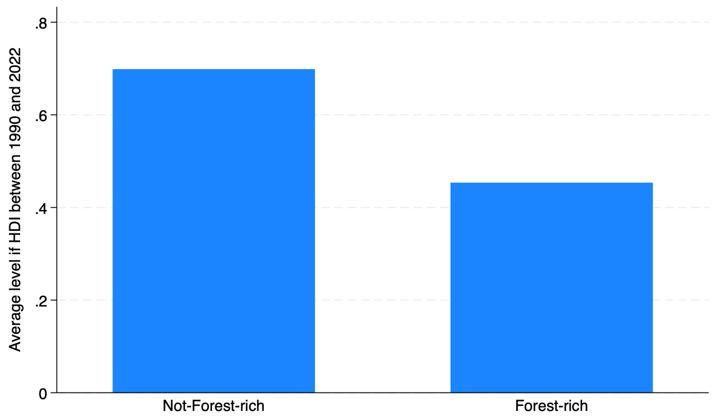


Figure 1.16: Average HDI for forest-dependent countries versus other countries
Sources : Our World in Data

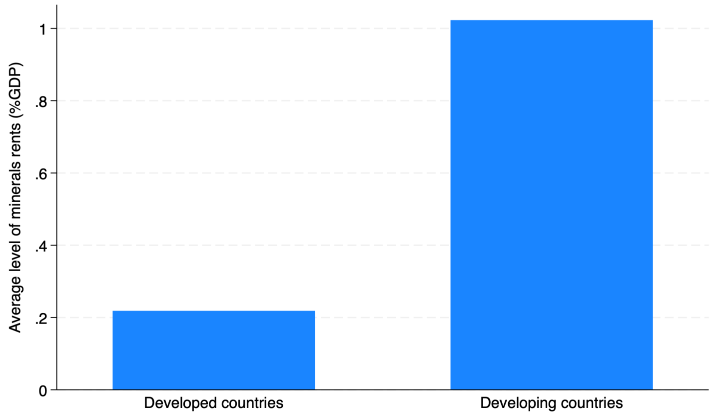


Figure 1.17: Average level of mineral rents for by income level
Sources : Authors from World Development Indicators

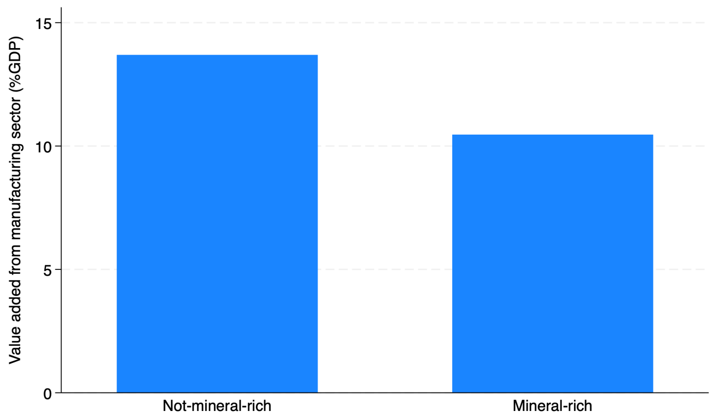


Figure 1.18: Value added from manufacturing sector for minerals-dependent countries versus other ones
Sources : Authors from World Development Indicators

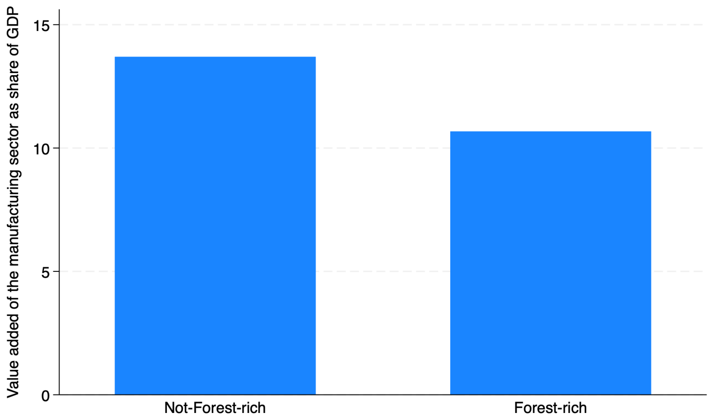


Figure 1.19: Value added from manufacturing sector for forest-dependent countries versus other ones

Sources : Authors from World Development Indicators

Part I

Forest resources

As stated above, the manuscript is structured in five chapters. Chapter 1 is the general introduction, followed by four original chapters. These four Chapters can be divided into two parts. In this first part, we present Chapters 2 and 3 related to forest resources. Chapter 2 explores the environmental (forest loss) consequences of mining activities, while Chapter 3 questions the presence of electoral cycles in forest rents. The last two chapters further explore the socio-economic impacts of mining activities.

Chapter 2

Mining the forests: do protected areas hinder mining-driven forest loss in Sub-Saharan Africa? *

This chapter is a joint work with Pascale Motel Combes (LEO-UCA), Jean-Louis Combes (LEO-UCA) and Youba NDIAYE (BETA)

African countries are natural resource-rich. The continent is endowed with natural forests, homes of endemic biodiversity and various ores. This richness brings hope for sustainable and inclusive development in a continent whose population is rapidly growing. It also raises fears of environmental degradation. This article studies mining-driven deforestation using unique fine-scale data from 2001 to 2019. The dataset covering all Sub-Saharan African countries entails 2,207 polygons with an average size of about 12,000 square kilometers. 926 polygons were forested in 2001, of which 198 hosted industrial mines. The results of the spatial autoregressive model evidence that the spatially lagged forest loss has a positive effect on deforestation, thus suggesting that deforestation decisions are complements at the local level. We find that an additional mine in a polygon, directly and indirectly, increases deforestation by about 155 square kilometers, whereas 100 square kilometers of protected areas enable a 9.7 square kilometers reduction in forest loss only: doubling protected areas could offset mining-driven forest loss. Protected areas cannot alone mitigate the adverse effects of mining on forest loss and other environmental consequences. Moreover, the effectiveness of protected areas is not uniform across space: it vanishes in highly conflicted regions.

Keywords: Deforestation, Mining · Protected areas · Panel data · Spatial econometrics · Sub-Saharan Africa.

JEL codes : C23, L70, O13, N57, Q23, Q32

* This chapter is available on HAL (Combes et al., 2023)

2.1 Introduction

Many African countries are rich in natural resources and aspire to better livelihoods. With a steadily growing population expected to be just under four billion by the end of the 21st century, [1] African countries face a challenge: achieving inclusive and sustainable development. Tapping natural resources, particularly ores, can generate significant income and likely reduce poverty. Today, according to the World Development Indicators, mineral and forest rents are above the world averages as a percentage of GDP. Still, natural resource extraction can also irreversibly damage essential natural assets for sustainable development, especially the forest.

21.7% of tropical African forests have been deforested since 1900 (Aleman et al., 2018). West and East African forests have practically vanished. In recent years, while deforestation has slowed down worldwide, it seems to have accelerated in Africa, with a net forest loss of 3.94 million ha per year from 2010 to 2020 against 3.4 million ha per year in the previous decade (Mansourian and Berrahmouni, 2021). The deforestation and forest degradation drivers are multiple. The literature (Geist and Lambin, 2002) distinguishes between the proximate causes of deforestation (agriculture and pastoral expansion, wood extraction, infrastructure extension, mining activities) and underlying causes (macroeconomic variables, societal factors). On a global scale, agriculture is the main proximate driver of deforestation. A meta-analysis unsurprisingly concludes that deforestation is more likely when the economic returns of agriculture are higher (Busch and Ferretti-Gallon, 2017).

Africa is on the verge of a mining boom (Edwards et al. (2014)). With its promise of high incomes, the mining sector is expected to grow in Africa. The 5th edition of the mining contribution index of the International Council on Mining and Metals (ICMM) evidences that five African countries, including the Democratic Republic of Congo and Madagascar, rank high in the list of mining-dependent countries. This dependency is likely to endure as 30% of the world's total mineral reserves is in Africa (Adu and Dramani, 2018). Existing literature evidence several effects of mining development in Sub-Saharan African (SSA) countries. For instance, mining positively impacted African agricultural sectors, though the authors also evidenced transient and gender-specific employment effects (Kotsadam and Tolonen (2016)). There is also evidence that mining fosters conflicts (Berman et al. (2017))

[1] United Nations, Department of Economic and Social Affairs, Population Division (2022). World Population Prospects 2022, Online Edition.

and deleteriously impacts local governance (Knutsen et al., 2017).

This paper focuses on mining-driven deforestation in SSA countries. To the best of our knowledge, the link between deforestation and mining activities is still little studied (Maddox et al., 2019), especially in Africa. Several authors attracted attention to the fact that SSA countries could undertake a mineral-fuelled forest transition (Rudel, 2013). Sub-Saharan countries' mineral resource occurrences are often located near or in forested areas that harbour outstanding endemic biodiversity. Mining is deemed to have a massive influence on the natural environment in Africa and especially on the forests (Edwards et al. (2014)). Mining damages the environment through the prospection, extraction, transport of inputs and outputs, or use of environmentally harmful inputs. Arsenic, cyanide, and mercury generate a persistent detrimental effect on the forest. Also, these chemical compounds could impact surrounding areas through waterways, sediments, or the atmosphere (Eisler and Wiemeyer, 2004; Eisler, 2004). Hence, the process of reforestation after mining activities is long-lasting. However, perspectives from local communities provide a balanced view with positive impacts of providing improved water sources, healthcare facilities, roads, and schools (Leuenberger et al., 2021).

Mining activities trigger direct and indirect effects on deforestation. On the one side, mining activities directly fuel forest clearances. They generate population shifts: local people may be forced to leave and relocate, while new employment opportunities attract others. These new populations may increase the demand for fuelwood and agricultural land. Overall, these movements can contribute to the deforestation pressure. Indirect channels pertain to the provision of communication infrastructures and buildings needed to develop mining facilities.

The literature on protected areas as an instrument for reducing deforestation in SSA generally concludes that they are effective (Bowker et al., 2017). Nevertheless, few studies assess the impact of protected areas in the context of deforestation accelerated by mining activities. However, the legal protection afforded by protected areas may differ depending on the nature of the economic activity that infringes on the forest. In the case of legal mining, mining companies may, in the context of corruption, escape environmental regulations. Artisanal-scale mining activities are often illegal and, therefore, not sensitive to environmental regulations.

This article studies the link between mining activities and deforestation and questions the effectiveness of protected areas in response to mining-induced deforestation. More precisely, we aim to answer the two following questions. How do mining activities contribute to deforestation? How do conservation instruments such as protected areas dampen mining- driven deforestation?

We estimate a deforestation spatial econometric model that allows us to consider interactions between neighbouring spatial units. Each spatial unit covers 12,070 square kilometres on average. Overall, we have 2,207 spatial units, namely polygons, from 2001 to 2019, of which 926 are forested at the beginning of the study period. The dataset gathers information on deforestation, mining activities, protected areas and other relevant socio- economic variables affecting deforestation. To our knowledge, our study is the first to address mining-driven deforestation using sub-national data. This level of analysis is the most relevant because clearing and land use conversion both take place at a fine spatial scale. Existing studies are conducted at the national level (Azomahou and Ouédraogo, 2021). We contribute to the literature on the effectiveness of protected areas in curbing deforestation since we examine the role of protected areas as a lever for mitigating deforestation induced by mining activity, which has never been investigated in SSA. The estimation results show that mining activities increase deforestation, while protected areas reduce deforestation. Moreover, it does not appear that the presence of protected areas dampens the impact of mining on deforestation. We highlight a spatial heterogeneity: the negative impact of mines on forests and the poor effect of protected areas occur when the local institutional quality is poor.

The remainder of the article is as follows. Section 2.2 reviews the existing literature. We present the econometric framework in Section 2.3. We detail the elaboration of the fine-scale data set from which we extract descriptive statistics in section 2.4. Section 2.5 successfully gives the main results and estimates how much mining drives forest losses in Sub-Saharan Africa. We provide concluding remarks in section 2.6.

2.2 Literature review

We will first present the studies devoted to the impact of mining activities on deforestation. We will then review the main findings of studies dealing with the relationship between protected areas (and forest management) and deforestation. Finally, we will describe the few studies focusing on the role of protected areas as a tool for mitigating the effects of mining on forest cover and present our hypotheses.

2.2.1 Mining activity and deforestation

Several studies have studied the link between mining activities and deforestation. Most of them focus on the Amazonian forest and use high-resolution geospatial data. For instance, mining significantly increased deforestation in the Brazilian Amazon (Sonter et al., 2017). Moreover, forest losses extend well beyond the mining lease boundaries and account for 9% of deforestation between 2005-2015. In Colombia, the contribution of legal mining activities inside concessions to deforestation grew during the 2010s and reached a 5.6% peak in 2017. The two minerals mainly causing deforestation are gold and coal (González-González et al., 2021).

Some artisanal-scale gold mining activities would be particularly detrimental to forest conservation. Indeed, these activities are often illegal and therefore do not comply with environmental regulations. This phenomenon is reported in several Latin American countries, for instance: Suriname (Peterson and Heemskerk, 2001) or Peru (Caballero Espejo et al., 2018). In the case of the Brazilian Amazon, deforestation of illegal gold mining increased by more than 90% from 2017 to 2020 (Siqueira-Gay and Sánchez, 2021). Furthermore, once abandoned, the mining area is not correctly restored, and therefore the regeneration of the primary forest is hampered. Periods of rising gold prices are particularly detrimental to forest conservation in the Peruvian Amazon (Swenson et al., 2011). In Latin America, the increase in the demand for gold after the international financial crisis fueled deforestation from 2007 to 2013 (Alvarez-Berríos and Aide, 2015).

Only a few studies have examined the impact of mining activities on deforestation in Asia. For instance, there is evidence of adverse effects of mining activities on forest cover at the district level in India (Ranjan, 2019). The effect is heterogeneous and depends on the mineral involved. In Indonesia, mining activities are increasingly responsible for the loss of forest cover from 2001 to 2016 (Austin et al., 2019). However, palm oil plantations encroachment outweighs mining activities since the former represents 23% of deforestation compared to 2%.

Africa has experienced lower deforestation rates for several decades compared to South America and South and South East Asia. For instance, oil and gas receipts substantially reduced deforestation from 2000 to 2005 (Rudel, 2013). The extractive sector's contribution to urbanisation may have hampered deforestation's proximate drivers. However, a recent study relying on panel data from 2001 to 2017 found a positive effect: a one-point percentage of GDP increase in mineral rents generated about 50 square kilometers of forest loss (Azomahou and Ouédraogo, 2021). An oil and mineral-fueled forest transition may have started in Africa, especially in the Congo basin humid forest. Indirect effects of deforestation in the surroundings of mining areas are likely at work. Direct deforestation within the mining areas concerns few countries while indirect deforestation is a problem for two thirds of tropical countries. The indirect deforestation impact is remarkably high in a couple of African countries such as Gabon and Zambia (Giljum et al., 2022).

2.2.2 Protected areas and deforestation

"A protected area is a clearly defined geographical space, recognised, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values." (IUCN Definition 2008).[2] 14.6% of the land area was designated as protected, and 16% of the forest fell within a legally established protected area in 2015. In Africa (Democratic Republic of Congo), the proportion of forest areas with legally protected areas was 23.37% (12.38%) in 2000 and 25.73% (18.45%) in 2020 (Ritchie et al., 2022).

A bulk of econometric studies study the effectiveness of protected areas. Early studies date back to the early 2000s (Joppa and Pfaff, 2009; Nelson and Chomitz, 2011). The main challenge is the location bias of protected areas (Cropper et al., 2001; Joppa and Pfaff, 2009). Authors usually address this issue by implementing matching methods with control groups. Once the location bias is controlled for, the authors found that protected areas reduce deforestation. Most existing results pertain to Latin America: Costa Rica (Andam et al., 2008; Pfaff et al., 2009; Robalino et al., 2015, 2017), Guatemala and Mexico (Bray et al., 2008), the Brazilian state of Acre (Pfaff et al., 2014) or Sumatra in South East Asia (Gaveau et al., 2009).

Heterogeneity effects in the impact of protected areas on deforestation may occur. For example, in the case of the legal Amazon, the protected areas with the highest impact are those located near cities and roads (Pfaff et al., 2015). Strictly protected areas are more effective. Existing studies on Brazil support that claim

[2]Protected areas can also be managed locally, nationally, or internationally. Moreover, the degree of legal protection provided by the protected area depends on their category. The different categories are the following: strict nature reserve (Ia); wilderness area (Ib); national park (II); natural monument of feature (III); habitat/species management area (IV); protected landscape/seascape (V); protected areas with sustainable use of natural resources (VI). The most restrictive categories are I, II and III. Categories IV, V and VI allow a sustainable use of resources. Source: IUCN available at https://www.iucn.org/theme/protected-areas/about.

once accounting for location bias (Nolte et al., 2013; Kere et al., 2017). The results hold with considering contextual bias and spatial dependence (Kere et al., 2017).

Spatial interactions are another critical issue. Deforestation in one location could impact deforestation in neighbouring areas, for instance, through transportation infrastructure development (Angelsen, 2001; Schwartz et al., 2022). These spatial interactions are likely at work in the "arc of deforestation" in Brazil. In addition, protected areas can foster deforestation leakages. Deforestation leakage occurred into forests from concession areas in the Peruvian Amazon (Oliveira et al., 2007). Parks facing tremendous deforestation pressure show more significant leakage in Costa Rica (Robalino et al., 2017). However, the proximity to a protected area can also contribute to reducing forestry activity, for example, by creating more difficulties in accessing the forest resource. Indigenous lands raise deforestation nearby, contrary to federal-protected areas in the Brazilian Pará State (Herrera et al., 2019). Strictly protected areas and indigenous lands allow reducing deforestation, unlike sustainable protected areas in the Brazilian Legal Amazonia (Amin et al., 2019). Moreover, these two types of protected areas generate a positive spillover effect: they reduce deforestation in their vicinity.

There are similar questions about the effectiveness of forest management plans which are considered a step towards sustainable forest management, particularly in the Congo Basin (Democratic Republic of Congo), which represents the second largest primary forest in the world (Karsenty et al., 2008). These plans detail a concession selective logging to ensure maximum harvest rates while at the same time preserving the resource. Protected areas urrounded by logging concessions operated with a forest management plan ("unified conservation landscape") could be considered as means to both achieve economic development and biodiversity conservation (Brandt et al., 2016). Deforestation and timber production are higher in concessions with registered forest management (Brandt et al., 2016, 2018) though the results are questioned (Karsenty et al., 2017). Between 2000 and 2010, deforestation was also found to be significantly lower in concessions operating under a forest management plan (Tritsch et al., 2020).

2.2.3 Mining, protected areas and deforestation

A very understudied issue is the effectiveness of protected areas in the face of mining- induced deforestation.Weisse and Naughton-Treves (2016) studied the effect of protected area buffer zones on formal and informal mining extent in the Peruvian

Amazon. These buffer zones have been poorly studied because of the ambiguity of their management rules and their sometimes-informal status. Nevertheless, these buffer zones cover more than 10% of the country and positively impact forest cover by limiting the extent of mining concessions. However, they could be more efficient in limiting the development of illegal mining activities.

Expanding mining concessions increased the forest cover loss from 1990 to 2010 in Democratic Republic of Congo (DRC) (Butsic et al., 2015). One of the particularities of the Congo Basin is the prevalence of conflicts. It appears that they fuel deforestation, but in times of conflict, the impact of mining concession on deforestation was mitigated. Moreover, protected areas reduced deforestation, even in times of conflict.

In this article, we seek to answer two questions. Is mining a driver of deforestation in Sub-Saharan Africa? Are protected areas an effective tool for mitigating the effects of mining on deforestation? These questions are relevant in the SSA context characterised by a low institutional quality where mining companies can use corruption to circumvent environmental regulation.

2.3 Methodology

We present first the econometric framework. It takes advantage of fine-scale data, allowing the investigation of spatial dependence in activities potentially contributing to deforestation. Then we discuss the identification of neighbours and how we intend to interpret the results.

2.3.1 Econometric framework

The spatial lag model is theoretically appropriate to investigate mimicking behaviours. An application of first generation of spatial econometric models could be seen in (Brueckner and Saavedra, 2001; Ollé, 2003). In this paper, we claim that deforestation in one area interacts with neighbours' deforestation.[3]

We estimate a spatial panel data model in which the level of deforestation in a spatial unit (see the definition of spatial units, namely polygons in section 4.1)

[3] There are two approaches in the empirical literature to assess the presence and direction of spatial interaction. The first generation of studies is based on spatial autoregressive modelling. The second generation of studies is based on the idea that evidence of sources of spatial dependence is hard to identify (Ndiaye, 2018). We add some references related to this literature in the conclusion.

depends on the level of deforestation in neighbouring units and on a set of observed local characteristics. Formally, let the index $i = 1, ..., N$ denotes a spatial unit and $t = 1, ..., T$ denotes a time period with $t = 2005$ for the 2001-2005 period, $t = 2010$ for the 2006-2010 period, $t = 2015$ for the 2011-2015 period and $t = 2019$ for the 2016-2019 period. Using average years rather than yearly data allows to grasp medium-term effects of mining activities and protected areas on deforestation.[4] Our identification strategy is based on a panel spatial autoregressive model (SAR) with spatial units and time-fixed effects. This model writes as follows:

$$\begin{aligned} \text{Forest\_loss}_{\,it} =& \rho \sum_{j=1, j\neq i}^{N} w_{ij} \text{ Forest\_loss}_{\,jt} + \beta_1 \text{ Mine}_{\,it} + \beta_2 \text{ LagPA}_{\,it} \\ &+ \beta_3 \text{ LagPA}_{\,it} \times \text{ Mine}_{\,it} + \gamma_k x_{it}^k + \mu_i + \eta_t + \varepsilon_{it} \end{aligned} \tag{2.1}$$

Where $Forest\_loss_{it}$ refers to the level of forest loss observed for the spatial unit i at period t. w_{ij} corresponds to the spatial weight's matrix, an NxN pre-specified row-normalised weights matrix with zeros on the diagonal. So, $\sum_{j=1,j\neq i}^{N} w_{ij}$ Forest_loss $_{jt}$ refers to the spatially lagged deforestation variable and represents the average deforestation of neighbouring spatial units. The spatial scalar parameter ρ reflects the endogenous spatial interaction between a spatial unit and its neighbours. $\rho = 0$ means no spatial interaction. If ρ is positive, the level of deforestation in a spatial unit tends to mimic the neighbours', suggesting a complementarity effect. On the other hand, a negative ρ suggests a substitution in deforestation levels that may be interpreted in terms of deforestation leakage.

LagPA $_{it}$ and Mine $_{it}$ are respectively the time lagged value by one year of protected areas, and the number of the mining activities for unit i at period t. The interactive variable LagPA $_{it}$ $\times$ Mine $_{it}$ is meant to assess the specific influence of protected areas on mining-driven forest loss. x_{it}^k is the $k-th$ control variable for unit i at period t. We add spatial unit-fixed effects μ_i to capture time-invariant spatial unit-specific attributes such as natural endowments or distance to markets, and period-fixed effects η_t to capture common trends in deforestation. The omission

[4]Moreover, five-year panel data are justified for other reasons: i) Some observations are not available every year. ii) This strategy allows to smooth out yearly variations in deforestation data that may be driven by measurement issues; iii) The inter-annual variability of some variables is low; iv) Not using annual data allows to neutralize the problems specific to time series: presence of a cointegration relationship or unit roots.

of these specific characteristics might bias the estimates in a panel data analysis (Elhorst, 2010; Baltagi and Baltagi, 2008).

Besides the simultaneity bias generated by the spatial lag of the dependent variable, i.e. lagged forest loss, another issue is related to the potential presence of additional endogenous variables. In particular, to avoid simultaneity bias between the protected areas and forest loss, we use time-lagged of protected areas variable (with a one-year time lag). Moreover, in the robustness check, we consider a spatial lag for each explanatory variable in the specification to reduce the finite-sample bias of endogeneity implied by measurement error and simultaneity (Fingleton and Corrado, 2011). ε_{it} is a spatially correlated error term such as $\varepsilon_{it} = \rho \sum_{j=1,j\neq i}^{N} w_{ij}$ Forest_loss $_{jt} + \mu_{it}$ where μ_{it} represents idiosyncratic shocks uncorrelated across spatial units and over time.

According to our hypotheses, one should observe:

$\beta_1 > 0$ namely mining activities favor deforestation;$\beta_2 < 0$ namely protected areas dampen deforestation. Moreover, if mining-induced deforestation is mitigated by protected areas then we have $\beta_3 < 0$, which means that the impact of mining on deforestation should be lower the larger protected areas.

The previous specification is the benchmark model to uncover spatial interactions in the deforestation level. We add another specification to check the validity of the results by allowing for strong cross-sectional dependence under the form of common factors (Pesaran, 2006; Chudik et al., 2011).[5] As a robustness check, we have the following equation:

[5]Initially, in panel data, a common strategy to deal with unobservable heterogeneity set about (i) using a transformation of variables (fixed effects model) or (ii) by setting out assumptions about the structure of the error term (random effects model). However, in these both cases, a restriction is made on the form of heterogeneity for each individual that is constant in the temporal dimension. By definition, common factors and spatial panels make it possible to capture interactions between individuals Salima et al. (2018). In addition, the presence of common factor allows to considering residual unobserved effects. In spatial econometrics, Shi and Lee (2018) proposed a decomposition of the error term in SAR panel into a common factor component (strong spatial dependence) and an idiosyncratic component (weak spatial dependence). In our study, as additive individual and time effects can potentially not be explained entirely the heterogeneity effects, we also add common factor component in order to verify the robustness of our results in presence of weak and strong cross-section dependence (Chudik et al., 2011).

$$
\begin{aligned}
\text{Forest\_loss}_{it} =& \rho \sum_{j=1, j\neq i}^{N} w_{ij} \text{ Forest\_loss }_{jt} + \beta_1 \text{ Mine }_{it} + \beta_2 \text{ LagPA }_{it} \\
&+ \beta_3 \text{ LagPA }_{it} \times \text{ Mine }_{it} + \Gamma_1 \overline{Forest\_loss_t} + \Gamma_2 \overline{Mine_t} + \Gamma_3 \overline{LagPA_t} \\
&+ \Gamma_4 \overline{LagPA \times Mines_t} + \gamma_k x_{it}^k + \mu_i + \eta_t + \varepsilon_{it}
\end{aligned} \tag{2.2}
$$

where is the cross-sectional average of the deforestation variable. $\overline{Mine_t}$, $\overline{LagPA_t}$, $\overline{LagPAMine_t}$ and $\overline{x_t^k}$ are the cross-sectional averages of the independent variables at time t. These common factors are treated as parameters to be estimated (Shi and Lee, 2018).

2.3.2 Spatial dependence and econometric issues

Estimating Equations (1) and (2) presents several challenges. Firstly, to test for spatial interactions of deforestation level, it is necessary to identify spatial neighbours. While various weighting schemes could be applied, we construct a commonly used spatial weight's matrix, namely the k-nearest matrix $k = 5$. $w_{ij} = 1$ if j is one of i's five nearest neighbours and 0 otherwise. We also consider two alternative weight matrices namely Gabriel neighbours and the inverse distance.[6]

Finally, since the coefficients from equations (1) and (2) cannot be interpreted directly due to the presence of a spatial lag variable, we compute partial derivatives, i.e. marginal effects (LeSage and Pace, 2009). In this perspective, the matrix of partial derivatives of $Forest\_loss_{it}$ with respect to an explanatory variable ζ_{it} is:

$$
\frac{\partial \text{ Forest\_loss }_{it}}{\partial z_{it}} = \left[\left(I - \rho \sum_{j=1, j\neq i}^{N} w_{ij} \right)^{-1} \right] \delta \tag{2.3}
$$

ρ is the coefficient of the explanatory variable ζ_{it}.

A change in a particular explanatory variable in a spatial unit has a direct effect on that spatial unit and an indirect effect on the neighbouring spatial units.

[6] Gabriel neighbours are defined by a Gabriel graph (Gabriel and Sokal, 1969). Inverse distance weight matrix is a geographical definition of neighbourhood based on the inverse geographical distance between spatial unit.

The total effect is the sum of the direct and indirect effects.[7]

2.4 Data

We build an original five-year-panel dataset. The following subsections describe the observation units, namely the spatial units which are polygons, and then present the variables and give descriptive statistics.

2.4.1 Polygons in Africa

We relied on geolocalised data obtained from (Hansen et al. (2013)) to build the most comprehensive dataset from 2000 to 2019. These data allow defining the units of study, namely square polygons covering all SSA countries.[8] Each polygon has an area of approximately 12,070 square kilometres. It is the finest possible subdivision which allows obtaining units with available observations. We departed from 2,207 polygons in SSA to get 926 forested polygons in 2001. Forested polygons in 2001 had at least 10% of their area covered by the forest (Figure A.1 in Appendix). We take advantage of the time dimension to define four five-year periods. We eventually have $926 \times 4 = 3{,}704$ observations.

We use raster files containing the necessary information for each variable to extract the geolocated data belonging to each polygon. These files are high-definition image files containing geolocated information for each variable and came from various sources. Table 2.8 in Appendix gives an overview of our variables and their sources.

2.4.2 Study variables

We present below the dependent variable, our interest variables and other controls.

[7]From a technical point of view, the direct effects are measured by the average of the diagonal entries of the spatial weight's matrix whereas the indirect effects are measured by the average of non-diagonal elements.

[8]Gridded data is quite widespread in econometrics when faced with a lack of data at the micro level. For example, Buys et al. (2009)), studying the determinants of digital division in SSA countries, used 993,401 square polygons. Interplay between pastoralism, climate change and conflict in Africa is another example McGuirk and Nunn (2020).

Dependent and interest variables

Forest_loss is our measure of deforestation that we borrow from Hansen et al. database (Hansen et al., 2013).[9] The variable covers the 2000 to 2019 period, and for different canopy densities, and the global forest gain. It is a fine scale dataset since measures are made at a approximately 30 × 30-meter resolution. In this database, tree cover is any vegetation taller than 5 metres. Thus, the tree cover could represent forests or artificial plantations. The loss of vegetation cover can refer to deforestation due to human activities or to natural causes such as extreme weather events or natural forest fires. The deforestation variable equals the loss of tree cover accumulated over each period in the polygon.

We retrieve the surface of protected areas from the World Database on Protected Areas (WDPA).[10] It allows to identify other effective area-based conservation measures (OECM). [11]These databases are products of the UN Environment Program and IUCN (International Union for Conservation of Nature).

The MinEx Consulting[12] database delivers information about the geolocalisation of each industrial mining operation, its state of operation, and its year of opening or discovery. Thus, for each unit, we have the number of industrial mines present for each period, irrespective of their status[13].

Control variables

We control for other drivers of deforestation such as climate conditions (*Temp* and *Rain*), night-time luminosity (*Activity*) population density (*Pop*) and violence (*Fatalities*). Climatic conditions influence the profitability of agricultural activity and thus the land use (Nelson and Chomitz, 2011). It is also possible that tem-

[9]https://glad.earthengine.app/view/global-forest-change#dl=1;old=off;bl=off;lon=20;lat=10;zoom=3. The data set comes from a collaboration between the GLAD (Global Land Analysis Discovery) lab, USGS, Google, and NASA. The global database consists of files with a spatial resolution of one arc-second per pixel, corresponding to approximately 30 meters per pixel at the equator. The data was generated using multispectral satellite imagery from Landsat 5, Landsat 7, and Landsat 8 satellites

[10]https://www.iucn.org/theme/protected-areas/our-work/world-database-protected-areas

[11]https://www.iucn.org/commissions/world-commission-protected-areas/our-work/oecms

[12]https://minexconsulting.com/useful-links/

[13]The number of artisanal mines is unknown.

peratures and rainfall have an effect on the occurrence and intensity of forest fires. Economic activity and population density are underlying drivers of deforestation. Night-time luminosity is a proxy of economic activity at the subnational level (Chen and Nordhaus, 2011). The effect of population could be ambiguous: on the one side population density fuels the demand for arable growth but, on the other side, it could favour the demand for forest products (Amin et al., 2019). The impact of violence and conflicts on deforestation is also ambiguous. On the one hand, insecurity could lead to greater deforestation: poor institutional quality that translates into violent events fosters deforestation while downgrading environmental protection and furthermore, deforestation provides a source of funding for armed insurrection. On the other hand, insecurity penalises economic activity, which can slow down deforestation (Prem et al., 2020).

$Temp$ is the absolute value of the deviation of the temperature from the period average. This variable comes from the GISS Surface Temperature Analysis (GISTEMPv4) database. $Rain$ is extracted from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database. $Activity$ comes from the Defense Meteorological Program -Operational Line-Scan System (DMSP-OLS) dataset. Pop is the population density from the Gridded Population of the World, Version 4 (GPWv4) database. We consider the death toll related to conflicts from the ACLED database to build $Fatalities$.

2.4.3 Descriptive statistics

Figure 2.1 provides the location of forest areas, protected areas and mining activities. Descriptive statistics are reported in Table 1 and Table 2.

Table 2.1 gives the basic characteristics of our dataset. The statistics are computed for all observations (3,704), namely they cover the all polygons over the four-year periods. Considering that a polygon's average area is 12,070 square kilometers, the forest loss amounts to 1.1% of the polygons surface while the figure for protected areas is 11.4%. It is in line with percentages of land area protected released on the literature (Chape et al. (2005)).

In Table 2.2, we report the total number of observations, the number of polygons on which these variables are observed, the probability of observing a non-zero value of the variable; the totalled and disaggregated values over the four periods; the mean of the variable per polygon.

The probability of forest loss close to one tells us that forest loss concerns almost all polygons over the period. When we break down by sub-period, we also see an increase in forest loss. One-fifth of the polygons contain mines. Protected areas are present in three quarters of the observed units. In the last six rows, we see the level of deforestation in the spatial units below and above protected areas (mines) median. We observe that the polygons with an area of protected areas above the median experience less deforestation on average. Deforestation is higher in polygons with mining activities on average. This observation concerning the deforestation impact of mining activities is still valid even in polygons where protected areas are above the median.

Considering the pairwise correlations (Table 2.9 in Appendix), we observe a significant and positive correlation between the number of mines and the extent of deforestation. Moreover, the surface of protected areas correlates negatively with mining activities and deforestation.

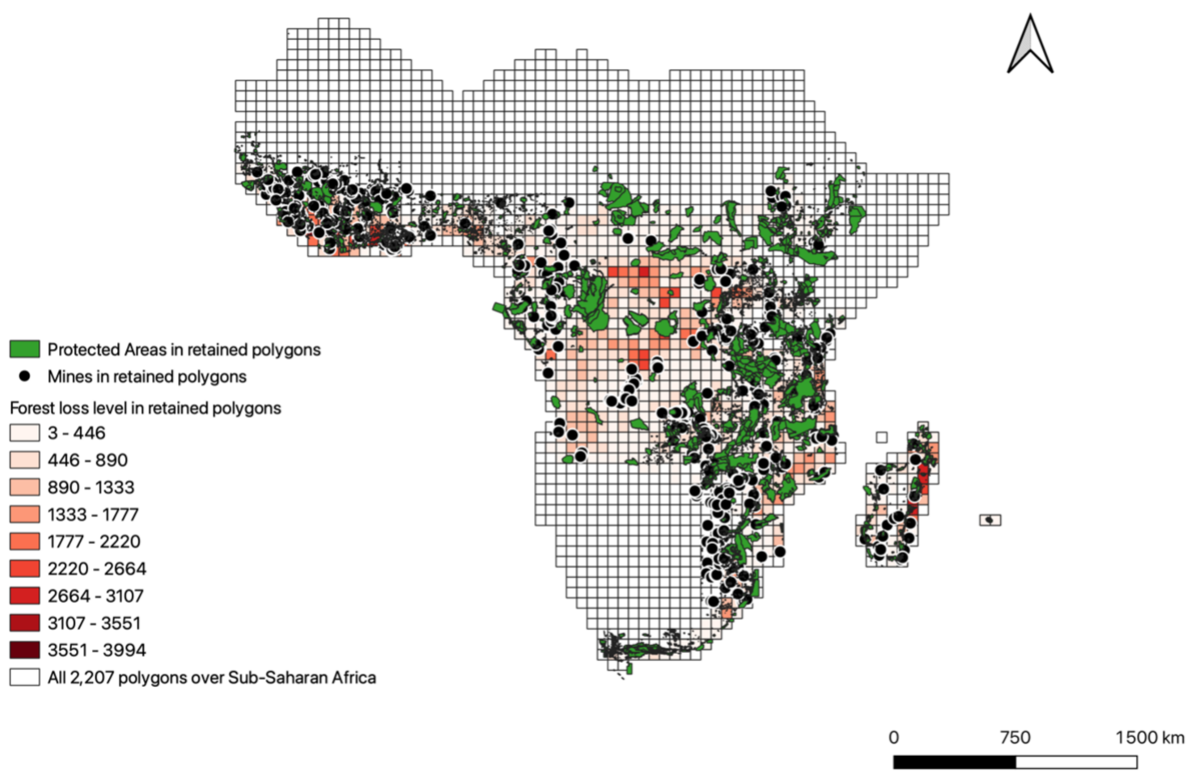


Figure 2.1: Forest areas, Protected areas and Mines 2000 2019

Sources : authors calculation; Hansen et al. 2013 database, MinEx Consulting Datasets and World Database on Protected Areas.

Table 2.1: Descriptive Statistics - Overview

Variables	Observations	Mean	Standard Deviation	Min	Max	Measurement unit
Forest_loss	3,704	139.640	184.698	0	1,927	Square kilometres
PA	3,704	1,371.197	2,276.034	0	11,793	Square kilometres
Mine	3,704	0.423	1.160	0	12	Integer
Temp	3,704	297.211	2.586	286	303	Kelvin degrees
Rain	3,704	1,202.968	559.936	0	3,321	Millimetres
Activity	3,704	0.313	1.285	0	15	Pixel (luminosity)
Fatalities	3,704	22.584	210.191	0	7,630	Units, number of deaths
Pop	3,704	57.063	113.776	0	1,562	Inhabitants per square kilometer

Table 2.2: Descriptive Statistics – Mines and Protected Areas in the Forest

				Whole period	Sub-periods				
Variable	**Obs.**	**Nb of polygons**	**Prob.**	**2001-2019**	**2001-2005**	**2006-2010**	**2011-2015**	**2016-2019**	**Polygon mean**
Forest_loss	3,704	926	0.999	517,227	67,930	98,142	156,120	195,034	140
Mine	3,704	926	0.197	1,566	303	383	435	445	0.4
PA	3,704	926	0.759	5,078,915	1,246,554	1,270,489	1,279,934	1,281,938	1,371
Forest_loss If $PA > Median$	1,850	468	0.999	218,503	29,962	43,991	65,663	78,887	118
Forest_loss If $PA < Median$	1,854	477	0.999	298,722	37,968	54,151	90,457	116,147	157
Forest_loss if Mine > 0	728	198	1	141,347	13,913	22,355	45,538	59,540	194
Forest_loss if Mine $= 0$	2976	772	0.999	375,879	54,017	75,787	110,582	135,494	126
Forest_loss if $PA >$ Median and Mine > 0	341	94	1	55,198	6,871	10,143	17,352	20,832	162
Forest_loss if $PA <$ Median and Mine $= 0$	1,467	394	0.999	212,575	30,926	41,939	62,271	77,439	145

2.5 Results

We first evidence the relevance of the spatial econometric model. Then, we assess the marginal impact of mines and protected areas on forest loss. Finally, we implement a robustness check and consider different heterogeneities.

2.5.1 Weak and strong spatial autocorrelation

We investigate the potential for weak and strong spatial autocorrelation of the level of deforestation in ASS countries. Table 2.3 displays the evolution of the standardised value of Moran's I statistic over the period for each spatial weight matrix. These results suggest that immediate proximity matters more for deforestation interactions. In particular, the Moran's I statistic is increasing over time, thus suggesting that the levels of deforestation are positively and significantly clustered in SSA areas. The computed statistics are consistent with the hypothesis of a positive spatial clustering of deforestation among nearby SSA polygons.

Table 2.3: Standardised Moran's I statistics

Year	std_nn5	std_dinverse	std_gabriel
2005	1,233.179***	1,327.680***	1,438.18***
2010	1,081.750***	1,187.847***	1,261.682***
2015	1,345.908***	1,431.672***	1,544.010***
2019	1,438.017***	1,534.271***	1,663.758***

$^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$

Table 2.4: Estimation results for the benchmark spatial autoregressive model

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
ρ	0.798***	0.791***	0.790***	0.790***	0.789***	0.789***	0.789***	0.789***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
λ	−0.228***	−0.228***	−0.230***	−0.230***	−0.228***	−0.228***	−0.226***	−0.228***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)

Dependent variable: Forest_loss; $^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$; Standard errors in parentheses; the list of variables in the different specifications are given in Table 6

Table 2.5: Estimation results for the spatial autoregressive model with common factors Dependent variable: Deforestation

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
ρ	0.798***	0.791***	0.790***	0.790***	0.789***	0.789***	0.789***	0.789***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
λ	−0.229***	−0.229***	−0.230***	−0.230***	−0.229***	−0.228***	−0.226***	−0.228***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)

Dependent variable: Forest_loss; $^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$; Standard errors in parentheses; the list of variables in the different specifications are given in Table 7

We estimate equations (2.1) and (2.2). We gradually introduce explanatory variables in the model to control for multicollinearity bias (Model 1 to 8). Table 2.4 reports the estimated spatial parameters ρ and λ for the standard spatial autoregressive model (Eq. 2.1).

Table 2.5 reports estimated ρ and λ for the spatial autoregressive model with common factors (Eq. 2.2). The estimated values ofρ and λ are consistent, whatever the specifications (Table 2.4 and Table2.5). [14]

[14]Following Pesaran (2015), we find evidence for strong spatial dependence while computing the

The spatial autocorrelation is positive and strongly statistically significant, corroborating that deforestation decisions are complements. The coefficients range from 78.9% to 79.1%. The smallness of the finest spatial units, namely the polygon, could explain this high level of interaction. When including strong cross-sectional dependence under the form of common factors (Table 2.5), the results of autoregressive coefficients are unchanged. Overall, our spatial interaction results align with previous studies on deforestation determinants outside Sub-Saharan African countries (Amin et al. (2019)). The evidence in Africa is scanter. Interestingly, (Hess et al. (2021)) found that Community-Driven Development (CDD) programs generated positive spillover effects of deforestation in West African drylands.

2.5.2 Impact measures

We find that estimated direct, indirect and total effects of all explanatory variables are very similar without (Table 2.6) or with common factors (Table 2.7). We interpret the total effects. As expected, *Activity* has a positive and significant impact on deforestation (Models 4 to 8 in Table 2.6 and Table 2.7). *Temp*, *Rain*, *Fatalities* and *Pop* remain statistically insignificant (Models 5 to 8 in Table 2.6 and Table 2.7). [15], [16]

correlation coefficients between the observations of each pair of spatial polygons in SSA. Pesaran's null hypothesis of cross-sectional dependence is that the values are only weakly cross-sectionally dependent. The test yields a statistic value of 442.28, which is strongly significant. We conclude that the spatial estimator should include both weak and strong spatial dependence. Although the coefficients vary slightly, the results are robust when common factors are included. In particular, significance and the sign of both the spatial parameters and the marginal effects of the different specifications remain broadly the same.

[15] We regress the error terms of our benchmark model (Eq. 2.1) on the set of explanatory variables. Results validate the hypothesis of no correlation between the error term and explanatory variables suggesting the effectiveness of our procedure in controlling for endogeneity. These results are presented in Table 2.12 in Appendix.

[16] In addition, to (i) Moran test for spatial autocorrelation and (ii) Pesaran test for cross-section dependence, we also perform additional tests in order to validate our empirical specification (Table 2.13 in Appendix for the full model including spatially lagged independent variables). First, using the robust version of the Hausman test to spatial autocorrelation of errors, the result leads to rejection of the null hypothesis of absence of correlation between individual effects and explanatory variables. Hence this test confirms that fixed effect models are statistically required. Second, we also test for spatial autocorrelation into account by SAR (LM_lag) or SEM (LM_error), the results confirm the rejection of the null hypothesis (taken independently) suggesting the inclusion of spatial parameter in lag form of the dependent variable (forest loss level) or via a spatial error component. In a more credible way, we also add robust versions of LM_lag, LM_error to test for the absence of a spatial autoregressive term when the model already contains a spatial autoregressive term in the error (Robust LM_lag), or vice versa (Robust LM_error). These robust versions are highly significant suggesting the choice of a fixed-effect model with both an autoregressive spatial process in the dependent variable and in the errors (SARAR). However, it should be noted that the test

Protected areas ($LagPA$) have a significant negative effect at the 5% or 1% level depending on the specification) on forest loss: models 4 to 8 in Table 2.6 and Table 2.7. Second, regarding mining activity, estimation results show a positive and significant (at the 0.1% level) effect of $Mine$ on deforestation, regardless of the specification. This result is consistent previous findings in DRC (Butsic et al. (2015)). This result also suggests that mines impact deforestation in their location polygons and neighbouring polygons. Thus, an additional mine leads to a forest loss of 39.8 km2 directly and 115.5 km2 indirectly (Table 2.6, model 4). The total effect is therefore important since an additional mine leads to a 155.4 km2 increase in forest loss. It is interesting to compare this result with that obtained for protected areas. An additional mine results in 155.4 km2 of forest loss in a polygon, whereas 1 km2 of additional protected area only prevents 0.097 km2 of forest cover loss. Put differently, an additional 1598 km2 in protected area would be required to offset the effect of one additional mine. Avoiding mining-driven forest loss, therefore, would at least necessitate a twice-fold increase in the average protected area if we assume that each extra square kilometre of protected area delivers the same reduction in forest loss.

We can assess whether protected areas dampen the harmful role of mining activities by considering the interactive variable: $Lag\_PA \times Mine$. The sign of the interactive variable is negative but not significant and this regardless of the specification used. In other words, the impact of mining on the forest does not decrease with protected areas. However, interpreting the coefficients on the mines and protected variables as the average effect of these variables on deforestation can be questioned (Brambor et al., 2006). We consider here the model including all explanatory variables (model 8 in Table 2.6). Figure 2.2(A) shows that the impact of mining on deforestation does not change significantly with the size of protected areas whose distribution is given in Figure 2.2(B). We observe that the impact of mining on forest loss is decreasing according to the distribution of protected areas, with values ranging between 155 to 150 km2. Mining activities do not condition the dampening effect of protected areas on deforestation.

statistic for a Robust LM_lag version is higher than that for a Robust LM_error version.

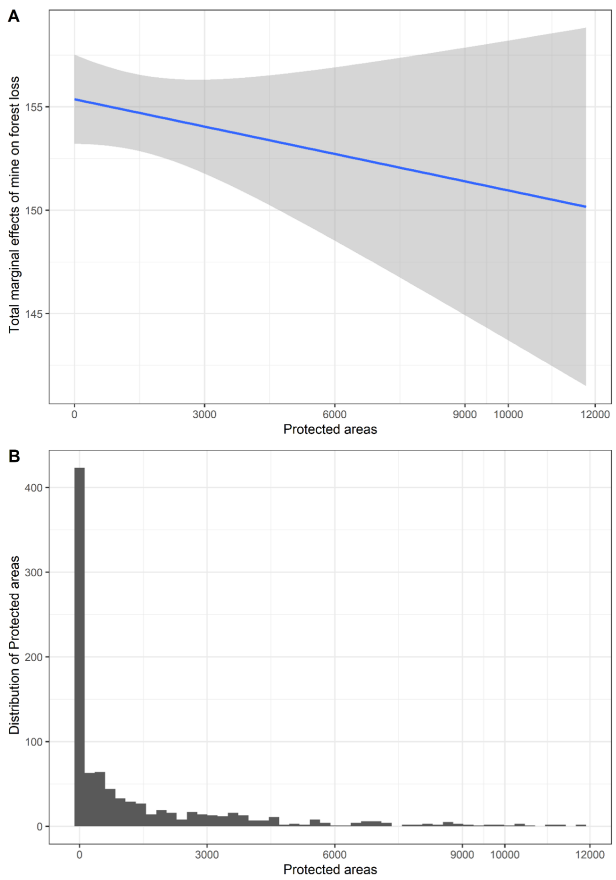


Figure 2.2: Marginal effect of mine on forest loss according to the distribution of protected areas

Note : The grey area represents the confidence interval at the 5% level.

Table 2.6: Marginal effects of covariates on deforestation; Spatial autoregressive model without common factors

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Direct								
Lag_PA	-0.014 (0.012)	-0.019 (0.012)	-0.017 (0.013)	−0.025** (0.013)	−0.025* (0.014)	−0.026** (0.012)	−0.026* (0.012)	−0.026* (0.012)
Mine		39.052*** (5.788)	40.670*** (6.335)	39.834*** (6.721)	39.843*** (6.068)	39.771*** (6.690)	39.550*** (6.709)	39.488*** (5.970)
Lag_PA × Mine			-0.002 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Activity				16.328*** (4.577)	16.148*** (4.825)	16.362*** (4.495)	16.274*** (4.233)	15.343*** (5.008)
Temp					2.297 (5.829)	2.420 (5.844)	2.374 (5.963)	2.522 (5.498)
Rain						-0.011 (0.010)	-0.011 (0.010)	-0.012 (0.010)
Fatalities							-0.008 (0.008)	-0.007 (0.007)
Pop								0.041 (0.082)
Indirect								
Lag_PA [2]	-0.042 (0.036)	-0.055 (0.035)	-0.048 (0.038)	−0.072** (0.037)	−0.074* (0.041)	−0.076* (0.037)	−0.075* (0.037)	−0.074* (0.039)
Mine		112.167*** (21.455)	117.210*** (23.046)	115.540*** (25.093)	115.508*** (22.638)	114.494*** (24.060)	113.648*** (23.373)	113.450*** (21.875)
Lag_PA × Mine			-0.004 (0.009)	-0.004 (0.010)	-0.004 (0.010)	-0.004 (0.009)	-0.003 (0.009)	-0.003 (0.009)
Activity				47.359*** (14.089)	46.813*** (15.118)	47.104*** (3.916)	46.763*** (12.550)	44.080*** (16.078)
Temp					6.658 (17.517)	6.966 (16.951)	6.821 (16.963)	7.246 (15.985)
Rain						-0.031 (0.029)	-0.032 (0.028)	-0.033 (0.029)
Fatalities							-0.023 (0.022)	-0.021 (0.021)
Pop								0.120 (0.248)
Total								
Lag_PA [2]	-0.056 (0.042)	-0.074 (0.047)	-0.065 (0.052)	−0.097** (0.050)	−0.0990* (0.054)	−0.102* (0.049)	−0.101* (0.049)	−0.100* (0.051)
Mine		151.219*** (26.528)	157.880*** (28.7748)	155.374*** (31.181)	155.351*** (27.993)	154.265*** (30.126)	153.198*** (29.455)	152.937*** (27.018)
Lag_PA× Mine			-0.006 (0.012)	-0.005 (0.013)	-0.005 (0.013)	-0.005 (0.012)	-0.004 (0.012)	-0.005 (0.012)
Activity				63.687*** (18.415)	62.961*** (19.742)	63.466*** (18.202)	63.037*** (16.596)	59.423*** (20.888)
Temp					8.955 (23.319)	9.386 (22.772)	9.195 (22.900)	9.767 (21.454)
Rain						-0.041 (0.040)	-0.043 (0.038)	-0.045 (0.039)
Fatalities							-0.031 (0.029)	-0.029 (0.029)
Pop								0.160 (0.329)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

Table 2.7: Marginal effects of covariates on deforestation; spatial autoregressive model with common factors

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Direct								
Lag_PA	-0.0140 (0.011)	−0.019* (0.011)	-0.017 (0.013)	−0.025* (0.013)	−0.025** (0.012)	−0.026** (0.014)	−0.026** (0.012)	−0.026** (0.013)
Mine		39.057*** (5.202)	40.707*** (6.333)	39.874*** (6.100)	39.883*** (6.720)	39.812*** (6.321)	39.590*** (5.819)	39.526 * ** (6.339)
Lag_PA × Mine			-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Activity				16.351*** (4.715)	16.171 * ** (4.442)	16.383*** (4.520)	16.295*** (4.659)	15.369*** (5.386)
Temp					2.290 (6.169)	2.411 (6.112)	2.365 (6.265)	2.513 (5.405)
Rain						-0.011 (0.009)	-0.011 (0.009)	-0.011 (0.010)
Fatalities							-0.008 (0.007)	-0.007 (0.008)
Pop								0.041 (0.081)
Indirect								
Lag_PA	-0.042 (0.034)	−0.056* (0.033)	-0.048 (0.039)	−0.073* (0.038)	−0.074** (0.036)	−0.077* (0.043)	−0.076* (0.038)	−0.075** (0.041)
Mine		113.523*** (19.420)	118.723*** (23.819)	117.066 * ** (22.638)	117.033*** (22.667)	116.004*** (23.000)	115.155 * ** (21.479)	114.945 * ** (24.452)
Lag_PA × Mine			-0.004 (0.009)	-0.004 (0.010)	-0.004 (0.009)	-0.004 (0.010)	-0.003 (0.009)	-0.004 (0.009)
Activity				48.005*** (14.742)	47.451*** (13.594)	47.738*** (14.941)	47.400*** (14.251)	44.693 * ** (16.552)
Temp					6.720 (17.943)	7.026 (18.158)	6.880 (18.717)	7.307 (16.223)
Rain						-0.031 (0.027)	-0.031 (0.026)	-0.033 (0.030)
Fatalities							-0.023 (0.022)	-0.022 (0.022)
Pop								0.112 (0.241)
Total								
Lag_PA [2]	-0.056 (0.045)	−0.075* (0.043)	-0.065 (0.042)	−0.097* (0.050)	−0.099** (0.048)	−0.103* (0.056)	−0.102** (0.051)	−0.101** (0.054)
Mine		152.580*** (23.984)	159.430*** (23.436)	156.939 * ** (28.076)	156.916 * ** (28.715)	155.815 * ** (28.469)	154.745 * ** (26.548)	154.471 * ** (30.159)
Lag_PA × Mine			-0.006 (0.012)	-0.006 (0.013)	-0.005 (0.012)	-0.005 (0.013)	-0.005 (0.012)	-0.005 (0.013)
Activity				64.356*** (19.242)	63.622*** (17.865)	64.121*** (19.234)	63.692 * ** (18.681)	60.062*** (21.750)
Temp					9.009 (24.089)	9.437 (24.844)	9.245 (24.955)	9.820 (21.599)
Rain						-0.041 (0.036)	-0.042 (0.035)	-0.045 (0.040)
Fatalities							-0.031 (0.029)	-0.0291 (0.030)
Pop								0.160 (0.032)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

2.5.3 Robustness check

To handle omitted variables in the spatial context, we also perform the spatial Durbin model (SDM) (Table 2.14 and Table 2.15 in Appendix). The main outcomes remain stable across specifications. The coefficients of the variables of interest retain the same sign, and most spatially lagged exogenous variables are insignificant. In addition, comparing the Akaike information criterion (AIC) and Bayes' information criterion (BIC), results show that models without including spatially lagged independent variables are better than those with the spatially lagged exogenous explanatory variables (Table 2.16 in Appendix)

2.5.4 Testing heterogeneities

Because of its importance, we choose to estimate a SAR model with spatial units and time- fixed effects only on the Congo Basin.[17] The marginal effects are presented in Table 2.17 in Appendix. A noticeable result is the lack of significance of the protected area variable. It is therefore likely that the unstable institutional context of the region makes this environmental protection instrument ineffective. This result is also in line with Brandt et al. (2016, 2018) though it was challenged by Karsenty et al. (2017). Our results also show that mining still promotes deforestation but to a lesser extent and less significantly. Mining-driven deforestation in Africa is important but unevenly spatially distributed.

We continue to explore the heterogeneity driven by local institutional variability. Poor institutional quality leads to many conflicts and violence. Hence, we split the sample into two sub-samples according to a threshold depending on the number of conflict deaths measured at the polygon level (*Fatalities*). We assume institutions are "good" when this number is below the sample median. [18] Protected areas reduce deforestation significantly only in polygons characterised by "good" institutional quality (Table 2.18 in Appendix: compared column 1 versus column 2; total effect). In addition, the impact of mines on deforestation is higher in polygons with "weak" institutions.

[17]The Congo Basin countries are: Angola, Burundi, Central African Republic, Cameroon, Democratic Republic of Congo, Congo Republic, Gabon, Rwanda, Tanzania, and Zambia. The number of polygons is 537.

[18]The sample was also split on the basis of the mean of the variable *Fatalities*. The results are unchanged.

We also studied the impact of mines according to mining status. [19] We consider the category of pre-operating mines as it concerns many polygons (163). The results are qualitatively unchanged (Table 2.18 in Appendix: column 3, total effect). In particular, protected areas do not mitigate mining-driven deforestation. In addition, an additional pre-operating mine appears to lead to a forest loss of 202.4 km2. This effect is more important than the one obtained with all the mines regardless of their status (155.4 km2; Table 6, model 4). Therefore, during the pre-operating phase, mining activity appears to have the highest impact on land use in the area surrounding the mine. Although the results favour the effectiveness of protected areas, these highlighted effects can also depend on the more or less strict character of the protected areas following the IUCN classification. We, therefore, break down protected areas into two groups. Both less stringent protected areas ($Laglarge_PA$) and strictly protected areas ($LagStrict_PA$) preserve the forest from deforestation (Table 2.10 and Table 2.11 in Appendix). Nevertheless, it is not possible to highlight the greater effectiveness of strictly protected areas. Moreover, even when we decompose protected areas into two groups, the interactive variable is still non- significant

[19]There are three mining status, namely (1) operating mines, (2) pre-operating mines and (2) closed mines. Pre-operated mines include mines in the feasibility study phase, mines under construction and mines awaiting commissioning.

2.6 Concluding remarks

This article studies mining-driven deforestation using fine-scale data from 2001 to 2019. We run spatial panel models controlling for spatial interactions. Mining activities harm the forest, and protected areas allow for reduced deforestation. We also find that protected areas do not dampen the impact of mining activities on deforestation. The result is robust to several econometric specifications. In addition, spatial heterogeneity prevails: the lower the institutional quality of the polygon, the greater the impact of the mine on deforestation. Furthermore, the effectiveness of protected areas is lost in areas characterised by low institutional quality.

The interpretation of the results may raise several questions. First, satellite data does not distinguish forest loss resulting from human actions or natural disasters. We cope with this issue with temperature and rainfall variables. Second, the presence of endogenous variables on the right-hand side is a common occurrence in econometric work. In particular, including variables related to protected areas could lead to localisation bias (Joppa and Pfaff, 2009). Nevertheless, the panel structure with period and polygon fixed effects and the one-year lagged value of protected areas address the bias.

It is feared that the likely development of mining activities in Africa in the coming years will increase the pressure on the forest resource. Smart mining attracts increasing attention, but offsets' contribution to forest preservation depends on many factors, such as enabling institutions and support of local communities (Maddox et al., 2019). It is not realistic to hope that protected areas alone will be able to preserve the forest from mining activities. The weight of mining activity must be contained by increased diversification, thus reducing the dependence on primary commodities. Lower dependence on natural resources and higher diversification is not only an economic imperative but also an environmental one.

2.7 Appendix

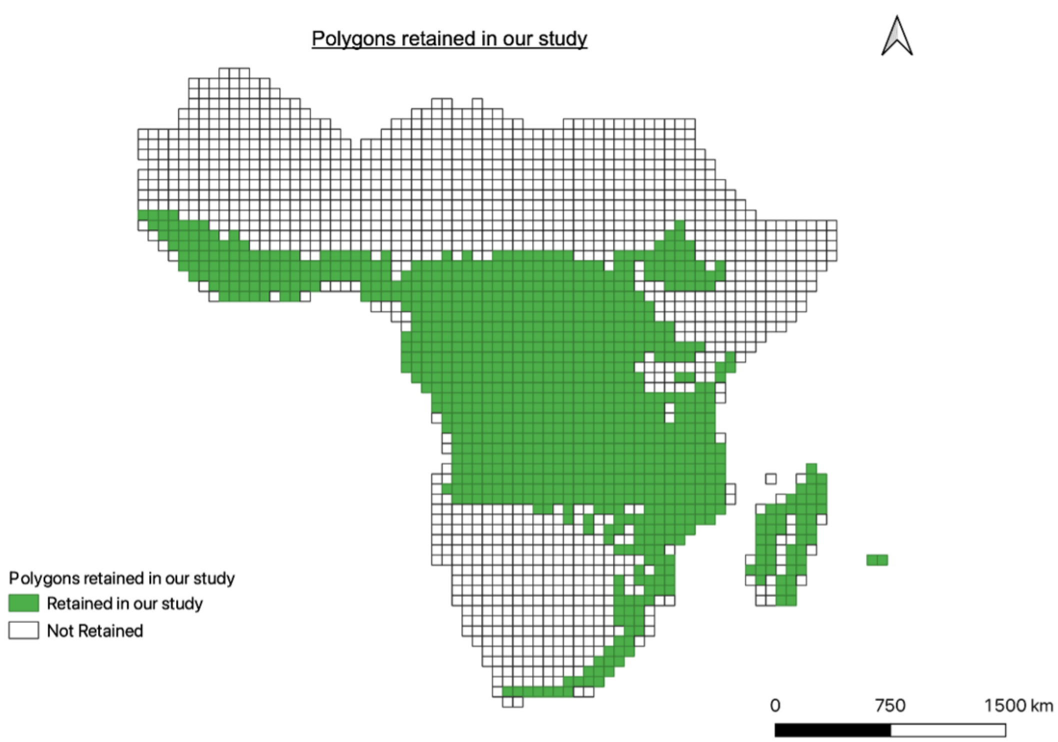


Figure 2.3: Polygons and the 926 forested polygons in 2001
Sources : authors' calculations. Forested polygons have at least 10% of their surface under forest

Table 2.8: Variables description

Variable name	Description	Source
Forest_loss	Forest loss	Hansen's database
Mine	Number of industrial mines present in each cell	MinEx database
PA	Surface of protected area for each study unit.	World Database on Protected Areas and world database on other effective area- based conservation measures
Temp	Absolute deviation of the temperature	GISS Surface Temperature Analysis (GISTEMPv4) database
Rain	Rainfall	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)
Activity	Night-time luminosity	Defense Meteorological Program -Operational Line-Scan System (DMSP-OLS) dataset
Fatalities	Number of deaths due to conflicts	ACLED database
Pop	Population density	The Gridded Population of the World, Version 4 (GPWv4)

Table 2.9: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Forest_loss	PA	Mine	Temp	Rain	Activity	Fatalities	Pop
(1) Forest_loss	1.000							
(2) PA	-0.069^{***}	1.000						
(3) Mine	0.167^{***}	-0.057^{***}	1.000					
(4) Temp	0.043^{***}	0.050^{***}	-0.011	1.000				
(5) Rain	0.210^{***}	-0.055^{***}	0.040^{**}	0.172^{***}	1.000			
(6) Activity	0.056^{***}	-0.029^{*}	0.058^{***}	-0.026^{*}	-0.109^{***}	1.000		
(7) Fatalities	-0.028^{*}	-0.018	0.006	-0.024	0.013	0.018	1.000	
(8) Pop	0.086^{***}	-0.100^{***}	0.079^{***}	-0.067^{***}	-0.074^{***}	0.620^{***}	0.072^{***}	1.000

$^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$

Table 2.10: Marginal effects of covariates on deforestation for heterogeneity PA; spatial autoregressive model without common factors

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10
	Direct									
$\text{Lag}_S trict_P A$	−0,004 (0.005)	−0,018 (0.018)	−0.035** (0.019)	-0.029 (0.020)	-0.037 (0.025)	−0.043^{-*} (0.022)	−0.043** (0.024)	−0.044* (0.022)	−0.044^{-*} (0.024)	−0.044* (0.022)
$\text{Lag}_L arge_P A$		−0,016 (0.021)	−0.034* (0.020)	−0.033* (0.021)	-0.042 (0.026)	−0.050** (0.023)	−0.050** (0.026)	−0.050* (0.023)	−0.050** (0.026)	−0.051* (0.024)
Mine			39.908*** (5.891)	41.890*** (5.972)	40.034*** (6.463)	39.009*** (6.550)	39.023*** (6.429)	38.961*** (7.412)	38.718*** (6.859)	38.626*** (6.787)
$\text{Lag}_S trict_P Ax$ Mine				-0.009 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)
$\text{Lag}_L arge_P Ax$ Mine					0.002 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)
Activity						15.271*** (4.262)	15.211*** (4.468)	15.377*** (4.756)	15.304*** (4.459)	14.023*** (4.470)
Temp							0.628 (5.843)	0.687 (5.888)	0.657 (5.953)	0.890 (6.071)
Rain								-0.010 (0.009)	-0.010 (0.010)	-0.011 (0.010)
Fatalities									-0.008 (0.008)	-0.007 (0.008)
[t]2* Pop										0.058 (0.077)
	Indirect									
$\text{Lag}_S trict_P A$	0,001 (0.001)	0,003 (0.004)	−0.103** (0.057)	-0.084 (0.059)	-0.106 (0.075)	−0.127* (0.068)	−0.126* (0.072)	−0.128* (0.066)	−0.128** (0.074)	−0.129* (0.068)
$\text{Lag}_L arge_P A$		0,003 (0.004)	−0.100* (0.060)	−0.097^{-} (0.061)	-0.121 (0.081)	−0.143** (0.073)	−0.143** (0.080)	−0.146* (0.069)	−0.145** (0.106)	−0.147* (0.074)
Mine			116.168*** (22.832)	121.996*** (22.236)	116.341*** (23.880)	114.058*** (23.904)	114.081*** (23.856)	113.150*** (25.787)	112.224*** (23.807)	112.003*** (23.787)
$\text{Lag}_S trict_P Ax$ Mine				-0.027 (0.020)	-0.024 (0.019)	-0.023 (0.021)	-0.023 (0.021)	-0.023 (0.021)	-0.023 (0.022)	-0.024 (0.020)
$\text{Lag}_L arge_P Ax$ Mine					0.006 (0.011)	0.008 (0.011)	0.008 (0.012)	0.008 (0.012)	0.008 (0.012)	0.008 (0.012)
Activity						44.650*** (14.582)	44.468*** (14.526)	44.658*** (14.758)	44.359*** (14.174)	40.662*** (13.910)
Temp							1.837 (17.1888)	1.995 (17.675)	1.906 (17.398)	2.580 (18.039)
Rain								-0.030 (0.028)	-0.030 (0.031)	-0.0331 (0.029)
Fatalities									-0.024 (0.023)	-0.023 (0.022)
[t]2* Pop										0.168 (0.232)
	Total									
$\text{Lag}_S trict_P A$	−0,003 (0.004)	−0,015 (0.015)	−0.139** (0.075)	-0.113 (0.079)	-0.143 (0.099)	−0.170* (0.089)	−0.170* (0.096)	−0.172* (0.088)	−0.172** (0.097)	−0.174* (0.090)
$\text{Lag}_L arge_P A$		−0,013 (0.017)	−0.134* (0.079)	−0.130* (0.081)	-0.162 (0.107)	−0.193** (0.096)	−0.192** (0.106)	−0.196* (0.091)	−0.196** (0.106)	−0.198* (0.098)
Mine			156.076*** (28.041)	163.887*** (27.364)	156.376*** (29.638)	153.067*** (29.793)	153.105*** (29.708)	152.111*** (32.535)	150.942*** (29.963)	150.628*** (29.884)
$\text{Lag}_S trict_P Ax$ Mine				-0.036 (0.026)	-0.033 (0.026)	-0.031 (0.028)	-0.031 (0.028)	-0.031 (0.028)	-0.031 (0.029)	-0.032 (0.027)
$\text{Lag}_L arge_P Ax$ Mine					0.001 (0.014)	0.010 (0.015)	0.010 (0.016)	0.011 (0.016)	0.011 (0.016)	0.011 (0.015)
Activity						59.921*** (18.629)	59.679*** (18.822)	60.036*** (19.334)	59.664*** (18.452)	54.685*** (18.200)
Temp							2.465 (23.008)	2.683 (23.538)	2.563 (23.326)	3.470 (24.083)
Rain								-0.040 (0.038)	-0.041 (0.041)	-0.045 (0.038)
Fatalities									-0.033 (0.030)	-0.030 (0.030)
Pop										0.226 (0.309)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

Table 2.11: Marginal effects of covariates on deforestation for heterogeneity PA; spatial autoregressive model without common factors

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10
	Direct									
Lag$_{PA}$	-0.004 (0.005)	-0.018 (0.018)	−0.036* (0.017)	-0.029 (0.019)	−0.037* (0.021)	−0.043** (0.023)	−0.043* (0.024)	−0.044** (0.021)	−0.044** (0.021)	−0.047* (0.025)
Lag$_{L}arge_{P}A$		-0.016 (0.019)	-0.0345 (0.019)	−0.033* (0.019)	−0.041* (0.022)	−0.049** (0.026)	−0.049** (0.025)	−0.050** (0.023)	−0.050** (0.023)	−0.051** (0.025)
Mine			39.923*** (5.475)	41.914*** (6.455)	40.047*** (6.490)	39.045*** (6.699)	39.060*** (6.611)	38.998*** (6.381)	38.754*** (6.284)	38.661*** (6.486)
Lag_Strict$_{P}A * Mine$				-0.009 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.006)	-0.008 (0.007)
Lag_Large_PA*Mine					0.002 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)
Activity						15.288*** (4.071)	15.229*** (4.154)	15.393*** (4.294)	15.321*** (4.426)	14.042*** (4.609)
Temp							0.619 (5.854)	0.680 (6.162)	0.647 (6.181)	0.880 (6.037)
Rain								-0.010 (0.009)	-0.010 (0.009)	-0.011 (0.009)
Fatalities									-0.009 (0.007)	-0.008 (0.008)
Pop										0.058 (0.078)
	Indirect									
Lag_Strict_PA	0.001 (0.001)	0.004 (0.004)	−0.105* (0.053)	-0.086 (0.059)	−0.108* (0.065)	−0.128** (0.072)	−0.128* (0.075)	−0.130* (0.065)	−0.130* (0.064)	−0.131* (0.074)
Lag$_{L}arge_{P}A$		0.003 (0.004)	-0.102 (0.058)	−0.098* (0.059)	−0.123* (0.069)	−0.146** (0.078)	−0.146* (0.078)	−0.150** (0.071)	−0.150** (0.070)	−0.150** (0.076)
Mine			117.600*** (20.877)	123.524*** (26.425)	117.779 * ** (23.912)	115.575*** (25.354)	115.598*** (24.723)	114.654*** (23.318)	113.722*** (24.504)	113.482*** (22.484)
Lag_Strict_PA*Mine				-0.027 (0.021)	-0.025 (0.022)	-0.024 (0.021)	-0.024 (0.021)	-0.024 (0.022)	-0.024 (0.020)	-0.024 (0.020)
Lag_Large_PA*Mine					0.007 (0.011)	0.008 (0.013)	0.008 (0.012)	0.008 (0.012)	0.008 (0.012)	0.008 (0.011)
Activity						45.253*** (13.473)	45.071*** (14.078)	45.257*** (14.290)	44.959*** (13.976)	41.217*** (15.346)
Temp							1.832 (17.469)	1.990 (18.417)	1.899 (18.026)	2.582 (18.158)
Rain								-0.029 (0.027)	-0.030 (0.027)	-0.033 (0.029)
Fatalities									-0.025 (0.021)	-0.023 (0.024)
Pop										0.170 (0.234)
	Total									
Lag_Strict_PA	-0.003 (0.004)	-0.015 (0.014)	−0.140* (0.070)	-0.115 (0.078)	−0.145* (0.085)	−0.172** (0.095)	−0.172* (0.098)	−0.174** (0.086)	−0.174* (0.085)	−0.176* (0.098)
Lag_Large_PA		-0.013 (0.015)	-0.136 (0.076)	−0.132* (0.078)	−0.166* (0.090)	−0.195** (0.104)	−0.195* (0.103)	−0.198** (0.094)	−0.198* (0.093)	−0.201** (0.101)
Mine			157.523*** (25.689)	165.438*** (32.244)	157.826 * ** (29.687)	154.620*** (31.345)	154.658*** (30.625)	153.651*** (29.061)	152.476 * ** (30.195)	152.143*** (28.296)
Lag_Strict_PA*Mine				-0.037 (0.085)	-0.033 (0.030)	-0.032 (0.028)	-0.032 (0.028)	-0.032 (0.029)	-0.032 (0.026)	-0.032 (0.027)
Lag_Large_PA*Mine					0.009 (0.015)	0.010 (0.017)	0.010 (0.016)	0.010 (0.016)	0.011 (0.016)	0.011 (0.015)
Activity						60.542*** (17.323)	60.300*** (17.999)	60.650*** (18.285)	60.280*** (18.180)	55.259*** (19.828)
Temp							2.451 (23.306)	2.667 (24.551)	2.546 (24.180)	3.461 (24.171)
Rain								-0.039 (0.036)	-0.041 (0.036)	-0.044 (0.038)
Fatalities									-0.033 (0.028)	-0.031 (0.031)
Pop										0.228 (0.312)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

Table 2.12: Regression of error terms of Table 6 on the explanatory variables.

	error1	error2	error3	error4	error5	error6	error7	error8
Lag_PA	0.004 (0.010)	0.003 (0.010)	0.005 (0.011)	0.005 (0.011)	0.006 (0.011)	0.007 (0.011)	0.007 (0.011)	0.006 (0.011)
Mine		0.940 (4.682)	2.202 (5.428)	1.455 (5.425)	1.483 (5.425)	1.562 (5.425)	1.578 (5.426)	1.595 (5.430)
Activity				2.052 (3.893)	2.474 (3.910)	2.274 (3.913)	2.269 (3.914)	1.755 (4.206)
Temp					-6.435 (5.853)	-6.548 (5.854)	-6.562 (5.854)	-6.531 (5.860)
Rain						0.012 (0.009)	0.012 (0.009)	0.011 (0.009)
Fatalities							0.0001 (0.006)	0.0003 (0.006)
Pop								0.024 (0.072)
Lag_PA × Mine			-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

Table 2.13: Standard tests in spatial panel models

	Statistics	Df
LM_lag	3906.8***	1
LM_error	3502.4***	1
Robust LM_lag	410.32***	1
Robust LM_error	5.9003**	1
Hausman	290.45***	16

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$;

Table 2.14: Estimation results for the spatial Durbin model with additive PA

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ρ	$0.799***$ (0.019)	0.791^{***} (0.019)	0.792^{***} (0.019)	0.792^{***} (0.019)	0.791^{***} (0.019)	0.794^{***} (0.019)	0.793^{***} (0.019)	0.794^{***} (0.019)
λ	$-0.229***$ (0.050)	$-0.229***$ (0.050)	-0.231^{***} (0.050)	-0.231^{***} (0.050)	-0.230^{***} (0.050)	$-0.236***$ (0.049)	-0.234^{***} (0.049)	-0.239^{***} (0.049)
Lag_PA	-0.011 (0.009)	-0.015 (0.009)	-0.014 (0.010)	-0.015 (0.010)	-0.015 (0.010)	$-0.021**$ (0.010)	-0.021^{**} (0.010)	-0.021^{**} (0.010)
Mine		$31.429***$ (4.458)	32.500^{***} (5.225)	32.513^{***} (5.226)	32.529^{***} (5.228)	31.894^{***} (5.206)	31.715^{***} (5.210)	31.514^{***} (5.203)
Temp				4.600 (5.559)	4.835 (5.572)	3.167 (5.554)	3.042 (5.563)	2.586 (5.545)
Rain					-0.008 (0.008)	-0.008 (0.008)	-0.009 (0.008)	-0.009 (0.008)
Activity						12.857^{***} (3.609)	12.786^{***} (3.612)	12.593^{***} (3.869)
Fatalities							-0.006 (0.006)	-0.006 (0.006)
Pop								0.009 (0.064)
SlagW_Lag_PA	0.0002 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
SlagW_Mine		3.928 (3.771)	3.914 (5.055)	4.052 (5.058)	3.968 (5.060)	3.389 (5.044)	3.461 (5.046)	3.115 (5.041)
SlagW_Temp				5.250 (16.210)	5.898 (16.240)	4.659 (16.166)	4.100 (16.195)	1.942 (16.176)
SlagW_Rain					-0.002 (0.009)	0.004 (0.009)	0.004 (0.009)	0.004 (0.009)
SlagW_Activity						7.638^{**} (3.477)	7.607^{**} (3.477)	15.105^{***} (4.447)
SlagW_Fatalities							0.008 (0.014)	0.008 (0.014)
SlagW_Pop								-0.132^{***} (0.049)
Lag_PA x Mine			-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
SlagW_Lag_PAxMine			-0.0001 (0.003)	-0.0002 (0.003)	-0.0001 (0.003)	-0.00002 (0.003)	-0.0001 (0.003)	0.0001 (0.003)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; standard errors in parentheses.

Table 2.15: Estimation results for the spatial Durbin model with heterogeneity PA

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
ρ	0.799*** (0.019)	0.799*** (0.019)	0.794*** (0.019)	0.794*** (0.019)	0.794*** (0.019)	0.796*** (0.019)	0.796*** (0.019)	0.795*** (0.019)	0.795*** (0.019)	0.796*** (0.019)
λ	−0.229*** (0.050)	−0.229*** (0.050)	−0.232*** (0.050)	−0.234*** (0.050)	−0.230*** (0.050)	−0.236*** (0.049)	−0.236*** (0.049)	−0.234*** (0.049)	−0.232*** (0.049)	−0.238*** (0.049)
Lag_Strict_PA	-0.004 (0.005)	-0.018 (0.018)	−0.028* (0.015)	-0.023 (0.015)	-0.030 (0.019)	−0.034* (0.019)	−0.034* (0.019)	−0.035* (0.019)	−0.036* (0.019)	−0.035* (0.019)
Lag_Large_PA		-0.015 (0.020)	−0.027* (0.016)	-0.026 (0.016)	−0.034* (0.020)	−0.039** (0.020)	−0.039** (0.020)	−0.040** (0.020)	−0.040** (0.020)	−0.040** (0.020)
Mine			32.021*** (4.494)	33.644*** (4.633)	31.874*** (5.306)	31.290*** (5.287)	31.321*** (5.288)	31.281*** (5.290)	31.090*** (5.294)	30.983*** (5.288)
Activity						11.915*** (3.533)	11.827*** (3.562)	12.102*** (3.577)	12.049*** (3.580)	11.535*** (3.824)
Temp							1.565 (5.514)	1.616 (5.524)	1.493 (5.534)	1.076 (5.511)
Rain								-0.008 (0.008)	-0.008 (0.008)	-0.008 (0.008)
Fatalities									-0.007 (0.006)	-0.007 (0.006)
Pop										0.024 (0.065)
Slag_Lag_Strict_PA	0.001 (0.002)	0.001 (0.002)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.001 (0.003)
Slag_Lag_Large_PA		-0.002 (0.002)	0.0001 (0.003)	-0.0001 (0.003)	-0.0001 (0.003)	0.0002 (0.003)	0.0002 (0.003)	0.0002 (0.003)	0.0002 (0.003)	-0.001 (0.003)
Slag_Mine			3.561 (4.992)	3.476 (4.991)	3.747 (5.006)	3.074 (4.993)	3.110 (4.994)	3.060 (4.995)	3.103 (4.996)	2.688 (4.991)
Slag_Activity						7.415** (3.437)	7.422** (3.444)	7.611** (3.482)	7.575** (3.482)	14.986*** (4.449)
Slag_Temp							3.407 (16.162)	3.773 (16.189)	3.153 (16.219)	0.838 (16.194)
Slag_Rain								0.004 (0.009)	0.004 (0.009)	0.004 (0.009)
Slag_Fatalities									0.007 (0.014)	0.007 (0.014)
Slag_Pop										−0.131*** (0.049)
Lag_Strict_Pa x Mine				-0.008 (0.005)	-0.007 (0.005)	-0.007 (0.005)	-0.006 (0.005)	-0.006 (0.005)	-0.006 (0.005)	-0.007 (0.005)
Lag_Large_PA x Mine					0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
Slag_Lag_Strict_PA x Slag$_{M}ine$			-0.00005 (0.003)	-0.00002 (0.003)	-0.0001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.0004 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Slag_Lag_Large_PA x Slag_Mine			0.0005 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

Table 2.16: Akaike's information criterion (AIC) and Bayes' information criterion (BIC) : Comparison tests for models with and without spatially explanatory variables

Criteria	Model without spatially lagged independent variables	Model with spatially lagged independent variables
Loglik	-23671.29	-23664.48
AIC	49222.58	49224.96
BIC	55066.72	55118.84

Table 2.17: Marginal effects of covariates on deforestation focusing on Congo Basin countries; spatial autoregressive model without common factors

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Direct								
Lag_PA	-0.099 (0.134)	-0.094 (0.129)	-0.092 (0.126)	-0.079 (0.143)	-0.081 (0.130)	-0.089 (0.129)	-0.086 (0.128)	-0.086 (0.138)
Mine		14.734*** (5.617)	12.633** (5.869)	12.182* (6.064)	11.882** (6.298)	11.842** (6.032)	11.699** (5.511)	11.650* (6.663)
Lag_PAxMine			0.00291 (0.0036)	0.00293 (0.0040)	0.00299 (0.0035)	0.00297 (0.0035)	0.00286 (0.0036)	0.00286 (0.0034)
Activity				9.976 (7.569)	9.689 (7.163)	9.584 (7.110)	8.810 (7.615)	8.203 (7.884)
Temp					35.936* (20.353)	36.351* (19.726)	36.341* (20.502)	36.527* (19.347)
Rain						-0.0182 (0.0189)	-0.0180 (0.0170)	-0.0178 (0.0166)
Fatalities							-0.009 (0.0059)	-0.009 (0.0058)
Pop								0.035 (0.099)
Indirect								
Lag_PA	-0.029 (0.0788)	-0.023 (0.0456)	-0.022 (0.047)	-0.020 (0.052)	-0.020 (0.053)	-0.024 (0.063)	-0.022 (0.053)	-0.022 (0.055)
Mine		3.550 (4.034)	2.987 (3.6413)	3.047 (3.415)	2.964 (3.826)	3.139 (4.013)	3.046 (3.689)	3.007 (3.284)
Lag_PAxMine			0.00068 (0.0013)	0.00073 (0.0017)	0.00074 (0.0013)	0.00079 (0.0017)	0.00075 (0.0015)	0.00074 (0.0015)
Activity				2.495 (3.604)	2.417 (3.854)	2.541 (4.044)	2.294 (3.8259)	2.117 (4.146)
Temp					8.964 (11.875)	9.637 (12.469)	9.462 (10.637)	9.426 (10.537)
Rain						-0.0048 (0.0089)	-0.0047 (0.0072)	-0.0046 (0.0071)
Fatalities							-0.0024 (0.0029)	-0.0024 (0.00313)
Pop								0.009 (0.041)
Total							b	
Lag_PA	-0.128 (0.195)	-0.116 (0.165)	-0.114 (0.162)	-0.099 (0.187)	-0.10 (0.172)	-0.112 (0.177)	-0.109 (0.173)	-0.108 (0.183)
Mine		18.285** (8.132)	15.620* (8.193)	15.229* (8.351)	14.846* (8.962)	14.981* (8.661)	14.745* (8.0512)	14.657* (8.821)
Lag_PAxMine			0.0036 (0.0046)	0.0037 (0.0054)	0.0037 (0.0045)	0.0038 (0.0048)	0.0036 (0.0049)	0.0036 (0.0045)
Activity				12.472 (10.347)	12.106 (9.882)	12.125 (10.025)	11.104 (10.422)	10.320 (11.171)
Temp					44.901 (28.975)	45.99* (27.71)	45.803* (26.759)	45.954* (26.529)
Rain						-0.023 (0.0258)	-0.023 (0.0223)	-0.022 (0.0221)
Fatalities							-0.012 (0.0079)	-0.0116 (0.008)
Pop								0.0439 (0.134)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

Table 2.18: Marginal effects of covariates on deforestation, Heterogeneities; spatial autoregressive model without common factors

	Quality of institutions (Fatalities)		Status of mines
	Weak (1)	Strong	
	(1)	(2)	(3)
	Direct		
Lag_PA	-0.022 (0.018)	−0.023* (0.014)	−0.022* (0.012)
Mine	64.261*** (9.737)	42.238*** (6.719)	
Activity	12.0342** (5.511)	18.092 * ** (5.994)	15, 075*** (4.854)
Temp	1.225 (8.267)	2.754 (6.477)	2,229 (5, 976)
Rain	-0.0226 (0.014)	-0.00428 (0.010)	-0.011 (0.009)
Pop	0.040 (0.093)	-0.035 (0.113)	0.040 (0.079)
Lag_PA x Mine	-0.00112 (0.004)	-0.00117 (0.003)	
Pre_Operating Mine			52.182*** (7, 531)
Fatalities			-0.009 (0.008)
Lag_PA×Pre_Operating mine			-0.0064 (0.004)
	Indirect		
Lag_PA	-0.064 (0.055)	−0.057* (0.035)	−0, 063* (0.037)
Mine	189.263*** (38.570)	104.197*** (21.877)	.
Activity	35.444** (17.494)	44.631 * ** (16.094)	43.384*** (15.112)
Temp	3.607 (24.792)	6.793 (16.415)	6,415 −17, 501
Rain	-0.067 (0.0439)	-0.010 (0.025)	-0.0308 (0.028)
Pop	0.118 (0.279)	-0.0872 (0.285)	0,115 (0.231)
Lag_PA×Mine	-0.0033 (0.0124)	-0.0029 (0.008)	=
Pre_Operating mine			150.177*** (28.404)
Fatalities			-0.026 (0.023)
Lag_PA×Pre_Operating mine			-0.0185 (0.012)
	Total		
Lag_PA	-0.085 (0.072)	−0.080* (0.049)	−0.084*** (0.049)
Mine	253.524*** (47.029)	146.434*** (27.74)	.
Activity	47.478 * * (22.868)	62.723*** (21.842)	58.459 * ** (19, 792)
Temp	4.832 (33.022)	9.5461 (22.857)	8.644 (23, 454)
Rain	-0.0892 (0.058)	-0.0146 (0.035)	−0, 042 (0.037)
Pop	0.158 (0.371)	-0.123 (0.397)	0,155 (0.310)
Lag_PA x Mine	-0.0044 (0.0165)	-0.0041 (0.0115)	.
Pre_Operating mines			202, 359 * ** (35, 029)
Fatalities			-0.035 (0.030)
Lag_PA x Pre_Operating mines			-0.0133162 (0.016)

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$; standard errors in parentheses.

Chapter 3

Political cycles of forest rents in developing countries [*]

In this article, we question the presence of electoral cycles in forest rents in developing countries. The presence of rents can be an additional motivation to stay in power as the incumbent can use them to finance elections without running a deficit or increasing taxes. Forest rents are particularly interesting to study in the context of climate change and the fact that forests' point resource characteristics make them more subject to political cycles. Our study covers eighty-three (83) developing countries from 1990 to 2018, using the method of ordinary least squares corrected for the possible Nickell's bias. The results show that cycles in forest rents only appear when the elections' competitiveness is considered. This presence of cycles is robust enough to use different robustness tests. Moreover, the cycles appear only in the event of representation of the candidate in power at the elections and in low-corrupted and high-human-freedom countries.

Keywords: Political cycles · Forest rents · Panel data · Developing countries.

JEL codes: C23, D72, E62, O13, O50, Q3

[*] This chapter is available on HAL (Doamba, 2023). It is currently under review in Policy & Politics

3.1 Introduction

Good institutions are essential for a country's sustainable development, especially in the context of climate change. However, in many developing countries, these institutions need to be improved. The same goes for democracy, which still is a luxury for most developing countries because of the difficulty of implementing and maintaining it. This situation can be explained by the absence of a democratic tradition and other structural factors such as the mobilization of the masses based on identity (manipulation of these masses on ethnic bases) (Rodrik, 2016). Another explanation of this situation in many developing countries is the consequences of natural resource exploitation.

The resources, and the forest resources in particular, constitute an essential source of financing for the economies of these countries. For example, Huang et al. (2020) shows that forest rents significantly contributed to the growth of developing countries in Asia between 1996 and 2016. In the same framework, Venables (2016) showed that among the 51 resource-rich countries in the world, 20 derive at least half of government revenue from resource rents. Furthermore, a more significant proportion of these countries, including developing countries, depend on these rents commercially.

Economic literature has pointed out an interaction between natural resources exploitation and institutional quality through natural resources curse theory (Auty et al., 1998; Sachs and Warner, 1995). Indeed, according to this theory, countries exploiting natural resources economically underperform for several reasons, among which is institutional quality deterioration. So, revenues from natural resources interact with the institutional and political sphere, as can be read in the literature about natural resources rents' political-budgetary cycles.

According to the literature on rents' political-fiscal cycles, rents are used formally or informally to finance the incumbent's re-election. These forest rents can be diverted from their primary role of financing development to financing re-elections. Indeed, the manipulation of elections is quite commonplace in developing countries. Politicians use natural resource rents to stay in power. Economic literature reports on these political manipulations, and this is what we find in the works of Nordhaus (1975), Rogoff and Sibert (1988), and Shi and Svensson (2006). The manipulations are due not only to the voters' solid preferences for physical well-being and high economic performance (Paldam, 2004; Franzese Jr, 2002), but also to the asymmetric information between voters and incumbent politicians such that voters are not entirely able to distinguish pre-electoral manipulations from incumbent competence (Shi and Svensson, 2006).

Moreover, this motivation to remain in power is more significant in the presence of natural resources. The presence of rents alters the conditions of the game since the incumbent has an extra string to his bow to fund spending to appease voters or secure the favor of the ruling class. Indeed, although voters have solid preferences for physical well-being and high economic performance, they can punish the candidate in the presence of a huge deficit or the event of a tax increase (Huntington, 1993). Thus, rents are a means for the incumbent to finance his re-election. They are a way to finance re-election without incurring the wrath of voters who do not see them as lost revenue, as in the case of taxes used for re-election purposes. In this logic, McGuirk (2013) and Bornhorst et al. (2009) point out that rents represent a loosening fiscal constraint on the incumbent. In countries with shallow institutional quality, rents can be used not to motivate voters but to secure the ruling class's support. This mechanism is part of rent-seeking behavior. In this case, rents could fall or increase in the run-up to an election, depending on how they are used. In the case of deficient institutional quality, negative cycles may be observed as rents are diverted to secure the favors of the ruling class. This diversion is done through bribes, as demonstrated by Uberti et al. (2019). There can be positive cycles if elections are competitive due to good institutional quality.

The literature on natural resources curse and rents' political-budgetary cycles have significant implications for developing countries. Indeed, weak institutions characterize these countries. The absence of accurate checks and balances and long-term economic reforms characterizes the political landscape. Thus, the various theories of fiscal-political cycles assume the quality of institutions and the presence of free and competitive elections. These assumptions are problematic because of the institutional weakness and non-competitiveness of elections in developing countries.

The present work fills a gap in the literature on electoral cycles in natural resource rents in developing countries. First, models developed to explain the presence of political-fiscal cycles implicitly assume the presence of regular and competitive elections (Nordhaus, 1975; Rogoff and Sibert, 1988; Shi and Svensson, 2006). For instance, Block (2001) shows that the political cycles are higher in developing countries with competitive elections. However, even in uncompetitive elections, we can observe political cycles at the level of rents. Indeed, the need to finance additional expenditures, acquire an electoral base, or ensure the support of partners requires the mobilization of resources, which is facilitated by the presence of rents in natural resources. The incumbent could use the rents, and in this case, forest rents, to finance his re-election, which is no longer guaranteed in advance given the high level of electoral competition, or to ensure the loyalty of its employees even if there is no competition.

Also, the literature places minimal emphasis on forest resources, particularly in developing countries [1], and this is a contribution of this paper to the literature. The interest of a study centered on forest rents lies in the fact that this directly impacts deforestation. Therefore, political cycles in rents can have environmental implications, particularly in developing countries that are more affected by climate change. Forest rents are easily manipulated due to the non-necessity of prospecting before exploitation. Thus, developing countries' governments can more easily grant logging permits on the eve of the elections. This paper aims to shed light on these possible cycles through a macroeconomic study of developing countries. Following the literature, in our study, forest rents should increase during competitive elections, but due to rent-seeking behavior, uncompetitive elections could give rise to negative cycles. Through this study, we perform a wide range of robustness and especially heterogeneity tests to better understand these countries' cycles.

We use a dynamic panel model on developing countries using the method of least squares corrected for the bias of Nickell (1981). The results suggest that, in general, we do not have forest rents' political cycles in developing countries, but these cycles appear when considering elections' level of competition. Competitive elections give rise to positive cycles in forest rents, while uncompetitive elections give rise to negative cycles. These results align with the literature that assumes that the presence of competitive elections leads to political cycles. These results are robust to our various robustness tests. Our results have also shown that, as expected from the literature, they only appear if the candidate in power is represented in the elections in low-corrupted countries and countries with high human freedom.

The rest of the paper is presented as follows: in Section 3.2, we review the literature relevant to our analysis. First, the one dealing with political-budgetary cycles, then the one dealing with natural resource rents and, more specifically, rent-seeking behavior for re-election purposes. Section 3.3 presents the data we used

[1] Authors like Klomp and de Haan (2016) mention this when analyzing the heterogeneity of their results.

to carry out our study, descriptive statistics, and stylized facts. The methodology used in the paper will be more fully described in Section 3.4 of our work. This section contains the model to be estimated and our chosen estimation methodology. Our results will then be presented in Section 3.5, the robustness and heterogeneity of which will be presented in Section 3.6 and Section 3.7, respectively.

3.2 Political cycles and forest rents: An overview of the literature

This work aims to study forest rents' political cycles in developing countries. We relate the literature on political-budgetary cycles to the literature on the effect of natural resources, particularly forest resources, on the political sphere. Thus, we first study literature dealing with political-budgetary cycles. Secondly, we study literature on the interaction of natural resources (specifically forest resources) with the political sphere.

3.2.1 Political and budgetary cycles in developing countries

A political budget cycle is a cycle in specific government budget components induced by electoral cycles. Put another way; it is an increase in public spending or deficit or a decrease in taxation in an election year, the objective of which is to favor the incumbent's re-election. There are two explanations for these cycles, which are often contradictory. The first explanation is that the incumbent may change government spending, the deficit, or taxation to please voters who prefer low or high government spending. However, this explanation is difficult to reconcile with voter rationality. Indeed, a rational voter would understand the manipulations of the outgoing candidate and will not be deceived in this case. The second explanation is that voters prefer good economic conditions (such as low unemployment or economic growth) and would be more likely to vote for the incumbent who would provide them with that.

Regarding the theoretical literature on the subject, Nordhaus (1975) and MacRae (1977) are the first articles to address the issue of political-budgetary cycles specifically. They model the occurrence of political-fiscal cycles. According to them, the incumbent will create inflation to take advantage of the relative advantage offered by the Philips curve in the short term[2] compared with the long term. However, these adaptive expectations models were revisited to consider rational expectations. Following these articles and pioneering models, Rogoff and Sibert (1988) present a model where the government tries to send signals of its competence to the population. The authors argue that the electoral cycles of some macroeconomic variables are due to a temporal informational asymmetry. A voter cannot observe the candidate's competence. The main conclusions of the models described above can be found in the basic model of Rogoff (1990). The major criticism of the above models is that we deal with results models, meaning politicians can finely manipulate macroeconomic aggregates. Recent literature, therefore, emphasizes cycles involving economic policy instruments such as public expenditure. Shi and Svensson (2006) develop a model using a moral hazard model to explain political cycles measured by cycles in a policy instrument (the budget). In this model, the magnitude of a budgetary election cycle depends on the politician's motivation to stay in power and the share of voters unaware of the politician's manipulative objectives.

As highlighted in the literature, the informational asymmetry can explain the presence of a political cycle. This informational asymmetry may correspond to the age of democracy, in which case voters do not have the necessary hindsight to understand the maneuvers of the politician in power or to access information. The experience of the electorate plays an essential role in its capacity to understand the manipulations, as underlined by Brender and Drazen (2005). The informational asymmetry may also correspond to access to information. Indeed, the lack or non-access to information on the management of natural resources or the candidate's motivations in power means that the leader can easily take advantage of it to find additional funds to ensure his re-election?Shi and Svensson (2006).

Tufte (1978) first empirically tested the theory of budgetary-political cycles in the specific case of the United States of America. However, a panoply of articles followed this first one. One of the most recent papers in this field concerning African countries is that of Iddrisu and Bokpin (2018). A very recent paper by Boly et al. (2023) shows the presence of political cycles in CO2 emissions, demonstrating the environmental effects of electoral cycles; and this last paper is fascinating to us because.

[2]The Phillips curve works on the principle of monetary illusion or nominal illusions. Employers reason for real wages, while employees reason in nominal terms. Thus, inflation in the short run reduces unemployment since employers will hire if inflation is higher than nominal wage growth. Also, this inflation increases consumption by increasing nominal wages.

Some articles highlight cycles in developing countries (Block et al., 2003; Mosley and Chiripanhura, 2016). However, applying the theory of political-fiscal cycles to developing countries raises questions. Indeed, the usual theories are based on a certain institutional quality that guarantees free and competitive elections. We must break down these assumptions to test these theories in developing countries. We will directly impact the model's predictions by questioning this given level of institutions, as authors such as Schultz (1995) and Block (2002) point out.

Several components of the state budget are subject to political-budgetary cycles. Forest rents constitute a means for the candidate for power to finance his re-election. The literature highlights the advantage of natural resource rents to the incumbent (Smith, 2004; Goldberg et al., 2008; Aaskoven, 2020).

3.2.2 Forest rents and their interaction with the political sphere

The abundance of natural resources should be a blessing for countries. However, in many cases, the abundance, especially the exploitation of these resources, has harmed countries. This contradictory effect of the abundance of natural resources can be explained by the curse of natural resources (Sachs and Warner, 2001). According to the authors, the discovery of resources leads to a fall in income due to a rise in the real exchange rate (Corden and Neary, 1982). Collier (2010) shows an interaction between the endowment of natural resources and the quality of institutions. When asked why natural resource endowments worsen the political situation in developing countries, one of the author's arguments is the lack of accountability of leaders to the population. Indeed, the abundance of natural resources creates a decline in institutional quality, which in turn creates a decline in economic growth (Leite and Weidmann, 1999). Other papers like Sala-i Martin and Subramanian (2013) and Isham et al. (2005) show that natural resources negatively impact economic activity when good institutions are not set up.

Forest resources are point resources. Unlike diffuse resources, point resources are spatially concentrated and can easily be controlled (Bulte et al., 2005). Hence, point resources are those that hurt institutions. These are, for example, oil resources, minerals, and plantations. The political sphere could be affected by the harmful effects of the abundance of natural and forest resources, which are point resources.

Significant revenues from natural resources have two effects on the incentives of political actors. First, the incumbent will have a greater incentive to stay in power. This could lead to political-fiscal cycles. He can, therefore, use the rent to ensure his re-election, either by currying favor with the electorate if the competition is great or by securing the ruling class's support if not. Second, other candidates will be more motivated to run for office, thus increasing electoral competition. In this case, the incumbent will do everything he can to win over the electorate.

In practical terms, large amounts of forest resources in a country affect the politicians' behavior: The politicians will have more motivation to stay in power, while other candidates will be motivated to run for office. Following this logic, leaders could increase or divert rents before elections to curry favor with the ruling class through a symbolic exchange system (Médard, 1991) or with the electorate through increasing public expenditure. Indeed, the incumbent must have as much support as possible to safeguard power. A rentier state sees its obligations of transparency and accountability to the population diminished since rents sometimes replace the existing tax system. Thus, rents lead, in the long run, to a situation where the population demands a minor change in a political regime (Beblawi and Luciani, 2015).

Aaskoven (2020) shows that natural resource rents to finance re-election can be obtained in two ways: directly by increasing revenues from the mining industry and national mining companies. However, in the case of African countries, most mining companies are private, and therefore, the state will go through taxation to increase its revenues from natural resources. Alternatively, in countries with low institutional quality, private companies may allow rent diversion to finance the incumbent's re-election in exchange for post-election contracts. Another more specific study Uberti et al. (2019) shows that governments can also go through unofficial channels to take advantage of the manna offered by natural resource rents to finance the incumbent's re-election. The candidate can increase production by increasing operating licenses instead of increasing taxation in the mining sector during an election period. He can also use the licenses to curry favor with the country's ruling class. According to the literature, the punctual or diffuse nature of the natural resource can impact its interaction with the political sphere. Concerning forest resources, it should be noted that unlike other resources, which require several studies and several years before their exploitation, they are more easily exploitable. Such a situation favors policies aimed at increasing the rent before the elections.

From all the above, we see that only some studies focus on forest rents.

Next, most of the articles conduct studies on political cycles from countries with a high level of electoral competition, thus excluding a good number of developing countries. In this study, we propose to investigate the presence of political cycles at the level of forest rents in developing countries by considering the level of electoral competitiveness. Therefore, we will test a set of hypotheses that allow us to shed light on the cycles in natural resource rents.

Political cycles in natural resource rents depend on the level of election competition. Overall, at the level of developing countries, we do not expect to detect positive electoral cycles in forest rents. However, considering electoral competition, we will not be surprised to see rent movements on the eve of the elections. A higher level of electoral competition may force the incumbent to use these rents to ensure he remains in power.

3.3 Data and Descriptive Statistics

In this section, we first present variables used in this study and their sources in Subsection 3.3.1, and then present descriptive statistics for our variables in Subsection 3.3.2.

3.3.1 Definition of variables

The final sample comprises eighty-three (83) rentier and not-rentier developing countries. The list of countries included in the analysis is in the Appendix (Table 3.6). Depending on data availability, we looked for electoral cycles in these countries from 1990 to 2018. The choice of developing countries is motivated by the will to include developing countries, most often absent from this analysis. Then, for robustness, we will limit the sample to rentier countries to see if the cycles are more pronounced.

The measurement of forest rents: $Forest\_rent$

The measure we use is the one introduced by Collier and Hoeffler (2009) that considers the fluctuation of world prices and extraction costs. The World Bank published the data for this new measure of rents (Lange et al., 2018). Its construction consists of several steps: The first consists of defining rent as the difference between the world price of resources and their extraction costs. The second step consists of multiplying this unit rent by the extracted volume. Then, each year, this product is divided by the GDP of the year concerned. This dependent variable of natural resources has advantages, such as disaggregating it into different types of resources. So, this global database gives the rents for different resources, and we will focus on the forest rents according to the objective of this analysis. This variable does not directly measure the share of rents going to the state accounts but is a good approximation. Klomp and de Haan (2016) showed a significant and robust correlation between the level of rents and state income from rents.

The variable of interest: *Elect*

Our variable of interest is the election period. In the previous literature dealing with issues of fiscal-political cycles, the variable used to capture the election period is a dummy variable, taking the value of 1 in election years and 0 in other years. Franzese (2000) proposed an alternative measure to this discrete measure. The proposed measure is a measure whose sum gives one, and this unit is split between the year of the election and the year before the election. Practically, Franzese (2000) creates the variable $elect_t$ for the election in year t, which is equal to $(M/12) + (d/D)/12$ the year of the election with M the number of whole months before the election, d the number of whole days in the month before the election and finally D the number of whole days in the year. In the year before the election, this variable is equal to $1 - ((M/12) + (d/D)/12)$. Klomp and de Haan (2016) used the simplified version of this variable. In the latter case, both authors defined their variable as $M/12$ in the election year and $(12 - M)/12$ in the year before the election. This variable allows for capturing the election period more accurately because it captures the electoral period more precisely. Indeed, let us imagine that the election was on February 1, 2000. The standard measure would have taken discrete and taken the whole year 2000 as the election year, while the campaign mainly took place in 1999. This *Elect* variable includes the elections that took place at the scheduled times and those that were delayed. Referring to the literature, when not considering the level of election competition, we expect to see either a positive and significant sign or non-significance for this variable, but not a negative and significant one.

Considering the competition level: $Elect \times Con$

As mentioned above, some papers, such as Schultz (1995); Block (2002), questioned the assumptions made by the models explaining the political and budgetary cycles. As our study concerns developing countries, which are not all democratic, it is necessary to consider the level of competitiveness of elections. In this way, the electoral variable will be weighted by an index, giving the level of political constraint. The political constraint variable comes from the database developed by Henisz (2005). The weighting makes it possible to retain the most significant number of elections, which makes it possible to have more observations with a non-zero election period. Second, weighting allows us to maintain the most significant variability within our variable, whereas excluding non-competitive elections would cause us to lose this variability. Finally, it avoids the exclusion of non-competitive elections. The exclusion of non-competitive elections must be done based on a threshold, and this threshold would be done on an arbitrary basis, which we avoid using the weighting method.

Henisz (2005) developed the POLCON database to consider the feasibility of policy change on the part of the government. In other words, how the change in the point of view of one of the actors affects the country's politics. This initial measure was improved to consider the heterogeneity within the main political parties. The author shows that homogeneity within the united opposition party was a sign of significant political constraint. This variable can, therefore, be used as a proxy for competition and the quality of elections. Indeed, it measures the existing counter-power. Robust checks and balances mean that the president in power must prove himself to stay in power and can, therefore, be ejected at the end of his term, which makes elections more competitive. Considering the election competition level, we expect a positive and significant sign for the $Elect\_Con$ variable. Other measures of political competition include the vote share of political parties or the number of political parties running for office. However, given the recurrent electoral fraud in many countries in our sample, using such measures would give highly biased results.

This interactive is essential since it considers the level of electoral competition. However, we may face a potential endogeneity problem due to the inverse causality between the level of electoral competition and rent. To tackle this problem, we use the Generalized Method of Moments (GMM) with lagged values of the level of electoral competition as instruments for a robustness test. This methodology enables us to deal with the endogeneity arising from the dynamic specification and reverse causality.

Control variables

We first include institutional variables such as the level of corruption ($Corruption$) and level of democracy ($Democ$) of the country as control variables. Indeed, according to the literature, the institutional factor is essential in determining a given country's rent level, and natural resource rents are also a key determinant of the institutional quality (Mehlum et al., 2006a). It is, therefore, necessary to include this factor in our analyses.

We also included the GDP per capita (GDP) level to consider the development level. The empirical literature underlines the role of economic development on the occurrence or magnitude of political-fiscal cycles. Already, the literature points out that such cycles are more likely to occur in the least developed countries. Several factors can explain this result. According to Shi and Svensson (2006), this is mainly due to differences in the institutional environment, while Brender and Drazen (2005) points to the weak democratic experience of low-income countries.

The third control variable is the depletion rate of natural resources ($Depl$). This variable has been used in the literature as a proxy for the level of natural resource rents globally. We use this variable instead of the total rent variable because it is mechanically linked to the level of forest resource rents, which is only one component. This variable of the rate of depletion of natural resources has the role of taking into account the country's mining activity. It shows the pressure on forest rents since the more other natural resources are depleted, the more countries will be tempted to turn to forest resources. Although calculated based on unit rents, the depletion rate only considers the excess of rents over natural growth [3]. It, therefore, takes into account the endowment of natural resources, which reflects a country's wealth in natural resources.

The last control variable is the urbanization rate ($UrbanPop$), which considers the part of the population that is subject to manipulations to the cycles. Indeed, in developing countries, the urban population is the most educated and able to understand the political programs of the various candidates. The urban population, therefore, impacts political cycles because, in developing countries, a large proportion of the urban population is the best-informed and has their finger on the political pulse. Rural populations are usually disconnected from the rest of the country and are poorly served by the public infrastructures.

[3] https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.ADJ.DRES.GN.ZS

3.3.2 Descriptive Statistics

This section on descriptive statistics describes the variables over the entire study period. We are working on 83 developing countries from 1990 to 2018.

Graph 3.1 shows the level of forest rents for the first year of our study period. It shows that most of the countries in our sample have forest rents. Central African countries depend highly on forest rents, which is only logical given their forest resources. The countries of Latin America, on the other hand, although rich in forest resources, are not heavily dependent on these rents.

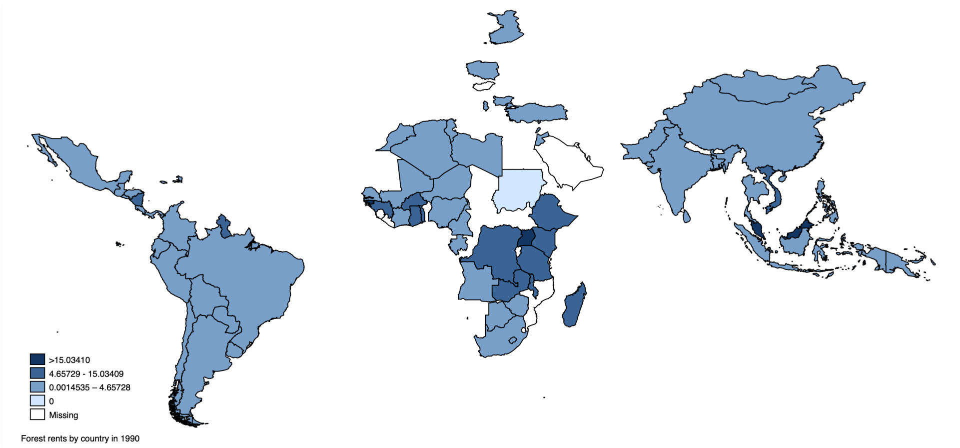


Figure 3.1: Forest Rents in 1990 for countries in our sample
Sources : World Development Indicators

Table 3.1: Descriptive Statistics

Variable	N	Mean	SD	SE	Min	Max	Measurement unity
Forest_rent	2368	3.0044	4.9857	0.1025	0.0000	36.0683	% of GDP
GDPperCap	2345	5045.0717	8613.2618	177.8673	164.3366	16648.7700	Constant Dollar
Democ	2377	3.9348	9.3384	0.1915	0	10	Index (0 to 10)
UrbanPop	2384	51.6228	21.7195	0.4448	11.0760	95.3340	% of Population
Corruption	2338	2.4300	0.9931	0.0205	0	6	Index (0 to 6)
Depl	2287	5.1173	6.8708	0.1437	0.0000	68.5665	% of GNI
Polcon	2218	0.2723	0.2080	0.0044	0.000	0.7256	Index (0 to 1)
Elect	2384	0.1293	0.2840	0.0058	0.000	1.0000	.

After studying the graph 3.1, we review the main descriptive statistics of our variables, summarized in the table 3.1. The dependent variable, the level of forest rents, has a mean of 3% of GDP. This means that, on average, in our sample, the countries are endowed with forest resources whereby generating forest rents as shown in graph 3.1. However, this level of forest rent is highly variable since the standard deviation is significant (4.985), larger than the average (3.004). Looking at the GDP per capita variable, we notice that our sample is quite heterogeneous and includes developing countries from the least rich to the most rich. Indeed, the standard deviation is far above the average. The same observation applies to the level of democracy. Our sample of 83 countries contains democratic and non-democratic countries, as we can see from the *Democ* variable.

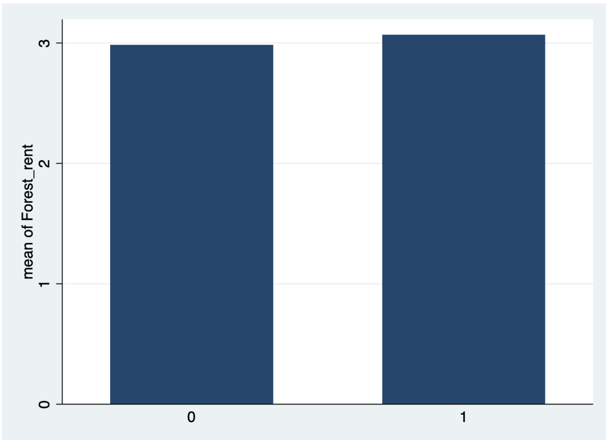


Figure 3.2: Average rents during electoral and non-electoral periods
Sources : Author calculation, WDI rent database and NELDA database

According to our assumptions, we should not observe a significant increase in forest rents during the election period. This is what we see this in the graph 3.2. Indeed, the difference of rent between electoral and not-electoral period is very slight.

The second key element of our study is to consider the level of competitiveness of the elections. For this purpose, we use the political constraint variable ($POLCON$). Graph 3.3 shows a negative relationship between the level of political constraint and the level of rents since the slope of the regression line is negative. So, a political constraint is associated with more excellent institutional quality and lower rent dependence.

A final point in favor of our hypotheses is the positive relationship between the level of forest rents and the length of time politicians have been in power, shown by graph 3.5. This positive relationship between natural resource rents and length of time in power was highlighted by Désiré Omgba (2007).

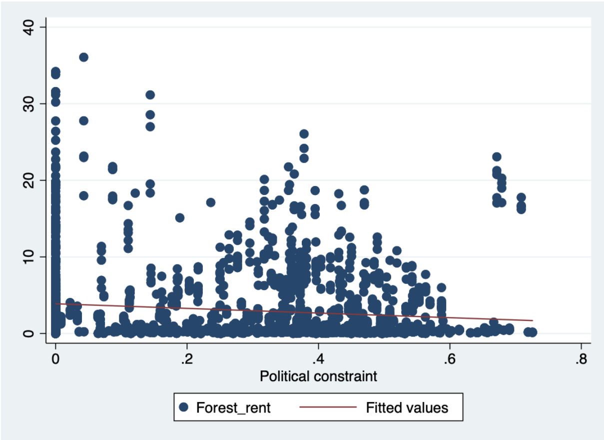


Figure 3.3: Relationship between Forest rents and Political constraint
Sources :: Author calculation, WDI rent database and POLCON database

These initial statistics provide us with a compelling starting point for understanding the intricate relationships between the variables. However, to truly grasp the depth of these connections, we must delve into a comprehensive set of other interactions. This is the path we will tread with our rigorous econometric approach, promising to unveil significant insights.

3.4 Econometric framework

We rely on a dynamic specification, which is theoretically interesting because it assumes a steady state value of the forest rent, towards which one country convergences conditionally on the Election variable and other conditioning factors. Furthermore, this is due to the inertia effect of resource rents. However, it makes estimates sensitive to the Nickell' bias (Nickell, 1981). This will lead us to a second part to discuss the choice of the estimator.

3.4.1 Econometric model

Regarding the econometric specification, we will use two approaches. The first approach will allow us to search for cycles in forest rents in elections, and the second will take into account elections' level of competitiveness. We will, therefore, have the following two equations:

$$Forest\_rent_{it} = \omega_i + \delta_t + \theta Forest\_rent_{it-1} + \phi Elect_{it} + \psi Z_{it} + \upsilon_{it} \qquad (3.1)$$

$$
\begin{aligned}
Forest\_rent_{it} = \omega_i + \delta_t + \theta Forest\_rent_{it-1} + \phi Elect_{it} + \rho Polcon_{it} \\
+\beta Elect \times Con_{it} + \psi Z_{it} + \upsilon_{it}
\end{aligned}
\tag{3.2}
$$

In the two equations, the subscripts i and t indicate the country and year involved. $Forest\_rent_{it}$ represents the forest rents variable as a percentage of GDP. The variable $Forest\_rent_{it-1}$ denotes the lagged value of the dependent variable.As mentioned above, the lag variable is interesting because of the inertia effect of the natural resources rents. A country does not become rentier overnight. Thus, a country with rents in an election year will likely have had rents the year before. Thus, not taking into account lagged values of annuities could lead to an erroneous analysis.

The variable ω_i is the variable that controls for the unobservable characteristics of the different countries in our sample; these are the country-fixed effects. The variable δ_t captures the time-fixed effects, that is, the unobservable characteristics of each year. The variable $Elect_{it}$ refers to our variable indicating the pre-election period. Z_{it} refers to our model's set of control variables. These explanatory variables are supposed to explain the rents received by the different countries partly, and we base ourselves on the literature for the choice of these variables. In equation 3.2 only, the variable $Polcon_{it}$ refers to our electoral competition variable, and finally, the variable $Elect \times Con_{it}$ is the interaction between our electoral variable $Elect_{it}$ and the variable $Polcon_{it}$.

3.4.2 The estimation method

The lagged variable in our specification makes the econometric techniques commonly used in the case of panel data inefficient. The Fixed Effects (FE) method is unsuitable for our specification because it would negatively correlate the error term and the lagged endogenous variable. This negative correlation of the fixed effects estimator is known as Nickell's bias (Nickell, 1981).

The standard solution usually used is the Generalized Moment Method (GMM). It is a method adapted to dynamic panel studies by controlling for the endogeneity of the variables that cause us problems while controlling for country and time-fixed effects. However, this method is challenging to implement because of the many conditions that must be respected for valid results. Conditions [4] which are described in detail by Roodman (2009).

The methodology chosen is the ordinary least squares corrected from Nickell's bias. The idea behind this method is to approximate the bias generated by the estimation with the inappropriate estimators to remove this bias from the estimation of the parameters. This method is based on the work of Nickell (1981). Indeed, in addition to highlighting the inadequacy of Ordinary Least Squares due to the bias, Nickell (1981) tried to approximate this bias. Monte Carlo simulations were performed to obtain the properties of the bias-corrected ordinary least squares estimator. These simulations showed that bias-corrected OLS outperforms the instrumental variable and GMM methods in terms of bias. Work such as Bun and Kiviet (2003) has successfully approximated up to 90% of the bias. In this study, we will use a version of this estimator developed by Bruno (2005), which is adapted to unbalanced and non-cylindrical panels. This methodology is becoming increasingly used in the literature (Trabelsi, 2016; Gootjes et al., 2021; Debrun et al., 2008), making it possible to perform certain types of studies on groups of countries, which was not possible with the GMM estimators.

In practice, bias-corrected ordinary least squares are obtained in two steps. The first step is to estimate the bias, and the second is to extract the bias from the ordinary least squares estimate. First, three methods described by Bruno (2005), are available for bias estimation. The different bias approximations are: $B_1 = c_1(T^{-1}), B_2 = B_1 + c_2(N^1T^{-2}), B_3 = B_2 + c_3(N^1T^{-2})$ with N the number of study units and $T = (1/N)sum_1^N T_i$ presents the average panel size of the group. Then, three estimators can be implemented to estimate this bias, depending on the type of bias chosen for the correction. It can be estimated either using the Anderson and Hsiao (1981) estimator or the difference estimator of Arellano and Bond (1991), or the system estimator of Blundell and Bond (1998)[5]

[4]Indeed, to validate the results following the use of the Generalized Method of Moments, the coefficient of the lagged dependent variable must be significant and less than 1. Then, due to the lagged variable's presence, we expect an autoregressive process of order 1 (AR(1)). However, there is no reason for an autoregressive process of order 2 (AR(2)). Finally, the instrumental variables must be valid, and this is verified through the Sargan and Hansen test.

[5]The Nickell bias-corrected least squares method is not a GMM estimator but uses GMM estimators to estimate Nickell's bias. Once the bias has been estimated, the equation $MCOC_i = MCO - B_i$, $i = 1.2$, or 3 can now be solved. The error term is obtained by a bootstrap method. In this analysis, we have chosen the most rigorous definition of bias. Furthermore, we estimated our main regressions using the Blundell-Bond estimator. However, our main results are reproduced by following the other two estimators, Arellano-Bond and Handerson-Hsiao. Moreover, we chose

3.5 Results and discussion

Table 3.2: Main Results

	1	2	3	4	5	6	7	8
	OLS	LSDVC	OLS	LSDVC	OLS	LSDVC	OLS	LSDVC
L.Forest_rent	0.6831***	0.7820***	0.6531***	0.7596***	0.6571***	0.7546***	0.6213***	0.7266***
	(0.0160)	(0.0157)	(0.0164)	(0.0163)	(0.0167)	(0.0191)	(0.0169)	(0.0210)
Elect	-0.1294	-0.1304	-0.3932**	-0.4217**	-0.1525	-0.1529	-0.4508***	-0.4826***
	(0.1029)	(0.1273)	(0.1659)	(0.1711)	(0.1057)	(0.1093)	(0.1721)	(0.1707)
Elect x Con			0.8616*	0.9465**			0.9409**	1.0350**
			(0.4672)	(0.4534)			(0.4784)	(0.5005)
Polcon			-0.8726***	-0.9307***			-1.0470***	-1.1070***
			(0.2125)	(0.2626)			(0.2280)	(0.2633)
Corruption					-0.1047**	-0.1176**	-0.1412***	-0.1560***
					(0.0483)	(0.0535)	(0.0491)	(0.0559)
GDPperCap					0.0001**	0.0001**	0.0000	0.0000
					(0.0000)	(0.0000)	(0.0000)	(0.0000)
Depl					0.0485***	0.0450***	0.0625***	0.0570***
					(0.0086)	(0.0109)	(0.0089)	(0.0109)
UrbanPop					0.0063	0.0118	0.0063	0.0146
					(0.0114)	(0.0156)	(0.0125)	(0.0177)
Democ					-0.0058	-0.0053	-0.0016	-0.0011
					(0.0040)	(0.0047)	(0.0042)	(0.0044)
N	2285	2298	2119	2119	2180	2180	2010	2010
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.93		0.93		0.94		0.94	
Countries	83	83	83	83	87	87	83	83

Notes: N=2010, t statistics in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$. We have opted to present the OLS regressions in order to present the R2 of the LSDVC regressions, since technically they are the same regressions, only with the added correction of Nickell's bias. The command does not provide an R2 for LSDVC regressions.

The main results in Table 3.2 consist of three parts. The first two columns of the table (Columns [**1-2**]) show a univariate regression, considering the electoral variable (*Elect*) as the only explanatory variable but taking care to control for fixed effects. The coefficient in front of the variable *Elect* is not significant. So, these two columns show us that elections generally do not give rise to increases in forest rents. The two following columns (Columns [**3-4**]) present a more enriched specification than the previous ones since we consider the level of competitiveness of the elections

100 bootstraps to calculate the error term.

here, as described above. These columns contain three explanatory variables, and the results already confirm our expectations. The coefficient in front of the interactive variable ($Elect \times Con$) is positive and significant. Competitive elections give rise to the manipulation of forest rents for re-election purposes. Columns [**5-6**] provide the same result as in Columns [**1-2**], but here we take care to control by critical variables. The last two columns (Columns [**7-8**]) are the most complete model of our analysis. They allow us to check the robustness of our results shown in Columns [**3-4**] by controlling for factors that can influence forest rents in a country.

The implications of our research findings are significant. Competitive elections in our sample countries lead to an increase in forest resource rents. The main result, as presented in Column [**8**] of Table 3.2, indicates that an increase in the level of competitiveness of the elections results in a corresponding increase in forest rents in the pre-electoral period. This finding underscores the potential impact of political competition on natural resource management.

Although competitive elections are a source of cycles in the countries in our sample, elections, in general, could have surprising results given the institutional quality of the countries studied. Indeed, our results also show that countries with weak political constraints tend to experience declines in forest rents on the eve of elections, as we can see with the negative and significative rent variable in column [**8**]. Thus, controlling for electoral competition, we find that countries with weak electoral competition experience negative cycles in forest rents.

At the average level of competition in our sample, there tends to be a negative cycle in forest rents, as many countries in our sample have low levels of political competition [6]. However, from the ninetieth percentile onwards, positive cycles tend to appear. This result shows two types of electoral cycles within our sample. Negative cycles highlight informal mechanisms, and positive cycles highlight formal mechanisms. Negative cycles can be explained by the fact that rents are used to secure the support of certain partners, not of the population (Médard, 1991).

In an election with strong competition, the need to finance projects to attract the population's favor leads to positive cycles since government revenues from mining activity are proportional to rents. Thus, to have more income, the government authorizes an increase in logging, leading to an increase in forest rents.

[6] This result is obtained by performing the following calculation: $-0.4826 + 0.2723 \times 1.035 = -0.200$

On the other hand, the absence of competition leads to negative cycles due to the diversion of income from logging to attract the favor of the ruling class. The rents are under-declared to be diverted to benefit the president's supporters in power since it is easier to use them directly for this corruption than the budget.

There is a great deal of corruption in the logging sector in developing countries. For example, a report by the African Development Bank[7] highlights the corrupt practices involved in granting logging licenses in Africa. Areas not intended for logging are even exploited with the agreement of local authorities. In this way, on the eve of competitive elections, the government, to finance its projects, can increase the number of licenses issued to boost its revenues simultaneously, leading to an increase in rents in the pre-election period. However, when the stakes are not high, increasing government revenues through higher rents is unnecessary. To avoid coups d'état, for example, the incumbent candidate, again due to corruption, uses revenues from forestry resources to win the loyalty of his supporters. In this case, this is done by under-declaring the rents.

In addition to our weighted electoral variable of the level of election competitiveness, our final model (the last two columns) includes other variables that yield intriguing results. The presence of political constraints is associated with lower forest rents, a result that can be attributed to the reduced risk of manipulation of exploitation rights granted to companies. The unexpected finding is the negative relationship between corruption and forest rents. One might expect a positive relationship, but this result underscores the complexity of the relationship between natural resource rents and corruption. High levels of corruption do not always translate to high rents, as these may not be declared in some instances. This is particularly relevant in our case, where we have already controlled for institutional quality through the level of political constraint.

3.6 Robustness analysis

In this section, we present the robustness of our result when considering the elections' competitiveness, and the results are presented in Tables 3.3 and 3.4. We first use the Anderson-Hsiao and Arellano-Bond estimators to estimate bias instead of the Blundell-Bond estimator, followed by other, less stringent bias corrections. Next,

[7]https://www.afdb.org/sites/default/files/documents/publications/illicit_timber_trade_report.pdf

we use an alternative estimator: the GMM method. Then, in the third section, we see the magnitude of our results for resource-dependent countries. Finally, we use additional control variables and placebo tests to confirm the robustness of our results.

Table 3.3: Exploring the robustness 1

	1	2	3	4	5	6
	AH	AB	B1	B2	GMM	Forest_dependent
L.Forest_rent	0.6917***	0.6726***	0.7235***	0.7232***	0.7740***	0.6724***
	(0.0217)	(0.0217)	(0.0211)	(0.0209)	(0.0356)	(0.0314)
Elect	-0.4613***	-0.4550***	-0.4820***	-0.4816***	-0.4443**	-1.0796***
	(0.1712)	(0.1666)	(0.1706)	(0.1706)	(0.1755)	(0.3634)
Elect x Con	0.9793*	0.9559*	1.0333**	1.0322**	0.9780**	2.6876*
	(0.5024)	(0.4897)	(0.5002)	(0.5002)	(0.4880)	(1.4295)
Polcon	-1.1156***	-0.9707***	-1.1063***	-1.1053***	-0.8760***	-2.9584***
	(0.2640)	(0.2544)	(0.2635)	(0.2634)	(0.2352)	(0.8870)
Corruption	-0.1415***	-0.1295**	-0.1558***	-0.1556***	-0.1313***	-0.4696***
	(0.0545)	(0.0528)	(0.0560)	(0.0559)	(0.0502)	(0.1514)
GDPperCap	0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0005**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Depl	0.0497***	0.0574***	0.0571***	0.0571***	0.0551***	0.1202***
	(0.0109)	(0.0105)	(0.0109)	(0.0109)	(0.0092)	(0.0223)
UrbanPop	0.0173	0.0056	0.0144	0.0143	0.0098	0.0111
	(0.0171)	(0.0160)	(0.0177)	(0.0177)	(0.0127)	(0.0451)
Democ	-0.0008	-0.0013	-0.0011	-0.0011	-0.0020	-0.0241
	(0.0045)	(0.0045)	(0.0044)	(0.0044)	(0.0043)	(0.0636)
N	2010	2010	2010	2010	2010	620
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Countries	83	83	83	83	83	25

Notes: N=2010, t statistics in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$. In column 6, the test results related to the GMM estimator are: AR1: -12.28***, AR2: 0.44, Sargan test: 9.83***.

3.6.1 Use of alternative bias correction.

The command developed by the authors of the model we use allows using several estimators to estimate Nickell's bias to correct the Ordinary Least Square estimator. In the primary model, we use the Blundell-Bond estimator. For robustness, we use the other estimators available in the command, namely the Anderson-Hsiao estimator and the Arellano-Bond estimator. The results are presented in the first two columns (Columns [**1-2**]) of Table 3.3. We see that these two results support our findings. Furthermore, the coefficients are qualitatively and substantially similar: Competitive elections lead to cycles in forest rents.

We also test the robustness of our results by using different levels of bias to estimate our results. As specified above, Nickell's bias can be corrected according to three possible estimates of this bias. The one we used in our primary model is the most restrictive possible. Columns [**3-4**] of Table 3.3 present the results for the other two bias estimates. Again, our results are confirmed, and the coefficients are qualitatively equal to those in our main results.

3.6.2 Use of GMM method.

Among the possible methods we could choose to estimate our dynamic panel model is the Generalized Method of Moments (GMM). However, we had chosen the generalized least squares corrected for Nickell's bias. In this part, we propose to re-estimate our primary model using GMM. This method is commonly used to estimate dynamic models because it solves endogeneity issues. Indeed, the presence of the lagged explained variable creates an endogeneity problem. Also, as specified above, there can be a double causality between the level of electoral competition and rent. Indeed, electoral competition can lead to an increase in rents in order to finance development projects. Also, high rents lead to increased electoral competition to monopolize these rents. This double causality results in a potential endogeneity issue, which can also be corrected using the GMM method. The results, presented in the Column [**5**]of Table 3.3, are robust to this alternative method. Furthermore, as in the other robustness tests, the coefficient is substantially equal to that of the main results.

3.6.3 Countries dependent on forest rents.

Our study takes into account developing countries without taking into account their level of dependence on forest resources. In this section, we intend to test the validity of our results by only retaining our sample countries that are highly dependent on forest resources. We constructed a sub-sample of countries with forest rents above the average. The results, presented in the Column [**6**] of Table 3.3, show once again that our obtained results are robust and, even more, qualitatively similar.

3.6.4 Use of additional control variables.

In this test, we add new control variables to show that our specification is stable and robust. We are introducing several control variables likely to impact the level of forest rents, particularly during an election period. The first variable we introduce is the level of internal conflict within each country ($InternalConflict$). This additional variable makes it possible to consider general and political instability. This instability can impact the quality of the elections that must be held. The second variable that we incorporate for robustness is the level of socioeconomic conditions of the population ($SocioeconomicConditions$). We get this variable from the ICRG database. The socioeconomic conditions of a population can make it remarkably docile to manipulation during an election period. The last variable this robustness test includes is the exchange rate ($Exrate$). Our results are presented in the three first columns (Columns [**1-3**]) of Table 3.4 and are still robust to these robustness tests.

3.6.5 Placebo tests

In this section, we perform placebo tests. For this, we have made shifts in the election dates to demonstrate that the cycles detected above do not appear during non-election periods. Indeed, the appearance of electoral cycles can be attributed to other cycles, such as cycles of corruption that occur during the same period. Therefore, we must ensure that the cycles captured are electoral cycles that only appear during the electoral period. In our exercise, we tried to detect cycles in the years following the elections. We have placed the election years as the one, two, and three years after the elections. Results are presented in the four last columns (Columns [**4-7**]) of Table 3.4. Moreover, in line with our expectations, we do not find cycles in forest rents during non-electoral periods. This result confirms our findings and constitutes the last series of robustness tests we implement.

3.7 Heterogeneity analysis

As mentioned above, our results are supposed to have a high degree of heterogeneity. We propose to test this, and the results are presented in Table 3.5. Firstly, we will look at how results vary according to whether or not the elections are early and whether the incumbent candidate is represented in the elections. In addition, factors such as the level of corruption and individual freedoms may influence our results. We, therefore, also analyze the sensitivity of our results to these two factors.

Table 3.4: Exploring the robustness 2

	1	2	3	4	5	6	7
	Conflict	Social	Exrate	Before	One year	Two year	Three years
L.Forest_rent	0.7274***	0.7263***	0.7278***	0.7272***	0.7267***	0.7264***	0.7275***
	(0.0210)	(0.0211)	(0.0194)	(0.0208)	(0.0210)	(0.0209)	(0.0209)
Elect	-0.4954***	-0.4817***	-0.4854**				
	(0.1695)	(0.1703)	(0.1973)				
Elect x Con	1.0620**	1.0285**	0.9868*				
	(0.4981)	(0.4993)	(0.5682)				
Polcon	-1.0737***	-1.1201***	-1.0865***	-0.9853***	-1.0271***	-1.0504***	-0.9234***
	(0.2642)	(0.2629)	(0.2809)	(0.2647)	(0.2651)	(0.2529)	(0.2630)
Corruption	-0.1473**	-0.1555***	-0.1593***	-0.1558***	-0.1557***	-0.1568***	-0.1557***
	(0.0574)	(0.0559)	(0.0582)	(0.0562)	(0.0561)	(0.0562)	(0.0559)
GDPperCap	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Depl	0.0572***	0.0567***	0.0561***	0.0571***	0.0572***	0.0573***	0.0568***
	(0.0109)	(0.0109)	(0.0105)	(0.0108)	(0.0109)	(0.0107)	(0.0109)
UrbanPop	0.0145	0.0154	0.0165	0.0150	0.0153	0.0153	0.0151
	(0.0177)	(0.0179)	(0.0179)	(0.0178)	(0.0177)	(0.0177)	(0.0178)
Democ	-0.0020	-0.0009	0.0010	-0.0002	-0.0003	-0.0001	-0.0003
	(0.0045)	(0.0044)	(0.0046)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
InternalConflict	-0.0432*						
	(0.0244)						
SocioeconomicConditions		-0.0248					
		(0.0436)					
Exrate			0.0000**				
			(0.0000)				
Before_elect				0.0003			
				(0.2040)			
Before_Con				0.1411			
				(0.5921)			
Elect1					-0.1540		
					(0.2028)		
Elect_Con1					0.4272		
					(0.5901)		
Elect2						-0.1092	
						(0.1975)	
Elect_Con2						0.5088	
						(0.5208)	
Elect3							0.1017
							(0.1641)
Elect_Con3							-0.2293
							(0.4981)
N	2010	2010	1971	2010	2010	2010	2010
Country FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Countries	83	83	83	83	83	83	83

Notes: N=2010, t statistics in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 3.5: Exploring the heterogeneity

	1	2	3	4	5	6	7
	Delayed	Incub_run	Dont_run	Hight_currup	Low_currup	Hight_Freed	Low_Freed
L.Forest_rent	0.7285***	0.7293***	0.7272***	0.7998***	0.6778***	0.8235***	0.7140***
	(0.0208)	(0.0209)	(0.0210)	(0.0252)	(0.0254)	(0.0243)	(0.0239)
Delayed	0.6080*						
	(0.3227)						
Delayed_comp	-0.8011						
	(1.0370)						
Polcon	-0.9374***	-1.0434***	-0.9995***	-0.3835*	-1.6981***	-0.3984*	-1.5872***
	(0.2551)	(0.2597)	(0.2570)	(0.2279)	(0.4465)	(0.2063)	(0.4616)
Corruption	-0.1537***	-0.1504***	-0.1565***	-0.0236	-0.3225***	-0.0816**	-0.2329***
	(0.0559)	(0.0557)	(0.0558)	(0.0452)	(0.1107)	(0.0389)	(0.0898)
GDPperCap	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Depl	0.0570***	0.0571***	0.0571***	0.0632***	0.0602***	0.0028	0.0702***
	(0.0109)	(0.0109)	(0.0109)	(0.0150)	(0.0145)	(0.0142)	(0.0128)
UrbanPop	0.0141	0.0138	0.0151	-0.0077	0.0476	0.0108	0.0131
	(0.0178)	(0.0177)	(0.0177)	(0.0140)	(0.0307)	(0.0103)	(0.0287)
Democ	0.0002	-0.0010	-0.0007	-0.0128*	0.0055	-0.0054*	0.0133
	(0.0045)	(0.0044)	(0.0045)	(0.0067)	(0.0082)	(0.0031)	(0.0097)
Incub_Run		-0.6604***					
		(0.1884)					
Incub x comp		1.1124**					
		(0.5664)					
Dont_run			-0.1863				
			(0.2181)				
Dont x comp			0.6009				
			(0.5650)				
Elect				0.1494	-1.0424***	-0.2938*	-0.6089*
				(0.1822)	(0.2943)	(0.1578)	(0.3245)
Elect_Con				-0.2965	1.7423*	0.7660**	0.8926
				(0.4645)	(0.9128)	(0.3729)	(1.0300)
N	2010	2010	2010	1049	961	907	1103
Country FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Countries	83	83	83	41	42	37	46

Notes: N=2010, t statistics in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

3.7.1 The difference between staggered elections and regular elections

According to the literature (Uberti et al., 2019), early elections do not allow the candidate in power to manipulate public opinion since the deadline would be too short. This is what we propose to test in this part. The database allows us to divide the elections depending on whether the elections are staggered. Therefore, we propose testing this by using our primary model on staggered elections. The result is presented in the first column of the Table 3.5. In this case, we see that staggered competitive elections do not give rise to the manipulation of forest rent. However, generally displaced elections result in higher forest rents. We see this in our results through the positive and significant coefficient of the variable *Delayed* in the first column. This result is explained by the delayed elections, which give the incumbent time to manipulate the voters' choices.

3.7.2 In case of representation of the candidate in power

We want to test the heterogeneity of our results by verifying whether cycles did indeed occur when candidates for power were represented. When the candidate stands for re-election or if his political party stands for re-election, he has every reason to carry out manipulations to signal his competence to be re-elected. Thus, one should see cycles in the case of the representation of the candidate in power. To test this, we break our elections down into two. Elections in which the president in power is running and elections in which the president in power is not running. The results are presented in the Columns [**2-3**] of Table 3.5. Consistent with our main results, election cycles appear when the ruling candidate runs for office again. We find results consistent with the literature.

3.7.3 Depending on the level of corruption

We also tested the sensitivity of our results by considering countries' levels of corruption. While it is true that we take into account the level of competitiveness of the elections, the level of corruption within the country can affect political cycles. Corruption can reduce the need to increase rents since results can be manipulated, for example. To test this, we have divided our countries into two groups according to the median. Our results in the Columns [**4-5**] of Table 3.5 are unsurprising. Political cycles at the level of forest rents are observed only at the level of countries with a low level of corruption, i.e., at the level of the group with the lowest level of corruption.

3.7.4 Depending on the level of freedom

According to the literature, the population's education level, the age of democracy, or even access to information are factors conditioning the probability of the appearance of political cycles. Indeed, these different factors affect the ability of the voting population to understand the manipulations of politicians and their intentions. We proposed to test the sensitivity of our results according to the level of freedom in the different countries. Our results in the two last columns (Columns [**6-7**]) of Table 3.5 show that countries with a high level of human freedoms experience rents' negative political cycles.

3.8 Conclusion

This paper aims to detect possible electoral cycles in natural resource rents in developing countries. Still-developing institutions and nascent democracies usually characterize these countries. We worked on a sample of eighty-three (83) countries and used the Nickel bias-corrected generalized least squares estimator proposed by Bruno (2005) and used by Gootjes et al. (2021); Debrun et al. (2008); Bogliacino et al. (2012). This estimator has the advantage of being operational even on small samples. Overall, our results suggest that forest rents in developing countries are not subject to cycles in the case of elections in general. However, the competitiveness of elections seems to be a factor that conditions electoral cycles in natural resource rents. Indeed, considering the elections' competitiveness, positive cycles appear. The most competitive elections are characterized by positive political cycles, while non-competitive elections give rise to negative political cycles due to a diversion of the rents.

We tested the robustness of these results using the Anderson-Hsiao and Arellano-Bover estimators. We also re-estimated our primary model using less restrictive Nickel bias corrections. In a third robustness test, we used the GMM estimator to tackle the endogeneity issue from the dynamic specification and the double causality between rents and electoral competition. We also added control variables to confirm the stability of the interest coefficients. We focused on more forest rents dependent countries and used placebo tests; the results remained the same. Finally, we reduced our sample to countries dependent on forest resources.

Our results come out robust after all these tests. The heterogeneity analysis showed us that it is mainly the elections during which the president is running for re-election. These cycles appear only in low-corrupt countries and countries with high human freedom.

Our work suffers from some limitations that could be sources of extension of the present study. The first is using total natural resource rents in place of the rents effectively received by governments. This is beyond our control and is due to the lack of data. The Extractive Industries Transparency Initiative (EITI)[8] database[9], which contains this information, exists but is too recent. In the coming years, as the time horizon of the database lengthens, higher-quality work could be done. Another limitation of our work is that the different channels could have been tested more thoroughly, depending on data availability and completeness. These include, for example, the number of operating permits granted or the tax rate in the mining sector over our study period. Indeed, it would be interesting to study how operating permits evolve with elections. As we have seen, elements of the literature show us that in certain precise countries, these exploitation permits were subject to cycles.

These different results lead us to draw some conclusions. The few competitive elections that take place generate cycles because of the manipulation of candidates for power due to the youth of democracies. On this basis, economic policy recommendations can be made. Indeed, manipulation for re-election purposes has adverse effects on the economy. Therefore, having solid institutions, including independent structures for natural resource management, is crucial. Also, since a high level of democracy is associated with an absence of cycles, developing countries should be encouraged to continue their march toward democracy, which cannot be done without the help of the international community. However, the same individuals who hold power will implement these various measures. The most effective way is to build a vibrant civil society. This refers to the human capital of countries. Therefore, a medium- and long-term fight against these political manipulations of rents should also involve investing in the population's education so that they can understand the political game during the election period.

[8] https://eiti.org/fr

[9] https://eiti.org/fr/donnees-ouvertes

3.9 Appendix

Table 3.6: List of countries included in the analysis

Albania	Algeria	Angola	Argentina	Armenia	Azerbaijan	Bangladesh	Belarus
Bolivia	Botswana	Brazil	Bulgaria	Burkina Faso	Cameroon	Chile	China
Colombia	Congo, Dem. Rep.	Costa Rica	Cote d'Ivoire	Ecuador	El Salvador	Ethiopia	Finland
Gabon	Gambia	Ghana	Guatemala	Guinea	Guinea-Bissau	Guyana	Haiti
Honduras	Hungary	India	Indonesia	Jamaica	Jordan	Kazakhstan	Kenya
Kuwait	Lebanon	Liberia	Libya	Madagascar	Malawi	Malaysia	Mali
Mexico	Moldova	Mongolia	Morocco	Mozambique	Namibia	Nicaragua	Niger
Nigeria	Pakistan	Panama	Papua New Guinea	Paraguay	Peru	Philippines	Poland
Qatar	Saudi Arabia	Senegal	Serbia	Sierra Leone	South Africa	Sri Lanka	Sudan
Tanzania	Thailand	Togo	Tunisia	Turkey	Uganda	Ukraine	Uruguay
Vietnam	Zambia	Zimbabwe					

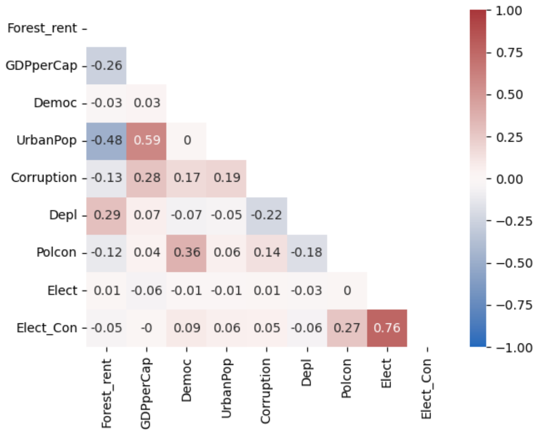


Figure 3.4: Correlation

Table 3.7: Correlation Table

	Forest_rent	GDPperCap	Democ	UrbanPop	Corruption	Depl	Polcon	Elect	Elect x Con
Forest_rent	1.0***	-0.26***	-0.03	-0.48***	-0.13***	0.29***	-0.12***	0.01	-0.05*
GDPperCap	-0.26***	1.0***	0.03	0.59***	0.28***	0.07**	0.04*	-0.06**	-0.0
Democ	-0.03	0.03	1.0***	0.0	0.17***	-0.07**	0.36***	-0.01	0.09***
UrbanPop	-0.48***	0.59***	0.0	1.0***	0.19***	-0.05*	0.06**	-0.01	0.06**
Corruption	-0.13***	0.28***	0.17***	0.19***	1.0***	-0.22***	0.14***	0.01	0.05*
Depl	0.29***	0.07**	-0.07**	-0.05*	-0.22***	1.0***	-0.18***	-0.03	-0.06**
Polcon	-0.12***	0.04*	0.36***	0.06**	0.14***	-0.18***	1.0***	0.0	0.27***
Elect	0.01	-0.06**	-0.01	-0.01	0.01	-0.03	0.0	1.0***	0.76***
Elect x Con	-0.05*	-0.0	0.09***	0.06**	0.05*	-0.06**	0.27***	0.76***	1.0***

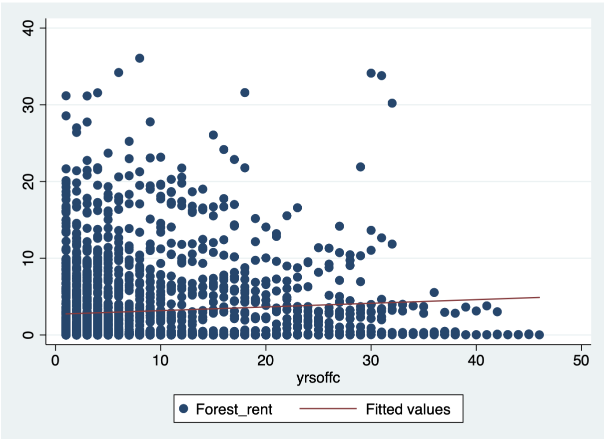


Figure 3.5: Relationship between Forest rents and tenure

Table 3.8: List and sources of variables

Variable	Definitions	Sources
Forest rents	Annual forest rents (%GDP)	World Bank Development Indicator (2019)
Political constraints	Political constraint index	POLCON by Witold Jerzy Henisz
Elect	Variable from the pre-election period	National Elections Across Democracy and Autocracy Dataset, 5.0 (NELDA)
Elect_Con	Elections taking into account their level of competitiveness	Calculation of authors using Elect and Polcon variables
Corruption	Level of corruption within a country	International Country Risk Guide[10]
GDP per capita	GDP per capita in constant dollars	World Bank Development Indicator (2019)
Urbanization rate	Share of the urban population in the total population	World Bank Development Indicator (2019))
Level of democracy	Degree of democracy in the country	POLITY5 Political Regime Characteristics and Transitions, 1800-2018
Exchange rate	Official annual exchange rate (Average for the period)	World Bank Development Indicator (2019)
Dependency ratio	Dependency ratio in the country (%working-age population)	World Bank Development Indicator (2019)

Part II

Mining and economic activity

This second part deals with the interaction between mining and economic activity. Chapter 4 addresses the effect of mining activities on the participation and positioning of countries in the global value chain. In contrast, Chapter 5 takes a micro perspective and assesses how far mining activities in the countries affect the firm's performance in developing countries.

Chapter 4

Mining and Structural Change: How Does Mining Affect Participation in the Global Value Chain ?*

We examine the relationship between mining activity and participation and positioning in the global value chain in 74 developing countries from 1995-2018. Mining activity can impact countries' participation and especially their positioning in this chain through the changes it induces in the industrial and institutional structure of countries. We use the event study method, taking the activation of mines as the event to be studied, with a study time horizon of five years. Our relatively robust results show that mining activity harms positioning in the global value chain through specialization towards start-of-the-chain industries. The type of mineral extracted and the mode of extraction play an essential role in this relationship. Institutional quality, level of openness and geographical position of countries condition our results.

Keywords: Dutch disease · natural resources · mining · global value chain.

JEL codes : L72, F15, Q23, F14

*This chapter is available on HAL (Doamba, 2024a). It is currently under review in Economics of Transition and Institutional Change (Economics of Transition)

4.1 Introduction

Globalization has had its heyday since the early 1980s, giving rise to the "Age of the World Value Chain." However, recent events, including the economic war between China and the United States, the COVID-19 crisis, and finally, the war in Ukraine, have led various governments to question their participation and positions on globalization Antràs (2020). Some authors, such as Jaax et al. (2023), even go so far speaking of a risk of deglobalization.

The global value chain can be defined in several ways. However, all definitions agree that it refers to the productive activities carried out by firms in different geographical areas. Furthermore, these globally fragmented activities aim to bring a product or service from the initial design stage to the final product or good stage (Freund et al., 2020; Amador and di Mauro, 2015). Therefore, the global value chain is only an essential part of globalization. Thus, it has been spreading rapidly since the 1980s, as has globalization. Several factors are at the origin of this growth at the world level. These are, among others, the revolution in the information and communication sector and a decrease in trade restrictions on manufactured goods, notably with China's entry to the WTO in 2001. Finally, the political changes that have brought several countries into the capitalist economic system (Freund et al., 2020; Antràs, 2015). This form of trade organization offers specialization and efficiency advantages and market access (Katz and Pietrobelli, 2018; Taglioni and Winkler, 2016).

Countries rich in natural resources have a natural advantage in participating in trade by exporting raw materials. Thus, in most cases, these countries are likely to end up at the beginning of the chain. Indeed, countries rich in natural resources export these resources, enabling them to participate in the global value chain. On the other hand, the disadvantage of this participation is that countries position themselves at the beginning of the chain by exporting natural resources, mostly raw materials destined for producing finished products. Faced with this ambiguity, it is legitimate to ask about the actual effect of the exploitation of natural resources on participation and positioning in the global value chain.

The literature on the Dutch disease and the Natural Resource curse shows that a shock of income due to natural resources could lead to a collapse of the industrial structure of a country, as stressed by Corden and Neary (1982) and Bresser-Pereira (2008). Indeed, according to this literature, the positive income shock resulting from the exploitation of natural resources leads to a loss of competitiveness in other sectors due to an appreciation of the real exchange rate. Also, the increase in mining revenues can lead to a deterioration in institutional quality, which will, in turn, impact the country's attractiveness and the companies' working environment. The second transmission channel that could explain our intuition is the relationship between the level of resource rents and human capital. Work such as that of Gylfason (2001) shows the negative relationship between natural resource rents and human capital. Indeed, in his work, he lists the different factors that caused the weak growth of countries rich in natural resources. These are the Dutch disease, the rent-seeking behavior of countries, overconfidence, and finally, the neglect of education. Natural capital crowds out human capital since in resource-rich countries, educational expenditures and education levels are relatively low (Gylfason et al., 1999; Gylfason, 2001). The third transmission channel, which can explain the relationship between rents and positioning in the global value chain, is the negative relationship between the level of rents and aggregate factor productivity (Gill and Kharas, 2015). Specialization in the export of natural resources leads countries to neglect technological development, which impacts aggregate factor productivity. Indeed, in the literature, several authors use natural resource returns as a factor in explaining the middle-income trap. Indeed, authors such as Ohno (2009) and Garrett (2004) before them have examined the question. They explain the difficulty of several middle-income countries by the fact that these countries rely on natural resources and foreign direct investment flows. Garrett (2004) notes the need for technological progress to enable middle-income countries to move beyond this trap.

A country with a given economic structure that experiences such a shock will likely change its participation and position within the chain due to the factors we have listed above. Exploiting natural resources or a rent shock can increase a country's participation in the global value chain. At the same time, this exploitation can negatively impact this participation by reducing the competitiveness of this country. The reasons why we are trying to answer two questions in our paper. First, how does mining affect participation in the global value chain? Second, how does a country's position in the GVC change following a shock at the level of these rents? The contribution of this paper to the literature is as follows: First, we study the relationship between a shock from natural resource rents, here is the start of mining activity, and positioning into the global value chain. To our knowledge, this relationship has yet to be addressed, and it is the first to study the process of loss of industrial competitiveness mentioned in the literature on Dutch disease. In this paper, we want to highlight the effect of a shock from the mining sector on the participation of a given country in the global value chain in the first part and the same effect on its positioning in that chain in the second part. Also, this study uses two built indexes (Backward and forward participation indexes) to assess the positioning in the global value chain and to see more clearly the effect of mining activity on the positioning in that chain. The richness of the MinEx database enables us to study the heterogeneity of the results that will be obtained. This database provides information on the type of ore mined, the size of the mine, and the mining method. Thus, this relationship is studied according to the size of the mines, the type of ore extracted, and the extraction mode. The originality of the study also lies in the method used. Indeed, we use an event study method as the primary method, and this allows us to see the relationship evolve over our chosen time window. Finally, our study focuses on developing countries over a more extended period than most studies in the field. All these elements make our contribution to the relevant literature.

We studied 74 developing countries from 1995 to 2018 according to data availability. The choice of developing countries is motivated by the literature. Indeed, according to this, these countries are experiencing significant changes within their industrial sector, and therefore, their industries are likely to be strongly impacted by shocks. Also, developing countries are the most affected by natural resource rent shocks due to the low diversification of their economies. Last but not least, the poor institutional quality in these countries makes them less able to put in place policies to take advantage of these rents and reduce their dependence on these resources. Therefore, using this logic, we focus on 74 of these developing countries in the context of our study.

To identify the relationship that we want to highlight, we use a methodology that allows us to consider the activation of a mine as a shock that can impact the economy's structure. As mentioned above, the methodology adopted is that of the event study. Kouevi-Gath et al. (2021) has used this method in studying the relationship between the banking crisis and democracy. This method allows us to study the repercussions of activating a mine over a time horizon of our choice and in our case, this horizon is five years.

The main finding highlighted in this article is that mining activity significantly negatively impacts positioning in GVC. Indeed, it is associated with a specialization in upstream value chain industries. This means that the industrial sector of countries is changing by moving towards less finished products, that is to say, less complex. The result was robust to the addition of additional control variables, to the use of an alternative explained variable, namely the economic complexity index, to the extension of the study horizon, and, finally, eliminating the base of countries having experienced the opening of more than one mine during the study period. Also, we highlight results depending on the type of resource extracted, the extraction method, and the country's geographical position.

The rest of the paper will be presented as follows: First, we will review the literature on the relationship between mine activity and positioning in the global value chain in Section 4.2. That section allows us to formulate assumptions presented in subsection 4.2.4. Then, we will study the different data used in Section 4.3. After that, we will present the model chosen to highlight the relationship between mining activity and participation in the global value chain in Section 4.4. Finally, in the last three parts (Section 4.5, 4.6 and 4.7), we will present the results, the robustness of these results, and their heterogeneity.

4.2 Literature

In this section, we will first present the literature on defining and measuring the GVC. Then, we will present the literature on the determinants of participating in the GVC, particularly for developing countries. Finally, we will present a study of the literature on the relationship between mining and participation in the GVC. We conclude with some hypotheses derived from our literature review.

4.2.1 Definition and measurement of the GVC

The global value chain refers to the decomposition of production steps between several countries (Antràs and Chor, 2022; Amador and di Mauro, 2015; Johnson, 2018). It gained momentum in the 1980s due to a combination of revolution in the information and communication technology sector, reduced trade barriers, and finally, the popularity of the capitalist system (Freund et al., 2020). Furthermore, the increasing importance of GVCs has resulted in a fragmentation of production in different countries according to the comparative advantages.

One of the most critical concerns is the measurement of GVC. The literature is broken down into macroeconomic studies that study the phenomenon at the level of the entire country and microeconomic studies that study the same phenomenon at the level of individual firms. At all levels, measuring the global value chain has been an essential step in understanding it (Johnson, 2018), and allows for a better comprehension of global economy mechanisms.

At the micro level, studies focus on firms. The availability of micro-level data makes it easier to identify the mechanisms behind firms' participation in the global value chain. They have been made possible by the laborious construction of firm-to-firm databases (Blum et al., 2010), by the use of customs data from certain countries, or even by data on firms available at the country level (Kramarz et al., 2020). Empirical work has shown that only a small proportion of firms in each country participate in the global value chain (Bernard et al., 2007). Also, the firms participating most in this chain are larger and have higher productivity than other firms in the same country, as pointed out in studies like Bernard and Jensen (1999); Clerides et al. (1998); Melitz (2007).

On the macro level, much of the work on the global value chain is based on global input-output tables. The measurement of participation in the GVC is based on the trade-in value added. This means measuring the participation of each country in value-added trade. General equilibrium models based on input-output linkages have been used extensively at the micro and macro levels to understand the global value chain phenomenon better. The most important aspect of this question is the possibility of measuring the position of a country in global value flows. This question refers to the notions of "upstreamness" and "downstreamness" (close to final demand) that we find in the works of Bosma et al. (2005), Antràs and Chor (2013) and Fally (2012). The position of a country in the global value chain can depend on the difference in productivity or geography. This availability of data and measurement of participation in the global value chain has made it possible to highlight the determinants of this participation.

4.2.2 Determinants of participating in the GVC

In the literature, the drivers of participation in the global value chain have been discussed at length. The main factors are the size of the market, the level of development, the structure of the industry, the location of the country, the level of foreign direct investment, the quality of the infrastructure, and finally, the regulations on trade openness at the level of each country (Kowalski et al., 2015). Firms or countries opened to the rest of the world are the most likely to participate in the global value chain. In this case, the literature has differentiated between importing and exporting countries. So opened countries participate differently to the GVC.

According to the World Bank report (Freund et al., 2020), all countries participate in GVC, but not in the same way. Thus, North American, Western European, and East Asian countries specialize in producing complex products, while Africa, Central Asia, and Latin America produce less complex intermediate goods. So, we have an implicit idea of the positioning of the different countries in the different regions in the GVC. This way, the first group of countries is located at the end of the chain, while the second group is at the beginning or middle. According to the literature, it is not easy to highlight a clear relationship between the level of development and participation in the GVC. Indeed, the difference in level of development may reflect the difference in labor or capital productivity, as well as the difference in institutional quality and business climate (Kowalski et al., 2015). Also, according to the literature, the economy's structure evolves along with the level of economic development, which is seen through participation in the global value chain. Thus, among developing countries, those at the beginning of the chain will tend to specialize in trading primary goods, while the wealthiest countries among developing countries will specialize in exporting finished goods. However, this relationship is not linear, as shown by (López González et al., 2012).

The participation of developing countries in the GVC should not be taken for granted (Taglioni et al., 2016; Bamber et al., 2014). These countries must implement the conditions to allow them to participate fully in the GVC. These include trade openness, human capital development, infrastructure development, and improving the quality of institutions and the business climate (Bamber et al., 2014; Publishing, 2013). In principle, for developing countries, participation in the GVC should guarantee entry into the global market. The specialization in the tasks allows the companies of these countries to participate in world trade without having to develop specific industrial fields beforehand (Rodrik, 2018). Countries rich in natural resources have a natural disposition to participate in the GVC, so the mining sector is a factor in participation in the GVC.

4.2.3 The mining sector as a factor in participation in the GVC

Two questions arise when discussing the relationship between mining and GVC: the first is whether mining promotes participation in GVC, and the second is whether it keeps countries at the beginning of the chain or leads them to specialize in it.

Firstly, the mining sector is a factor of participation in the global value chain because countries with natural resources have a comparative advantage. The need to export natural resources is leading countries to open up and participate in the global value chain. Around one-fifth of world trade is made up of natural resources. The share of natural resources in international trade proliferated between 1900 and 1955 before declining and rising again, as we can read in Ruta and Venables (2012). Thus, differences in natural resource endowment can explain differences in participation in the global value chain.

Secondly, when we talk about mining activity and positioning in the GVC, we are referring in part to the literature on Dutch disease, the first studies of which date back to Corden and Neary (1982) and Corden (1984). Indeed, in the literature on Dutch disease, it is demonstrated that the economy's structure can change following positive shocks (notably the discovery of natural resources, an increase in the international price of exported goods, or a massive and sustained influx of capital). Moreover, this change in structure is characterized by a contraction or stagnation in sectors other than those affected by the positive shock. In practical terms, in countries that have experienced Dutch disease, there has been a contraction in the manufacturing and agricultural sectors (Corden and Neary, 1982). Thus, a high income for a given country, particularly from natural resource rents, could affect the productivity of the country's manufacturing sector in question and thus, by ricochet, impact its participation and positioning in the global value chain. Also, through the resource curse mechanism, low growth induced by mining revenues can, in turn, impact the productivity and competitiveness of a given country and, thus, its participation in the GVC.

The relationship between mining activity and participation in the global value chain also calls upon the literature on the curse of natural resources, the notion of which was introduced by Sachs and Warner (1995). Indeed, natural resource rents, which should be sources of growth for the countries that hold them, have very often been shown to be obstacles to their growth and, therefore, to their development (Gelb, 1988; Sachs and Warner, 2001). Still, in this sense, North (1991) already underlined the decline of the kingdom of Castile, which was rich in natural resources. Several factors, such as the deterioration of institutional quality and the increase in the risk of conflicts, contribute to keeping countries at the bottom of the GVC. Studies show that the natural resource curse only appears in countries with institutional quality (Mehlum et al., 2006a). New approaches have been developed concerning the relationship between the natural resource curse and globalization. Works such as those of Adams et al. (2019), Kolk and Lenfant (2010), and Kopiński et al. (2013) address the issue in the sense of globalization. According to these works, the curse of natural resources could be explained by globalization and, more precisely, by the behavior of multinationals in the mining sector. Indeed, companies in countries rich in natural resources implement various strategies, such as legitimization, tax evasion, and transfer pricing, depriving countries of potential resources to finance development. In other words, mining is a factor of natural resources curse which can negatively impact countries participation to the GVC.

In addition to these well-stocked literatures, the questions we try to answer also refers to the literature on the relationship between natural resource rents and human capital. The economic literature has highlighted a negative relationship between rents and human capital. Gylfason (2001) shows that the education sector is neglected in rentier countries. The most important factor he highlights is that natural capital crowds out human capital. This results in a low level of educational expenditure in the rentier countries (Gylfason et al., 1999; Gylfason, 2001). The last literature to which we will appeal is that of the middle-income trap and that one dealing with the aggregate productivity factor. Countries dependent on natural resource exports neglect technological development, leading to low aggregate factor productivity. This theory explains the middle-income trap, in which many countries depend on natural resources and foreign direct investment (Ohno, 2009; Garrett, 2004).

From the above, we note that a country's participation in international trade generally depends on its productivity and geography. Also, mining can favor this participation or not. It is therefor important to study the relationship between mining and participation to the GVC.

4.2.4 Assumptions

From different elements of the literature, we can formulate a set of testable hypotheses :

- The first hypothesis concerns the overall effect of mining activity on participation in the global value chain. Given the resource curse and Dutch disease theories, the relationship between rents and human capital, and aggregate factor productivity, we expect mining to have a negative impact on a country's participation in the global value chain. However, at the same time, mining activity can boost that participation while it can increase exportation. The effect is, therefore, ambiguous.

- Given the commodity nature of natural resources, we expect to see a positive effect between mining activity and specialization in industries at the lower end of the value chain. Indeed, resource-rich countries are often not very diversified, which leads them to export mainly natural resources in a raw form, thus placing them at the bottom of the global value chain. The countries' development level or institutional quality could condition this result. Furthermore, mining activity should be negatively correlated with end-of-pipe industrial activities. This is explained by the fact that, as in the previous case, since rentier countries mainly export raw resources, they are at the bottom of the scale.

4.3 Data

The data presentation section will be divided into two main parts. In the first part, we will present variables, their construction, and their sources. Then, in the second part, we will present descriptive statistics and stylized facts that will give us a first intuition of the results we can obtain.

4.3.1 The variables

Dependent variables

Among the main variables in our study are those related to participation and positioning in the global value chain, which comes from the UNCTAD-Eora database,[1] the methodology of which is described in Casella et al. (2019). This UNCTAD-Eora database offers us a large global coverage (about 189 countries) and a broad time horizon (from 1990 to 2018). However, the number of countries is much smaller due to missing data. From this database, we find key indicators of GVC participation, namely foreign value added (FVA), domestic value added (DVA), and indirect value added (DVX). FVA is the foreign value added contained in the exports of a given country; DVX is the domestic value added of a given country contained in another country's exports; and finally, DVA is the domestic value added which is embodied in this country's exports. These indicators helped us to construct our main variables. Following Aslam et al. (2017), De Backer and Miroudot (2014) and Najarzadeh et al. (2021), we use the following ratios to determine the upstream

[1] Casella et al. (2019)

and downstream participation of each country in the global value chain. In the literature, the terms backward and forward are also used to designate the position of countries in the GVC. Backward refers to downstream participation, and forward to upstream participation. We use the notions of backward and forward to name our GVC participation variables.

$$Backward_{it} = \frac{FVA_{it}}{GrossExports_{it}} \tag{4.1}$$

$$Forward_{it} = \frac{DVX_{it}}{GrossExports_{it}} \tag{4.2}$$

To construct the gross exports variable, we based ourselves on the work of Koopman et al. (2010) and Koopman et al. (2014) who decompose these exports into two components: foreign value added (FVA) and domestic value added (DVA). Thus, the sum of these two indicators in the UNCTAD-Eora database allows us to reconstruct the gross exports.

The *Backward* variable is defined from the FVA variable "Foreign Value Added" (which is the foreign value added contained in the exports of a given country) as we see in the equation 4.1 above. This refers to downstream participation in the global value chain in the literature. This is referred to as "Backward GVC participation" or "Downstream GVC participation". The variable measures the dependence of a country's exports on imported products. The higher the values of this variable for a country, the further forward in the GVC that country is.

The *Forward* variable is the second component of the global value chain that we will use. It was constructed from the DVX variable (defined as the domestic value added of a given country contained in another country's exports) as indicated above in equation 4.2. In the literature, this variable refers to upstream participation in the global value chain. It is referred to as "Forward GVC participation" or "Upstream GVC participation". The higher the values of this variable for a country, the closer it is to the beginning of the value chain.

Finally, the *GVC* variable is the sum of the previously described variables. In a formal way: $GVC = Backward + Forward$. We saw that participation in the global value chain could be in both directions. Participation in the global value chain involves activities located upstream and downstream of the global value chain.

A supplier country upstream of the chain provides value-added (intermediate goods) to a downstream country. The latter will add value to the intermediate goods received to produce products for export. More synthetically, the variable GVC corresponds to the participation variable in the global value chain, while $Backward$ and $Forward$ variables correspond to those of positioning in this chain.

It is important here to differentiate between participation in the global value chain and commercial openness. Both are all linked to trade, but do not reflect the same reality. In this sense, Wang et al. (2019) precised that trade volume, trade openness, and GVC participation are not substitutable. GVC participation mainly refers to the extent of a country's involvement in vertical international specialization. Participation in the global value chain only considers added value, while trade openness considers the total value of trade with the rest of the world. Countries with greater trade openness tend to have greater participation in the global value chain since this allows firms to access inputs from other countries, which can lead to greater specialization and efficiency in production.

Interest variable

This variable of interest is a dummy variable taking the value 1 in the year a mine becomes operational and the following five years and zero value otherwise. The MinEx database gives this information.[2] This database gives the geolocalized position of each mine, the date of discovery of each mining deposit, and especially the date of the start of activity of the deposit and its date of closure in case of closure. Based on this database, we constructed a dummy variable *Activity* capturing mining activation. Thus, for example, for a given country, it takes the value of 0 for all the years except the year of the opening of a mine and the four years following the opening. This allows us better to capture shocks to the effects of natural resource revenues. This variable offers us the advantage of having the mine opening date, which is essential for measuring the effect of mines using the event study methodology.

Control variables

To add control variables to our analysis, we rely on the literature that lists the critical factors of mining activity in a country and, to some extent, the key determinants of participation in the global value chain. Among these factors, the first

[2] https://minexconsulting.com

is the country's development level. In order to take this determinant into account, we take the logarithm of GDP per capita as a variable ($LogGDP$). We also consider the country's economic dynamics through the growth of GDP ($GDPgrowth$). These two variables are essential since, to put a mine into operation, exploration work is first necessary, which is quite expensive and therefore depends on the economic conditions of each country. The degree of openness in the countries concerned is also a determining factor. Indeed, openness is a key determinant of a country's ability to trade with the rest of the world, and it conditions the import and export capacities of different countries. To this end, we have included an analysis of the degree of trade openness variable from Penn World Table ($Openness$). [3] We include the urbanization rate ($UrbanPop$) from the World Development Indicator (WDI) database. This variable is a good proxy of the industrial transformation stage in which a country is. Indeed, when the agricultural sector becomes more productive, we have a shift of workforce from rural areas to urban ones. So, this variable will control for the level of industrial development. The level of natural resources rent ($Rent$) given by the World Development Indicator (WDI) database has also been included, as it is an important factor in positioning in the global value chain. The final control variable we included is the level of capital openness ($Capital$) since the capital allows financing investment, which can affect the positioning in the GVC. We do not include institutional variables, since one of the transmission channels of the relationship we want to highlight is the degradation of institutional quality.

4.3.2 Descriptive statistics and stylized facts

The various descriptive statistics are summarized in table 4.1, and variables' definitions and sources are available in table 4.11. Table 4.1 allows us to get an idea of the distribution of our variables.

Then, the first graph (graph 4.1) allows us to see the evolution of the average participation in the global value chain. Moreover, following the literature highlighting a trend increase in participation in the global value chain, we observe an apparent increase over the years of this participation. This increase was slowed down by the economic crisis of 2008. Moreover, since then, this upward trend is no longer clear.

Figure 4.2 contains two graphs representing the evolution of the average

[3] Feenstra et al. (2015)
https://www.rug.nl/ggdc/productivity/pwt/

Table 4.1: Descriptive Statistics

	Unit	Mean	SD	Min	Max	N
			Dependent variables			N
GVC	Share	0.47	0.12	0.23	0.94	1,776
Backward	Share	0.18	0.10	0.03	0.58	1,776
Forward	Share	0.29	0.11	0.08	0.81	1,776
			Interest variable			N
Activity	Dummy	0.45	0.50	0	1	1,776
			Control variables			N
Openness	Percentage	72.83	33.07	0	290	1,776
Manufacture	Percentage	14.15	6.40	2	50	1,619
GDPgrowth	Percentage	2.49	4.01	-31	33	1,759
Capital	Percentage	0.14	1.44	-1.92	2.31	1,747
LogGDP	Percentage	7.82	1.23	4.63	11.35	1,767
Rent	Percentage	9.41	11.28	0.00	61.95	1,766
UrbanPop	Percentage	56.21	21.06	12.85	100	1,761

Note: As a reminder, the control variable is a binary variable taking the value 1 over the five years following the opening of a mine.

positioning in the GVC for countries. These graphs allow us to see the dynamic of countries in the chain. Each of these two graphs can be divided into three main parts. The first part covers the period before 2001 and corresponds to the development period of specialized industries on average. The second part corresponds to the period between 2001 and 2008. During this period, there were both a drop and a development in specialization, so there was more participation to the GVC characterized by some countries exporting raw materials while others export more complex products. Finally, the last part in these two graphs corresponds to a slow-down of the specialization process.

Furthermore, graphs 4.3 allows seeing the distribution of this participation and this positioning between the five years following the mine and the others years. Indeed, let us recall that our variable of interest is dichotomous, taking the value one over our "period of interest" and the variable 0 otherwise. Over our period of interest, namely the five years following the activation of a mine, we have a greater participation in the global value chain than in the other years. This activation of a mine is also associated with industries located at the beginning of the chain.

Graph 4.4 shows us that this effect is more significant at the level of rentier countries. Indeed, we divided our sample in two according to the initial level of natural resource rents to highlight the correlation between resources from mining activity and participation in the global value chain. Furthermore, we see that for rentier countries, the effect of activating a mine is more significant in reducing participation in the global value chain.

Regarding our mine activation variable, 53 countries experienced at least one mine opening, and the mine opening dynamic has been growing until 2010, when it started decreasing. The graph 4.9 clearly shows us the dynamic of the mine activation.

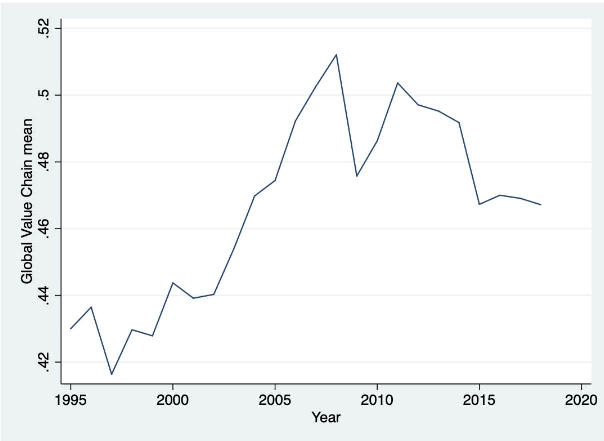
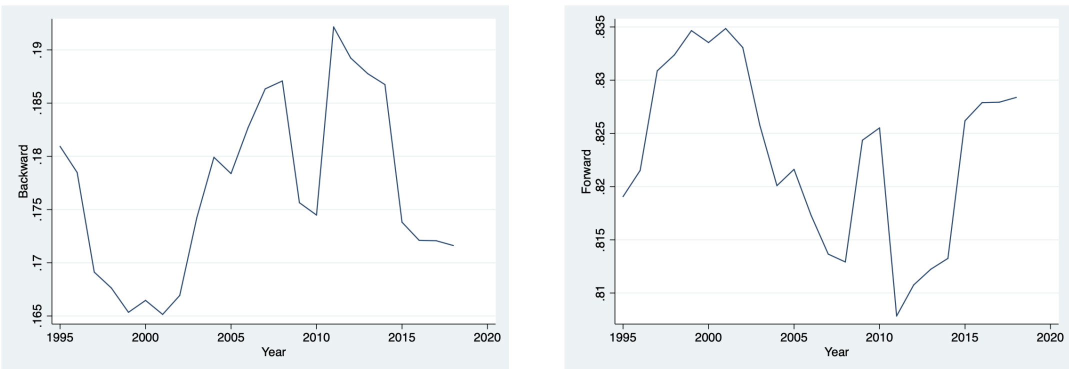


Figure 4.1: Evolution of the average participation in the global value chain
Sources : EORA database



Backward participation | Forward participation

Figure 4.2: Evolution of the average positioning in the Global Value Chain
Sources : EORA database

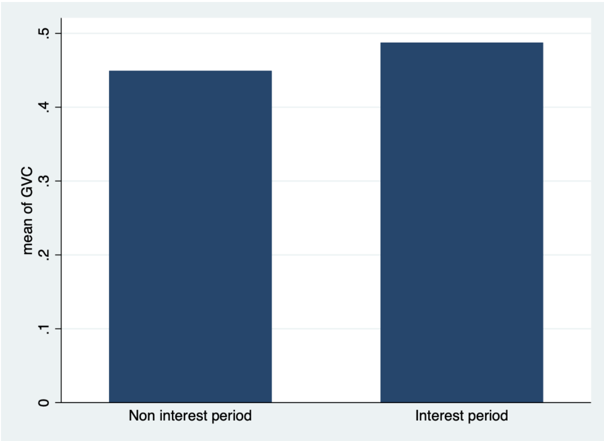
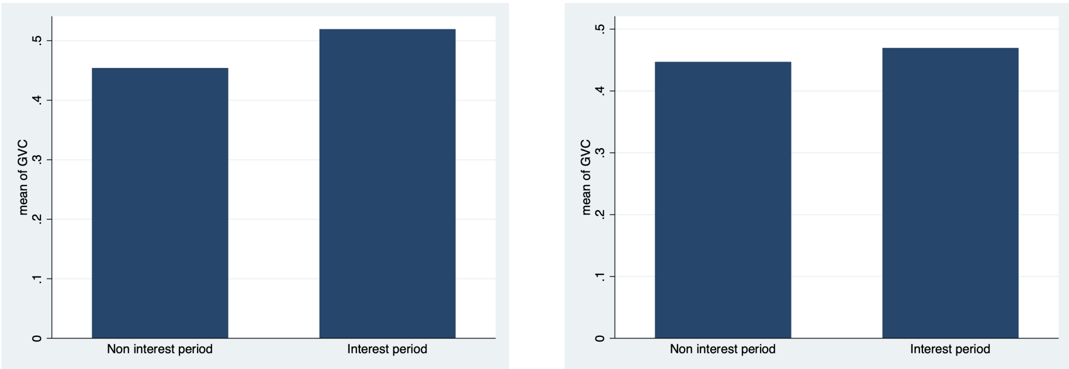


Figure 4.3: Participation between our two types of periods
Sources : EORA database and author calculation



Rentier countries Non-rentier countries

Figure 4.4: Participation between our two types of periods for rentier and non-rentier countries
Sources : EORA database and author calculation

4.4 Econometric setup

This paper aims to establish the effect of mining activity on participation in the global value chain in one and, in the other, the effect of mining activity on positioning in this chain. Furthermore, the objective is to isolate the causal effect of mining activity on participation and positioning in the GVC. In the literature, the gravity model is usually used. However, using such a model would not suit us, since the construction of participation indices in the GVC causes losing this bilateral nature of the data.

Among the multitude of methodologies available to estimate the desired effect, we have opted for the event study methodology (Corrado, 2011). The choice of this methodology is to shed light on the effect of the activation of a mine on a country's evolution participation and positioning in the GVC. The event study methodology was initially used to measure effects of economic events, such as the effect of price shocks on firm performance, and is very popular in the financial world. It has been adopted by the macroeconomics research community to measure the effect of events such as interest rate announcements or central bank policies on economic variables, or to study the effect of banking crises on various economic variables (Kouevi-Gath et al., 2021).

We will use this methodology to study a mine activation's effect on a country's participation and positioning in the GVC. To do so, we must go through the two steps necessary in the event study methodology. The first step is to define the event around which we will study the evolution of our variable of interest. This event will be the activation of a mine. We will then study the evolution of the position in the global value chain following the opening of a mine. The estimated equation will be the following:

$$Depend_{it} = \alpha + \beta Activity_{it} + \Sigma_{j=1}^{j} \rho_j X_{jit} + \delta_i + \mu_t + \epsilon_{it} \qquad (4.3)$$

In this equation, the *Depend* variable refers to one of our three dependent variables: GVC, $Backward$, and $Forward$. The variable *Activity* represents our variable of interest. It has been constructed as a dummy variable taking the unit value over the period $t + d$ (in our case here $d = 4$), with t the year a mine is in operation. The variable X_j refers to the control variables used in our study. These are the logarithm of GDP per capita, the level of trade openness, The value added of the manufacturing sector as a percentage of GDP, GDP growth, the level of internal stability captured by the level of internal conflict, and the level of corruption. In addition to these control variables, we control for country and year fixed effects, represented respectively in the equation by δ_i et μ_t. Finally, ϵ_{it} represents the error term.

The choice of a study window is a difficult one, as it involves a trade-off between the length of the study period and the time horizon for studying the impacts of mine development. The longer the study window, the shorter the estimation period. Also, the smaller the study window, the smaller our study horizon. In this logic and according to our period of study, we first study the repercussions in the first five years after the setting of the activity of the mine and, thus, in our case, $T = 5$. In addition to the reasons cited above, the choice of the five-year study horizon allows us to capture the effect of mining activity essentially. Indeed, taking a broader horizon, the captured effect could be confused with policies supporting the industrial sector or boosting exports following the consequences of mining activity.

We test our model with a Tobit model on a panel dataset of 74 countries from 1990 to 2018 as the participation and positioning variables in the chain are between 0 and 1 and our sample only contains some values of all possibles values (censored data). The use of this method requires two particular conditions. The first condition is the hypothesis of parallel trends between the countries that have experienced the activation of a mine and the other countries. We tested this hypothesis through the introduction of a time trend variable and the interaction of this variable with our variable of interest. The interaction variable is insignificant, table 4.14.

The second condition is that the activation of a mine must be exogenous. The activation of a mine can undoubtedly depend on several macroeconomic factors, such as the level of stability of the country. Nevertheless, when we take a closer look, more macroeconomic factors, such as the world level of commodity prices, determine the start-up of mines. Mines are active even in countries at war, for example.

4.5 Results

In line with the literature on event study methodology, we will focus only on the mining activity variable and will study its significance and sign in the first part, and its magnitude in the second.

Table 4.2: Main Results and additional controls robustness

	Main model			Robustness: Econfree			Robustness: FDI		
	GVC	Backward	Forward	GVC	Backward	Forward	GVC	Backward	Forward
Activity	0.0032	-0.0060***	0.0090***	0.0025	-0.0064***	0.0087***	0.0028	-0.0062***	0.0089***
	(0.0024)	(0.0020)	(0.0020)	(0.0025)	(0.0021)	(0.0022)	(0.0024)	(0.0020)	(0.0020)
Openness	0.0009***	0.0008***	0.0001	0.0010***	0.0011***	-0.0001	0.0008***	0.0008***	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Manufacture	-0.0022***	-0.0004	-0.0018***	-0.0013***	-0.0002	-0.0012***	-0.0022***	-0.0004	-0.0018***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0010***	0.0005***	0.0005***	0.0009***	0.0004*	0.0005**	0.0010***	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	0.0003	0.0006***	-0.0003	-0.0007**	0.0002	-0.0009***	0.0002	0.0006**	-0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Capital	-0.0009	0.0000	-0.0008	-0.0019	-0.0012	-0.0006	-0.0010	-0.0001	-0.0008
	(0.0012)	(0.0010)	(0.0010)	(0.0015)	(0.0012)	(0.0013)	(0.0012)	(0.0010)	(0.0010)
LogGDP	0.0251***	-0.0012	0.0263***	0.0264***	0.0035	0.0229***	0.0255***	-0.0009	0.0265***
	(0.0023)	(0.0019)	(0.0019)	(0.0026)	(0.0021)	(0.0022)	(0.0023)	(0.0019)	(0.0019)
Rent	0.0002	-0.0005***	0.0006***	-0.0001	-0.0008***	0.0006***	0.0001	-0.0006***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ecofree				0.0077***	0.0048**	0.0033			
				(0.0029)	(0.0024)	(0.0025)			
FDI							0.0005***	0.0003**	0.0002
							(0.0001)	(0.0001)	(0.0001)
Observations	1589	1589	1589	1281	1281	1281	1588	1588	1588

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the main results as well as the robustness results by adding additional control variables.

Estimations:

The results are presented in the first three columns of table 4.2. First, there is no significant effect in the first column presenting the GVC variable. This result shows that mining does not reduce a country's participation in the global value chain. Then, in the column [**2**], the results concerning the Backward variable. The relationship between this variable and mining activity is negative and significant at the 1% level. Finally, the third column (column [**3**]) shows a positive and significant at the 1% level relationship between our Forward variable and mining activity.

So far, our results suggest that mining activity impacts positioning in the global value chain. Indeed, Columns 2 and 3 of our main results table (table 4.2) show that mining activity tends to change the placement of countries in the global value chain, causing them to export fewer and fewer finished products. The higher the Forward index, the greater the participation in the industries at the beginning of the chain. Moreover, here, the mining activity positively impacts our index. Then, the higher the Backward Index, the more industries the country has at the end of the chain, and results shows that mining hurts our Backward Index.

An important result is that the coefficient of the GVC participation variable (GVC) in column [**1**] is insignificant. This means that although the activation of a mine increases the participation in the GVC through a greater export of ore, it is accompanied by the decline of the export in other sectors such that the final effect is not significant. This result supports the results of the following two columns.

Magnitude of the effects

Our results show an impact on participation in the global value chain by moving countries towards less and less complex industries. To better understand the scope of these changes induced by mining activity, comparing these different coefficients to the averages of the Forward and Backward variables is necessary. First, regarding the Forward variable, the mean is 0.8232, and the mean for the Backward variable is 0.1768. Thus, a country with an average annual forward participation index of 0.8232 will increase its forward participation index by 1.09 percent. A country with an annual average backward participation index of 0.1768 will drop backward participation by 3.39 percent. The results, therefore, have reasonable proportions.

4.6 Robustness

In this section, we will first analyze the robustness of our results by adding additional variables to our baseline model. Then, we will extend the study horizon and remove from the sample countries that have experienced several simultaneous mines openings. Finally, we will use the economic complexity index to measure positioning in the global value chain.

4.6.1 By varying our control variables

A method used to demonstrate the results' robustness is adding other control variables. We do this by successively including the economic freedom index ($Ecofree$) and the level of foreign direct investment (FDI). These two variables can affect the participation in the global value chain. First, economic freedom is a natural determinant of participation in the global value chain, as it is necessary for consumption and production activities that impact participation in the chain. Next, FDI can lead a country to have a more productive industrial sector, leading to a better positioning in the GVC. Results are presented in Table 4.2. Columns [**4-6**] of the table 4.2 show that our results are robust to adding economic freedom. The last three columns (columns [**7-9**]) confirm this robustness after adding the FDI level variable. Another exciting result of this robustness analysis is that economic freedom and net foreign direct investment flows counteract the adverse effects of mine development, as shown in Table 4.2. Greater economic freedom and foreign direct investment allow countries to better benefit from the activation of mines by increasing participation in GVC through an evolution towards the end of the chain.

4.6.2 By extending the study horizon

As we indicated in the section dealing with the methodology, the choice of the study horizon of the repercussions of initiating a mine is the result of a compromise. We undertake to widen the time horizon here as a robustness measure. So, instead of taking the five years after the opening of the mine, we take the ten years after it opened. We expect the results to be qualitatively similar to the primary results. This is what we observe in columns [**1-3**] of Table 4.3. It means that the effect of the mine opening has relatively long-lasting effects.

We also included lagged variables of mines activation to see what happened before the mine opened and ten years after. So, the new window is composed of five years before the mine activation and ten years after that opening. The results remain qualitatively the same, as we can see in graphs 4.5, 4.6, and 4.7. Mine activation is like a rupture in the trend of our GVC positioning variables. In the short term, there is no effect of mine activation on participation in the GVC. But there is an effect on position, as found in the main results. In the medium term, however, the trend is beginning to change, as we can see that employee participation is starting to rise again, probably as a result of company adaptation and adjustment policies.

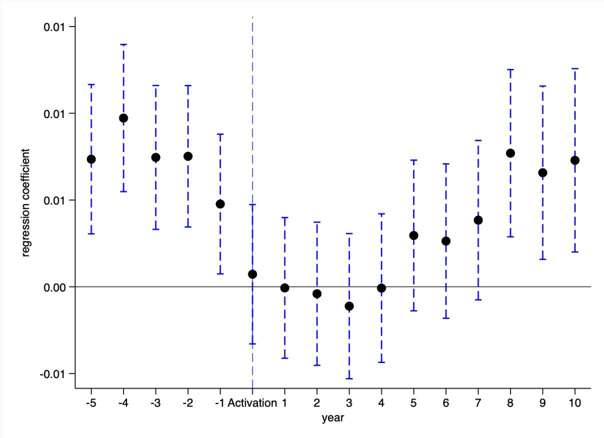


Figure 4.5: Effect of Mine activation on the GVC participation (GVC variable)

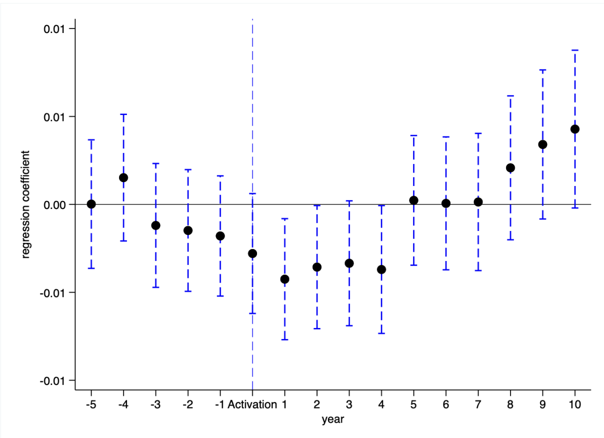


Figure 4.6: Effect of Mine activation on the GVC positioning (Backward variable)

4.6.3 By removing the countries for which there has been more than one mine opening

Several mines may open during the same study horizon. We look at how sensitive our results are to overlapping mine opening periods. In this robustness test, we exclude countries experiencing this situation. Thus, we expect to have results that are qualitatively similar to the main results. The results are presented in columns

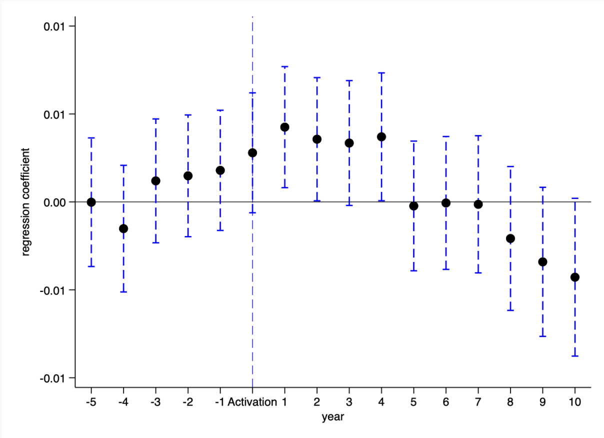


Figure 4.7: Effect of Mine activation on the GVC positioning (Forward variable)

[**4-6**] of table 4.3, confirming our expectations. The only difference with the main result is that the coefficient of the *Forward* is no longer significant. However, the conclusions of the results remain the same since the coefficient of the *Backward* variable is significant and negative, meaning that mines' opening leads to the move away from the final product.

4.6.4 Using an alternative explained variable: the economic complexity index

The fourth robustness test consists of using an alternative explained variable. We use the economic complexity index (ECI). This index measures the production capacity of an economic system, especially countries. According to statistical models, the economic complexity index is a crucial explanatory variable explaining growth and competitiveness. It considers not only the level of complexity of the national industry but also the level of human development. A country improves its index by improving the quantity and complexity of its products. Since this index allows us to see the evolution towards a more complex industry, it can be used in the case of our study as an alternative measure of participation or positioning in the global value chain. Some authors, such as Ndubuisi and Owusu (2021), show that upgrading in the GVC is equivalent to exporting more complex products. The result is presented in the column [**7**] of the table 4.3. Our results remain qualitatively the same. Thus, the relationship between mining activity and participation and positioning in the global value chain we highlighted is confirmed. With our economic complexity variable, we conclude that mining activity leads to a decrease in the complexity of the products exported by a country.

Table 4.3: Robustness Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	10 years window			Excluding more than one mine opening			ECI
	GVC	Backward	Forward	GVC	Backward	Forward	ECI
Activity(10 years)	-0.0007	-0.0072***	0.0065***				
	(0.0022)	(0.0022)	(0.0020)				
Openness	0.0004***	0.0006***	-0.0002***	0.0008***	0.0009***	-0.0001	0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0007)
Manufacture	-0.0018***	-0.0002	-0.0016***	-0.0026***	-0.0003	-0.0022***	0.0102***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0027)
GDPgrowth	0.0005***	0.0004**	0.0001	-0.0008***	-0.0000	-0.0008***	0.0022
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0029)
UrbanPop	-0.0011***	-0.0001	-0.0010***	-0.0016***	-0.0013***	-0.0003	0.0195***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0030)
Capital	-0.0022**	0.0005	-0.0027***	-0.0028**	0.0015	-0.0043***	0.0191*
	(0.0010)	(0.0010)	(0.0009)	(0.0013)	(0.0010)	(0.0013)	(0.0109)
LogGDP	-0.0173***	-0.0270***	0.0098***	-0.0027	-0.0073**	0.0045	-0.2064***
	(0.0030)	(0.0029)	(0.0026)	(0.0046)	(0.0035)	(0.0045)	(0.0352)
Rent	-0.0007***	-0.0006***	-0.0001	-0.0009***	-0.0008***	-0.0000	-0.0140***
	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0023)
Activity				-0.0033	-0.0055**	0.0022	-0.0357*
				(0.0029)	(0.0022)	(0.0028)	(0.0205)
R^2							0.9123
Observations	1589	1589	1589	798	798	798	1579

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the results of robustness tests. Columns **[1-3]** present results about the study window extension. Columns **[4-6]** present results about excluding countries that have experienced more than one mine opening. The last column (column **[7]**) presents the result of the robustness test when using economic complexity index as explained variable.

4.7 Heterogeneity

4.7.1 Heterogeneity depending on the mine properties

Depending on the type of mineral

Table 4.4: Heterogeneity by Mineral Type for the GVC variable

	(1) Gold	(2) Copper	(3) Coal	(4) Nickel	(5) Zinc
	1	2	3	4	5
Gold	0.0071***				
	(0.0026)				
Openness	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Manufacture	-0.0021***	-0.0022***	-0.0022***	-0.0021***	-0.0022***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0010***	0.0010***	0.0010***	0.0010***	0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Capital	-0.0008	-0.0007	-0.0009	-0.0009	-0.0008
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
LogGDP	0.0245***	0.0261***	0.0256***	0.0253***	0.0252***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Rent	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Copper		-0.0043			
		(0.0038)			
Coal			-0.0007		
			(0.0072)		
Nickel				0.0072	
				(0.0057)	
Zinc					0.0044
					(0.0048)
Observations	1589	1589	1589	1589	1589

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table shows the results of the heterogeneity analysis according to mineral type for the GVC variable, which is the global variable for participation in the global value chain. Our main minerals are gold, copper, coal, nickel, and zinc.

The different mines in our database produce different minerals. Thus, it would be interesting to study the impact of each type of mineral extraction on the position in the global value chain. Gold, copper, coal, nickel, and zinc are the main

Table 4.5: Heterogeneity by Mineral Type for the Backward variable

	(1) Gold	(2) Copper	(3) Coal	(4) Nickel	(5) Zinc
Gold	-0.0019				
	(0.0022)				
Openness	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Manufacture	-0.0004	-0.0004	-0.0005*	-0.0004*	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0005***	0.0005**	0.0005**	0.0005***	0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	0.0006**	0.0006***	0.0007***	0.0006**	0.0006**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Capital	-0.0001	0.0002	-0.0003	-0.0001	-0.0001
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
LogGDP	-0.0018	-0.0004	-0.0020	-0.0019	-0.0023
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
rent	-0.0006***	-0.0005***	-0.0005***	-0.0006***	-0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Copper		-0.0132***			
		(0.0032)			
Coal			-0.0200***		
			(0.0060)		
Nickel				-0.0055	
				(0.0048)	
Zinc					0.0024
					(0.0040)
Observations	1589	1589	1589	1589	1589

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table shows the results of the heterogeneity analysis according to mineral type for the Backward variable. The Backward variable refers to “Backward GVC participation” or ”Downstream GVC participation”. The higher the values of this variable for a country, the further forward in the GVC that country is. Our main minerals are gold, copper, coal, nickel, and zinc.

Table 4.6: Heterogeneity by Mineral Type for the Forward variable

	(1) Gold	(2) Copper	(3) Coal	(4) Nickel	(5) Zinc
Gold	0.0089***				
	(0.0022)				
Openness	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Manufacture	-0.0017***	-0.0017***	-0.0017***	-0.0017***	-0.0017***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0005**	0.0005***	0.0005***	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	-0.0003	-0.0003	-0.0004	-0.0003	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Capital	-0.0005	-0.0008	-0.0004	-0.0006	-0.0006
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
LogGDP	0.0263***	0.0266***	0.0277***	0.0273***	0.0276***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Rent	0.0007***	0.0007***	0.0006***	0.0007***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Copper		0.0086***			
		(0.0032)			
Coal			0.0191***		
			(0.0060)		
Nickel				0.0125***	
				(0.0047)	
Zinc					0.0018
					(0.0040)
Observations	1589	1589	1589	1589	1589

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table shows the results of the heterogeneity analysis according to mineral type for the Forward variable. The Forward variable refers to ”Forward GVC participation” or ”Upstream GVC participation”. The higher the values of this variable for a country, the closer it is to the beginning of the value chain. Our main minerals are gold, copper, coal, nickel, and zinc.

extracted minerals; the other minerals are minor. So, we have broken down the mines into groups according to the main ore extracted. Our results, presented in tables 4.4, 4.5 and 4.6, show significant heterogeneity in the relationship we have uncovered.

Gold is the only mineral that affects the participation in the GVC (see column [**1**] of Table 4.4). Two minerals have significant coefficients when we observe the aggregate positioning variable in the global value chain in tables 4.5 and 4.6. These are copper and coal. The significant results of these three minerals agree with our main results.

The observed heterogeneity in the relationship is a direct result of the distinct properties of the various ores. Some ores lend themselves to on-site transformation, while others do not, often due to technological limitations. Additionally, certain ores confer an advantage to the industry sector, particularly those that find application in the manufacturing industry. These factors contribute to the diverse impact of mineral extraction on the global value chain.

Depending on the extraction method

In this section on the analysis of the heterogeneity of our results, we analyze the sensitivity of the results according to the ore extraction method. We have three main methods of extracting ore: surface mining, underground mining, and finally, surface and underground mining. The method of ore extraction depends on the type of ore and the deposit size. As seen above, the type of mineral plays a role in the relationship we have highlighted. It, therefore, makes sense to see the sensitivity of the results depending on the extraction method. The results of the breakdown of mines by mode of exploitation confirm our intuition, since surface mines negatively impact positioning in the global value chain, as shown in table 4.7. In contrast, underground and both open and underground mines positively impact the participation in the GVC. Surface mines require less investment than underground mines. Low investments are linked to low raw material processing, which leads countries to export raw materials, thus explaining our result.

Table 4.7: Heterogeneity by extraction method

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Both open and underground				Open			Underground	
	GVC	Backward	Forward	GVC	Backward	Forwward	GVC	Backward	Forwward
Both	0.0100***	-0.0004	0.0102***						
	(0.0031)	(0.0026)	(0.0026)						
Openness	0.0008***	0.0008***	0.0001	0.0009***	0.0008***	0.0001	0.0008***	0.0008***	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Manufacture	-0.0022***	-0.0004	-0.0018***	-0.0022***	-0.0004	-0.0018***	-0.0022***	-0.0004	-0.0018***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0010***	0.0005***	0.0005**	0.0010***	0.0005***	0.0005***	0.0010***	0.0005***	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	0.0002	0.0006**	-0.0003	0.0003	0.0006***	-0.0003	0.0002	0.0006**	-0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Capital	-0.0010	-0.0001	-0.0008	-0.0009	0.0000	-0.0008	-0.0010	-0.0001	-0.0008
	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0010)
LogGDP	0.0245***	-0.0020	0.0266***	0.0251***	-0.0012	0.0263***	0.0245***	-0.0020	0.0266***
	(0.0023)	(0.0019)	(0.0019)	(0.0023)	(0.0019)	(0.0019)	(0.0023)	(0.0019)	(0.0019)
Rent	0.0002	-0.0006***	0.0007***	0.0002	-0.0005***	0.0006***	0.0002	-0.0006***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Open				0.0032	-0.0060***	0.0090***			
				(0.0024)	(0.0020)	(0.0020)			
Under							0.0100***	-0.0004	0.0102***
							(0.0031)	(0.0026)	(0.0026)
Observations	1589	1589	1589	1589	1589	1589	1589	1589	1589

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table shows the results of the heterogeneity analysis according to the extraction method for our two variables of participation in the global value chain. The GVC variable refers to the global index of participation in the global value chain. The Backward variable refers to “Backward GVC participation” or ”Downstream GVC participation”. The higher the values of this variable for a country, the further forward in the GVC that country is. The Forward variable refers to ”Forward GVC participation” or ”Upstream GVC participation”. The higher the values of this variable for a country, the closer it is to the beginning of the value chain. There are three extraction methods: open (surface) mining, underground mining, and mining combining both (open and underground).

4.7.2 Heterogeneity depending on macroeconomic factors: Transmission channels

Quality of institutions and level of openness

Talking about participation in the global value chain also leads to discussing countries' levels of trade openness. This level of openness is a significant determinant of countries' participation in world trade. We should test the sensitivity of our results according to the countries' trade openness level by examining the interaction between our variable of interest and the new trade openness. We did the same for the level of institutional quality, represented in our case by the level of corruption. Indeed, institutional quality can significantly impact economic activity and participation in world trade.

The results obtained are presented in table 4.8 and are highly instructive [4]. Indeed, whether for the level of institutional quality (in the first three columns) or the level of trade openness(in the three last columns), the effect is significant on participation and forward positioning in the global value chain. This is what we observe at the level of the significance of the interactive variables. These results are somewhat intuitive. Institutional quality is a factor that directly affects the level of economic activity. This level of economic activity directly impacts the goods and services produced and participation in the chain. The same applies to trade openness, which directly impacts the goods and services traded with the rest of the world.

Geographical position

In the introduction, we specify that countries do not participate similarly in the global value chain according to Freund et al. (2020). Indeed, in international trade, we have the formation of sub-regional industrial clusters. For example, Europe, North America, and East Asia specialize in manufacturing complex products with high added value. In contrast, for the countries of Africa, Latin America, and Central Asia, it is instead the opposite. Based on this information, we have decided to study the sensitivity of our result according to the geographical area to which each country belongs. We thus have six regions to which our countries belong according to the IMF classification. These are East Asia and Pacific(EAandP), Europe and Central

[4] As the interpretation of interactions in the Tobit model is complex and open to debate, we have reproduced this table using ordinary least squares. The results are shown in the table 4.16.

Table 4.8: Heterogeneity by quality of institutions and level of openness

	(1)	(2)	(3)	(4)	(5)	(6)
	Institutional quality			Trade openness		
	GVC	Backward	Forward	GVC	Backward	Forward
Activity	0.0132**	-0.0035	0.0167***	0.0180***	-0.0076*	0.0254***
	(0.0057)	(0.0047)	(0.0047)	(0.0052)	(0.0044)	(0.0043)
Openness	0.0008***	0.0008***	0.0000	0.0009***	0.0008***	0.0001**
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Manufacture	-0.0021***	-0.0003	-0.0018***	-0.0022***	-0.0004	-0.0018***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0010***	0.0005**	0.0005***	0.0010***	0.0005***	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	0.0001	0.0005*	-0.0003	0.0003	0.0006***	-0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Capital	-0.0011	0.0003	-0.0012	-0.0008	-0.0000	-0.0007
	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0010)
LogGDP	0.0257***	0.0007	0.0251***	0.0244***	-0.0011	0.0256***
	(0.0023)	(0.0019)	(0.0019)	(0.0023)	(0.0019)	(0.0019)
Rent	0.0002	-0.0004***	0.0006***	0.0002	-0.0005***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Corruption	-0.0032**	0.0003	-0.0034***			
	(0.0015)	(0.0013)	(0.0013)			
Activité_Corruption	-0.0044**	-0.0010	-0.0035*			
	(0.0021)	(0.0018)	(0.0018)			
Activité_Openness				-0.0002***	0.0000	-0.0002***
				(0.0001)	(0.0001)	(0.0001)
Observations	1581	1581	1581	1589	1589	1589

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table shows heterogeneity according to quality of institutions and level of openness analysis' results. The GVC variable refers to the global index of participation in the global value chain. The Backward variable refers to "Backward GVC participation" or "Downstream GVC participation". The higher the values of this variable for a country, the further forward in the GVC that country is. The Forward variable refers to "Forward GVC participation" or "Upstream GVC participation". The higher the values of this variable for a country, the closer it is to the beginning of the value chain.

Asia(EandCA), Latin America and the Caribbean(LAandC), Middle East and North Africa(MEandNA), South Asia(SA), and Sub-Saharan Africa(SSA). Our results in tables 4.9 and 4.10 show that Sub-Saharan African countries mainly explain the main results. For the countries of these regions, the opening of mines leads to a movement towards less complex industries.

Table 4.9: Heterogeneity by geographic position 1

	Sub-Saharan Africa			South Asia			Middle East and North Africa		
	1	2	3	4	5	6	7	8	9
SSA	-0.0012	-0.0122***	0.0107***						
	(0.0039)	(0.0033)	(0.0033)						
Openness	0.0009***	0.0008***	0.0001	0.0009***	0.0008***	0.0001	0.0009***	0.0008***	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Manufacture	-0.0021***	-0.0003	-0.0018***	-0.0022***	-0.0004	-0.0018***	-0.0022***	-0.0004	-0.0017***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0010***	0.0005***	0.0005**	0.0010***	0.0005***	0.0005**	0.0010***	0.0005***	0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	0.0003	0.0007***	-0.0004	0.0003	0.0006**	-0.0003	0.0003	0.0006**	-0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Capital	-0.0008	-0.0001	-0.0006	-0.0008	-0.0001	-0.0006	-0.0007	-0.0001	-0.0005
	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0010)
LogGDP	0.0256***	-0.0016	0.0273***	0.0251***	-0.0022	0.0274***	0.0247***	-0.0023	0.0270***
	(0.0023)	(0.0019)	(0.0019)	(0.0023)	(0.0019)	(0.0019)	(0.0023)	(0.0019)	(0.0019)
Rent	0.0002	-0.0005***	0.0007***	0.0002	-0.0006***	0.0007***	0.0001	-0.0006***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
SA				0.0307***	0.0078	0.0227**			
				(0.0111)	(0.0094)	(0.0093)			
MEandNA							0.0260***	0.0053	0.0205***
							(0.0069)	(0.0058)	(0.0058)
Observations	1589	1589	1589	1589	1589	1589	1589	1589	1589

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table shows heterogeneity according to geographical analysis' results. The GVC variable refers to the global index of participation in the global value chain. The Backward variable refers to "Backward GVC participation" or "Downstream GVC participation". The higher the values of this variable for a country, the further forward in the GVC that country is. The Forward variable refers to "Forward GVC participation" or "Upstream GVC participation". The higher the values of this variable for a country, the closer it is to the beginning of the value chain.

4.8 Conclusion

This article presents an empirical analysis of the relationship between mining activity and participation and the positioning in the global value chain in a sample of 74 developing countries from 1995 to 2018. Using an event study methodology that

Table 4.10: Heterogeneity by geographic position 2

	Latin America and Caribbean			Europe and Central Asia			East Asia and Pacific		
	1	2	3	4	5	6	7	8	9
LAandC	-0.0013	-0.0040	0.0030						
	(0.0045)	(0.0038)	(0.0037)						
Openness	0.0009***	0.0008***	0.0001	0.0009***	0.0008***	0.0001	0.0009***	0.0008***	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Manufacture	-0.0022***	-0.0004	-0.0017***	-0.0022***	-0.0004*	-0.0018***	-0.0021***	-0.0004	-0.0017***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDPgrowth	0.0010***	0.0005***	0.0005**	0.0010***	0.0005**	0.0005**	0.0010***	0.0005***	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	0.0003	0.0006**	-0.0003	0.0002	0.0006**	-0.0003	0.0003	0.0006**	-0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Capital	-0.0008	-0.0001	-0.0006	-0.0008	-0.0001	-0.0005	-0.0009	-0.0001	-0.0006
	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0010)	(0.0010)
LogGDP	0.0256***	-0.0021	0.0277***	0.0263***	-0.0017	0.0281***	0.0254***	-0.0021	0.0275***
	(0.0023)	(0.0019)	(0.0019)	(0.0023)	(0.0019)	(0.0019)	(0.0023)	(0.0019)	(0.0019)
Rent	0.0002	-0.0006***	0.0007***	0.0002	-0.0006***	0.0007***	0.0002	-0.0006***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
EandCA				-0.0154**	-0.0078	-0.0080			
				(0.0068)	(0.0057)	(0.0057)			
EAandP							0.0122*	-0.0026	0.0147**
							(0.0071)	(0.0059)	(0.0059)
Observations	1589	1589	1589	1589	1589	1589	1589	1589	1589

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table shows heterogeneity according to geographical analysis' results. This table shows heterogeneity according to geographical analysis' results. The GVC variable refers to the global index of participation in the global value chain. The Backward variable refers to "Backward GVC participation" or "Downstream GVC participation". The higher the values of this variable for a country, the further forward in the GVC that country is. The Forward variable refers to "Forward GVC participation" or "Upstream GVC participation". The higher the values of this variable for a country, the closer it is to the beginning of the value chain.

allows us to measure the effect in the medium term (five years here), we first found that mining activity does not affect countries' participation in the global value chain in the short term. In other words, it does not reduce or increase that participation. However, it led countries to specialize in industries at the beginning of chains by producing less complex products. This result is consistent with the literature on Dutch disease and the natural resource curse. However, when we look at the medium term, the effect of mining on the global value chain starts changing due to adaptation and policies implemented. This relationship highlighted is very heterogeneous depending on the type of ore extracted and the mode of extraction of the ore, as well as on the level of trade openness, the institutions' quality, and the geographical position.

Three transmission channels explain how mining activity could impact participation in the global value chain. The first is the mechanism highlighted in the Dutch disease theory. The second is the decline in human capital due to abundant natural resources. Finally, the third is the negative relationship between rents and total factor productivity.

This paper makes a significant contribution to the literature by being the first to delve into the relationship between mining activity and participation in the global value chain. Using a start of mining as an event to study, our innovative approach allows for precise measurement of mining activity. From a theoretical standpoint, we've shed light on the link between natural resource rents and the industrial sector's competitiveness. We've taken this relationship further by examining how mining activity directly impacts participation in the global value chain, a crucial aspect of the industrial sector's competitiveness.

The contribution of this paper in terms of economic policy recommendations is immense. Indeed, countries with large reserves of resources should implement policies to transform these resources locally into semi-finished materials instead of exporting them raw. Indeed, this will bring more value to the exports of the various countries. This will increase the country's income and the resources to finance development. The second recommendation lies in protecting other sectors other than the extractive sector. As we have seen, the non-extractive sectors lose competitiveness following income shocks from the extractive sector through investments in these sectors.

This paper presents limitations that represent avenues for improvement. The first limitation of the database is the absence of oil sites in our database. Indeed, the MinEx database needs to take into account oil sites. However, we know from the literature that oil is a resource that impacts the economy the most. Thus, one of the possible extensions of this work is to focus on the effect of the activation of oil mines on participation and positioning in the global value chain. For this, each activation date will be necessary. The other limit of our paper lies in our sample size, which only includes 74 developing countries due to missing data from our various databases. Thus, a more complete base will make it possible to produce more precise results.

4.9 Appendix

Table 4.11: List and definition of variables

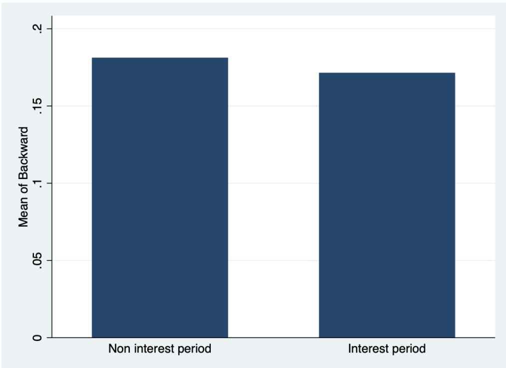
Variables	Definition	Nature	Unity	Source
1. Dependent variable				
Activity	Dummy	Discrete		Calculation of authors based on MinEx
2. Variables of interest				
GVC	Global Value Chain participation	Continuous	Percentage	UNCTAD-Eora Casella et al. (2019)
Forward	Forward GVC participation	Continuous	Percentage	UNCTAD-Eora Casella et al. (2019)
Backward	Backward GVC participation	Continuous	Percentage	UNCTAD-Eora Casella et al. (2019)
eci	Economic Complexity Index	Continuous		The Atlas of Economic Complexity
3. Control variable				
LogGDP	Log of GDP per capita	Continuous		Calculation of authors and WDI
Openness	Trade openness	Continuous		Feenstra et al. (2015)
Manufacture	Manufacturing VA	Percentage	Percentage	WDI, World Bank
GDPgrowth	Annual GDP growth	Percentage	Percentage	WDI, World Bank
Corruption	Level of corruption	Continuous		ICRG
UrbanPop	Urbanization rate	Continuous	Percentage	WDI, World Bank
Rent	Rents from natural ressources	Continuous		WDI, World Bank
Capital	Financial Openness	Continuous		The Chinn-Ito index

Table 4.12: List of countries

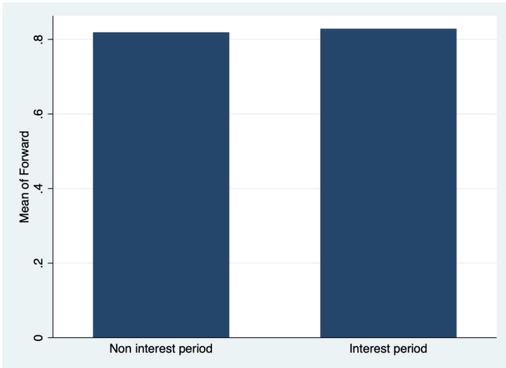
Angola	Sri Lanka	Ecuador	Qatar	Botswana	Namibia	India	Turkey
Albania	Morocco	Egypt, Arab Rep.	Russian Federation	Chile	Nigeria	Iran, Islam. Rep.	Tanzania
Argentina	Madagascar	Finland	Saudi Arabia	China	Nicaragua	Jamaica	Uganda
Armenia	Mexico	Gabon	Senegal	Cote d'Ivoire	Pakistan	Jordan	Ukraine
Azerbaijan	Mali	Ghana	El Salvador	Cameroon	Panama	Kazakhstan	Uruguay
Bangladesh	Mongolia	Guatemala	Togo	Congo, Dem. Rep.	Peru	Kenya	Venezuela, RB
Bulgaria	Mozambique	Honduras	Thailand	Colombia	Philippines	Kuwait	Vietnam
Bolivia	Malawi	Hungary	Trinidad and Tobago	Costa Rica	Papua New Guinea	Lebanon	South Africa
Brazil	Malaysia	Indonesia	Tunisia	Dominican Republic	Poland	Liberia	Zambia
Algeria					Paraguay		

Table 4.13: Cross-correlation table

Variables	GVC	Backward	Forward	Activity	Openness	Manufacture	GDPgrowth	UrbanPop	Capital	LogGDP	Rent
GVC	1.000										
Backward	0.461	1.000									
Forward	0.629	-0.400	1.000								
Activity	0.164	-0.049	0.212	1.000							
Openness	0.303	0.512	-0.136	-0.099	1.000						
Manufacture	0.139	0.186	-0.019	-0.041	0.014	1.000					
GDPgrowth	0.061	0.101	-0.025	0.048	0.069	0.057	1.000				
UrbanPop	0.115	0.112	0.020	0.049	0.077	0.106	-0.106	1.000			
Capital	-0.023	0.181	-0.204	-0.126	0.195	-0.059	-0.036	0.319	1.000		
LogGDP	0.160	0.216	-0.025	0.062	0.179	0.137	-0.035	0.780	0.348	1.000	
Rent	0.160	-0.428	0.540	0.104	0.142	-0.243	-0.029	0.131	-0.023	0.097	1.000



Backward participation



Forward participation

Figure 4.8: Positioning in the GVC between our two types of periods
Sources : EORA database and author calculation

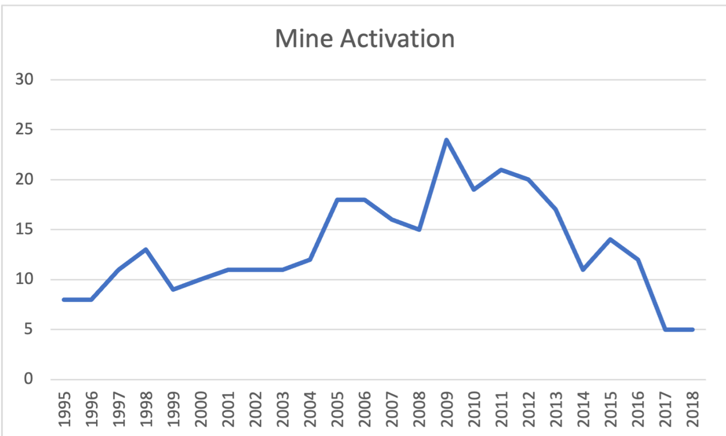


Figure 4.9: Evolution of number of mines activation
Sources : MinEx database and author calculation

Table 4.14: Parallel trend assumption test

	(1) GVC	(2) Backward	(3) Forward
Activity	-0.0062	-0.0124**	0.0124**
	(0.0056)	(0.0055)	(0.0055)
Trend	0.0025***	0.0010	-0.0010
	(0.0007)	(0.0007)	(0.0007)
Interact	0.0003	0.0004	-0.0004
	(0.0004)	(0.0004)	(0.0004)
Openness	0.0004***	0.0006**	-0.0006**
	(0.0001)	(0.0002)	(0.0002)
Manufacture	-0.0018***	-0.0002	0.0002
	(0.0006)	(0.0007)	(0.0007)
GDPgrowth	0.0005	0.0004*	-0.0004*
	(0.0004)	(0.0003)	(0.0003)
UrbanPop	-0.0011	-0.0001	0.0001
	(0.0010)	(0.0010)	(0.0010)
Capital	-0.0021	0.0006	-0.0006
	(0.0024)	(0.0018)	(0.0018)
LogGDP	-0.0177**	-0.0276***	0.0276***
	(0.0083)	(0.0087)	(0.0087)
Rent	-0.0007*	-0.0006**	0.0006**
	(0.0004)	(0.0003)	(0.0003)
R^2	0.9460	0.9408	0.9408
Observations	1589	1589	1589
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

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

Table 4.15: Result from the representation

	(1) GVC	(2) Backward	(3) Forward
main			
-5	0.0074***	0.0000	0.0074***
	(0.0026)	(0.0022)	(0.0021)
-4	0.0097***	0.0015	0.0082***
	(0.0026)	(0.0022)	(0.0021)
-3	0.0075***	-0.0012	0.0087***
	(0.0025)	(0.0021)	(0.0021)
-2	0.0075***	-0.0015	0.0090***
	(0.0025)	(0.0021)	(0.0020)
-1	0.0048*	-0.0018	0.0066***
	(0.0024)	(0.0021)	(0.0020)
Activation	0.0007	-0.0028	0.0035*
	(0.0024)	(0.0021)	(0.0020)
1	-0.0001	-0.0043**	0.0042**
	(0.0025)	(0.0021)	(0.0020)
2	-0.0004	-0.0036*	0.0031
	(0.0025)	(0.0021)	(0.0021)
3	-0.0011	-0.0033	0.0022
	(0.0025)	(0.0022)	(0.0021)
4	-0.0001	-0.0037*	0.0036*
	(0.0026)	(0.0022)	(0.0021)
5	0.0030	0.0002	0.0027
	(0.0026)	(0.0022)	(0.0022)
6	0.0026	0.0001	0.0025
	(0.0027)	(0.0023)	(0.0022)
7	0.0038	0.0001	0.0036
	(0.0028)	(0.0024)	(0.0023)
8	0.0077***	0.0021	0.0056**
	(0.0029)	(0.0025)	(0.0024)
9	0.0066**	0.0034	0.0031
	(0.0030)	(0.0026)	(0.0025)
10	0.0073**	0.0043	0.0030
	(0.0032)	(0.0027)	(0.0026)
Observations	1589	1589	1589

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

Table 4.16: Heterogeneity using OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	1	2	3	4	5	6
Activity	0.0107**	-0.0058	0.0165***	0.0075	-0.0098*	0.0173***
	(0.0043)	(0.0041)	(0.0038)	(0.0047)	(0.0060)	(0.0038)
Openness	0.0004***	0.0006***	-0.0002***	0.0004***	0.0006***	-0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Manufacture	-0.0018***	-0.0001	-0.0017***	-0.0018***	-0.0002	-0.0016***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
GDPgrowth	0.0005**	0.0004**	0.0001	0.0005**	0.0004**	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
UrbanPop	-0.0010***	-0.0002	-0.0008***	-0.0011***	-0.0001	-0.0010***
	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
Capital	-0.0019*	0.0008	-0.0027***	-0.0020*	0.0006	-0.0026***
	(0.0011)	(0.0009)	(0.0009)	(0.0011)	(0.0009)	(0.0009)
LogGDP	-0.0167***	-0.0241***	0.0074**	-0.0178***	-0.0268***	0.0090***
	(0.0035)	(0.0035)	(0.0031)	(0.0033)	(0.0035)	(0.0032)
Rent	-0.0007***	-0.0005***	-0.0002	-0.0007***	-0.0006***	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Corruption	0.0032**	0.0006	0.0026**			
	(0.0013)	(0.0012)	(0.0011)			
Activity_Corruption	-0.0058***	-0.0009	-0.0049***			
	(0.0016)	(0.0014)	(0.0015)			
Activity_Openness				-0.0001***	0.0000	-0.0002***
				(0.0001)	(0.0001)	(0.0000)
R^2	0.9465	0.9420	0.9526	0.9462	0.9406	0.9520
Observations	1581	1581	1581	1589	1589	1589

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

Chapter 5

Mining booms' effects: When booms from the mining sector affect firms' performances *

Mining currently capitalize on the energy transition that fuels the demand for ores. However, the macroeconomics literature has extensively documented the adverse effects of booming sectors on the other sectors of the economy. This study uses firm-level data to examine the effects of mine activation on firm performance in developing countries. Drawing from the Dutch disease and the resource curse literature, we examine whether mining affects the manufacturing sector using a multilevel mixed model. We build an original dataset that merges data from the World Bank Enterprise Surveys data and the MinEx database on mining. The dataset leaves us with a sample of 15,642 firms disseminated in 44 developing countries from 2006 to 2020. The results show that manufacturing firms underperform when mining grows, thus supporting the Dutch disease hypothesis. Our main finding is robust to several checks. We examine various transmission channels provided by the Dutch disease literature: competitiveness losses induced by the exchange rate appreciation, poor institutional quality, and labor force shifts. Our results highlight the potential conflict between energy transition and firm performance.

Keywords: Resources booms · Natural resources · Developing countries · Manufacturing firm performance · Mixed Multilevel Model

JEL Classifications: C21, Q33, Q32, D22, D24

*This chapter is available on HAL (Doamba, 2024b). It is currently under review in World Economy

5.1 Introduction

Mining is booming due to the need for certain minerals to support economic activity and the energy transition in particular (Gielen, 2021). This growth in the mining sector brings to light questions related to the impact of the exploitation of natural resources on economies. The literature reports the presence of a particular natural resource curse and the mechanism of Dutch disease. These two phenomena have the effect of slowing down economic activity and causing, in some cases, a weakening of the industrial sector and manufacturing firms (Van der Ploeg, 2011; Torvik, 2001).

Historically, economic development has always been associated with industrialization (Kaldor, 1957, 1966; Cornwall, 1980). When a country achieves a sustained rise in gross national product, the central part of that rise is from the growing national output in the industrial sector. Many authors have shown the positive relationship between economic development and industrialization Kaldor (1967); Fagerberg and Verspagen (1999); Szirmai and Verspagen (2015) and countries' development strategies feature plans to develop manufacturing. The private sector mainly leads this industrialization process, as do manufacturing firms, under the supervision of the central government.

This private sector is critical in developing countries' development process (Schulpen and Gibbon, 2002). For instance, it is a main driver in domestic investment and technical capabilities development. It is, therefore, a source of innovation and employment in countries with high unemployment. The efforts of this sector complement those of the public sector to ensure dynamic economic activity. In developing countries, in particular, the private sector is even the main driver of economic activity, given the quality of the institutional framework. The state's central role was abandoned in the 1980s, and the private sector became the key player in development policies in developing countries, as it is perceived as more efficient and productive than the public sector (Schulpen and Gibbon, 2002).

So, firms — mainly manufacturing ones — are crucial to the economies of developing countries since they are the primary driver of industrialization (Timmer and De Vries, 2009). Nevertheless, firms in developing countries face many difficulties that prevent them from participating fully in economic activity. These difficulties are, for example, limited access to capital, infrastructure deficiencies, political instability, the limited skilled workforce, the poor regulatory environment, and the need for secure property rights.

Shocks in the mining sector are a main factor to consider when discussing firms' competitiveness, particularly in the manufacturing sector.According to the Dutch disease and natural resource curse phenomena, the competitiveness of an economy can be significantly reduced due to the abundance of natural resources or shocks in the natural resources sector. For instance, Looney (1990, 1991) examined the impact of Dutch disease on the economy's different sectors and found that it hampers sectors like agriculture, manufacturing, and mining.

Firms, especially those in manufacturing, can lose their competitiveness, which fosters deindustrialization (Buiter and Purvis, 1980; Corden and Neary, 1982; Corden, 1984; Krugman, 1987; Aizenman and Lee, 2010). Indeed, according to the Dutch disease theory, the shock originating in the natural resources sector results in a loss of competitiveness for the economy, and companies also lose competitiveness. Some articles like Corden and Neary (1982) and Corden (1984) show that the positive shock leads either to inflationary pressures that decrease exporting firms' competitiveness or relocation of production factors towards the mining sector from the manufacturing sector. This loss of competitiveness eventually hurts firm performance, of which activities plummet. According to the natural resources curse literature, a drop in institutional quality due to rent-seeking behavior accompanies booms in the mining sector. This degradation of institutional quality also leads to a drop in domestic firms' performance.

This study contributes to the literature on Dutch disease and the natural resource curse in several respects. Firstly, while the Dutch disease and natural resource curse literature usually focuses on macroeconomic indicators, we merge firm-level data from the World Bank Enterprise Surveys (WBES) with fine-scale mining data provided by the MinEx database. The Dutch Disease and the Natural Resource Curse literature usually focuses on macroeconomic indicators. To our knowledge, only some studies explore their underlying mechanisms at the firm level. Secondly, we explore several channels through which mining booms affect firm performance. These are the exchange rate appreciation, poor institutional quality, and labor force shifts. Thirdly, we pay specific attention to ores extracted by mining companies. Our results highlight the potential conflict between energy transition and macroeconomic performance.

We econometrically quantify the relationship between mining and firms' performance using a mixed multilevel model that controls for country, industry, and year-fixed effects and allows clustering at the country level (e.g., Kouamé and

Tapsoba (2019)).

When it comes to shedding light on the mechanism that leads to the loss of performance following the start-up of a mine, chronology is essential. We looked at a window of three years after the mine opening to see how the mine start-up affects institutional quality, the exchange rate, and workforce distribution in the economy to test the different transmission channels highlighted by the literature to see which one could explain our results.

Alternative estimators, fixed effects, and entropy balancing do not qualitatively change our main result. Likewise, our results are robust to an alternative firm performance measure and additional controls.

Firms' characteristics affect the relationship between mining booms and firms' performances. Indeed, the oldest firms, the biggest ones, and those opened abroad are the most affected by mining booms. Finally, we tested the three transmission channels mentioned in the literature. We found that the degradation of institutional quality, exchange rate appreciation, and workforce shift explain our results.

The remainder of the paper is organized as follows: Section 5.2 provides a comprehensive literature review, covering the effects of mining sector booms on economic competitiveness and the relationship between economic competitiveness and firm performance. Section 5.3 presents the data and variables used in our analysis, along with the presentation of stylized facts. Section 5.4 details the robust methodology employed in our paper, while Section 5.5 presents our main results, the sensitivity of which will be discussed in section 5.6. Section 5.7 offers a deeper understanding of the mechanisms underlying our results, and Section 5.8 concludes after a discussion.

5.2 Literature review

Several factors can influence firm performance. Among these factors are booms in the mining sector. In this section, we present elements of the literature showing the relationship between mining sector booms and firm performance. In the first part (subsection 5.2.1), we present how mining sector booms affect economic activity and economic competitiveness in particular. Secondly (subsection 5.2.2), we highlight the literature talking about firm performance determinants and, mainly, the one linking economic competitiveness and firm performance.

5.2.1 Mining activities expansion and the economic activity

Macroeconomic effects of mining activities expansion

:

The discovery and development of mines are seen as signals of future dynamic economic activity. However, these expectations are disappointed (Sachs and Warner, 1995, 2001; Kretzmann and Nooruddin, 2005; Ross, 2004, 2006; Collier and Hoeffler, 2005). Until the 1980s, economic orthodoxy viewed the presence and abundance of natural resources as promoting economic growth. Indeed, natural resources allow rich countries to increase their wealth and import purchasing power. This is said to have the effect of increasing investment and economic growth. Also, exploiting natural resources can lead to developing infrastructures and industries and developing and transferring technologies. Nevertheless, this hypothesis is challenged because of a paradox: Countries rich in natural resources experienced lower growth and poor institutional quality on average compared to countries with few natural resources.

Some economic papers such as Gelb (1988) have questioned growth based on natural resources. In the same vein, North (1991) points to the decline of the kingdom of Castile, which was rich in natural resources. It was not until 1993 that Richard Auty designated this paradox as the resource curse (Auty, 2002). Later, Sachs and Warner (1995) were the first to demonstrate at a global level the harmful effects of abundant natural resources on growth. The authors show a negative relationship between the rate of economic growth and the ratio of exports of natural resources to GDP in a sample of 97 developing countries from 1971 to 1989. This result is robust even when controlling for the difference in income level, economic policy, and institutional quality. Subsequent research found the same conclusions: natural resource exploitation leads to an institutional destabilization, weak economic performances, appreciation of the interest rate and a loss of competitiveness (Sachs and Warner, 2001; Kretzmann and Nooruddin, 2005; Ross, 2004, 2006; Collier and Hoeffler, 2005; Corden and Neary, 1982). All these works generally focus on the repercussions of natural resource rents or ores price shocks. We expand on this literature by focusing on a shock that can influence the economy: mine openings, often called mining booms.

There is an extensive literature on the impact of mining booms on the economy. These mining booms can be the discovery of new mineral deposits or the start-up of mining operations (Bawumia and Halland, 2017; Khan et al., 2016). The advantage of studying such shocks is that they are practically exogenous, easing, the identification strategy. The other advantage of mine discoveries or activations is that we have a starting point, allowing again better identification, as we can track the evolution of the repercussions. They impact economic growth, the quality of institutions, the exchange rate, industrialization, access to financial markets, participation in the global value chain and, last but not least, countries' sovereign debt ratings (Kretzmann and Nooruddin, 2005; Harding et al., 2020; Khan et al., 2016; Doamba, 2024b). For example, the literature highlights the negative impact of the discovery of mining deposits, particularly on fiscal policy and sovereign debt, with an increase in the risk of crises. According to the literature, these discoveries are also associated with a deterioration in institutional quality, giving rise to autocratic regimes (Lei and Michaels, 2014; Tsui, 2011) and increase of corruption until the local level (Knutsen et al., 2017). However, booms in the mining sector do not only have adverse effects, as some papers show a positive effect. For example, the literature shows that booms in oil and gas resources encouraged stable foreign direct investment in sectors not concerned by these resources (Van der Ploeg, 2011). Our paper seeks to support or reject this thesis.

Mining boom and economic competitiveness

The competitiveness of an economy is defined by a set of institutions, policies, and factors that determine the level of productivity in a given country. Thus, a country's level of competitiveness depends on a set of factors, all of which upon a closer look are impacted by shocks in the mining sector (Mien and Goujon, 2021; Paldam, 2013; Nülle and Davis, 2018). Indeed, it is clear from the literature that the mining sector has repercussions not only on institutional quality and the political sphere but also on macroeconomic variables such as the exchange rate (Sachs and Warner, 1995, 2001; Kretzmann and Nooruddin, 2005; Ross, 2004, 2006; Collier and Hoeffler, 2005; Doamba, 2024b). This is summed up by the mechanisms of the Dutch disease, which can be defined as "the resource-induced revaluation of the real exchange rate" (Paldam, 2013) and that of the resources curse. For example, following gas reserves discoveries in the sixties, the Netherlands saw its exportation decline (The Economist, 1977). We can easily find a large body of economic literature highlighting the relationship between the mining sector and economic competitiveness. First, the literature on the resource curse shows us that a degradation of institutions and political institutions usually accompanies mining. According to the definition of the competitiveness of an economy given above, this reduces a country's competitiveness as the institutions are no longer favorable to economic activity. Also, booms in the mining sector lead to macroeconomic changes that impact a country's competitiveness. Indeed, income shocks from the mining sector lead to an appreciation of the real exchange rate. This appreciation of the real exchange rate, in turn, reduces the competitiveness of the country's exports affected by the shocks (Harding et al., 2020; Beverelli et al., 2011). This mechanism is known as Dutch disease. Nevertheless, in some cases, mining helps develop the country and increases institutional quality. In that case, mining can be a source of high competitiveness, as explained above (Van der Ploeg, 2011).

5.2.2 Economic competitiveness and firm performance

Firms' performance in the literature

There are several definitions of firm performance (Taouab and Issor, 2019). Initially, the performance of a firm was defined as its organizational efficiency, which refers to the ability of a firm to achieve its objectives using limited resources (Georgopoulos and Tannenbaum, 1957). Then, this definition evolved, and authors like Siminică et al. (2008) define a firm's performance as its ability to be both effective and efficient. For Bartoli and Blatrix (2015), a firm's performance refers to notions of growth, profitability, efficiency, and productivity.

The literature has two main schools of thought about factors affecting firm performance. The first emphasizes external market factors defining corporate success, giving little weight to internal factors. The second stream of thought sees organizational factors and their fit with the environment as the determinants of firm performance. However, these two schools of thought should not be seen as contradictory since each explains part of a firm's performance (Hansen and Wernerfelt, 1989). The literature includes theoretical models that explain the factors behind firm performance. Despite the multitude of models, most show that the main determinants are the characteristics of the sector in which the firm operates, the firm's position relative to its competitors, and, finally, the quantity or quality of the firm's resources (Hansen and Wernerfelt, 1989; Sosnick, 1970).

A comparison between firms in the most competitive areas of the world and those in the least competitive areas allows us to have an idea of the factors at the origin of these differences and therefore explains the performance of firms. Already, we can note that the success of East Asian countries shows us that labor-intensive sectors can drive growth and are, therefore, competitive in the early stages of a country's growth. Also, economic studies show that the slow growth of productivity is the source of the stagnation of African firms, particularly those in the industrial sector. They show that these firms still use obsolete technologies and machines. Additionally, African firms have less advanced know-how than other areas, notably Asia (Pack, 1987; Biggs et al., 1995; Lall, 1999). Thus, due to globalization, the accumulated delay in technical know-how and technology has led to the decline of African firms internationally and domestically. Another factor in the competitiveness of firms is the environment in which they operate, as already shown above. Indeed, most developing countries' firms operate in a risky environment, with high production and transport costs and great macroeconomic uncertainty (Collier and Gunning, 1999).

The empirical literature, thanks to the availability of data on firms, has studied the determinants of productivity, growth, and, therefore, the competitiveness of firms. Results show that characteristics such as the size of the firm, its age, the ethnicity of the manager, and finally the orientation of the market are the main factors at the origin of the difference in productivity (Bigsten et al., 2000; Fafchamps, 2001; Mazumdar and Mazaheri, 2003; Söderbom and Teal, 2004; Van Biesebroeck, 2005).

Economic competitiveness and firm performance

There is a link between economic competitiveness and firm performance (Goldszmidt et al., 2011). A competitive economy is the sign of competitive firms, but Choi and Pyun (2020) show that a depreciation of the real exchange rate leading to a loss of competitiveness can incite firms in innovation to be more competitive. The competitiveness of an economy also refers to the productivity of its agents and, therefore, of firms. Indeed, successful firms abroad are a sign of a competitive economy. Similarly, firms that perform well in the domestic market are firms that are competitive with other companies in the rest of the world present in that market. In this vein, Aron (2000) and Yasar et al. (2011) show that the competitiveness of an economy refers to the quality of the environment in which firms operate, more particularly the property rights. Property rights enforcement mitigates bureaucratic red tap and rent-seeking activities. Pioneering work has been done to highlight domestic institutions' role in firms' competitiveness (North, 1990; Wright et al., 2005). Quality institutions reduce transaction and transformation costs. For Loayza et al. (2005) high-quality institutions increase productivity by allowing knowledge transfer and investment in technologies. Later, Dixit (2009) highlights the supportive role of functioning legal institutions. However, this competitiveness depends on the type of good, and the response of that competitiveness depends on it.

As we discussed above, booms in the mining sector have repercussions on economic competitiveness. In this particular case, the start-up of a mine can make an economy less competitive, mainly due to exchange rate appreciation and the move of the workforce from the manufacturing sector to the mining sector in the short term and in the long term by a deterioration of institutional quality. This loss of competitiveness has repercussions on firms' performance. For example, sales fall as exchange rate appreciation makes exports more expensive, so the goods produced by local firms become less competitive abroad. In the domestic market, imports have become cheaper, making foreign firms more competitive in the local market. However, in the local market, the loss of price competitiveness does not necessarily translate into weaker performance since this depends on the degree to which sales respond to this loss of competitiveness. Consumers' national preferences or policies can make firms more efficient. So, through this paper, we plan to verify whether the booms lead to an increase or a decrease in firms' performance.

5.2.3 Our assumptions

We, therefore, see a need for more empirical work testing the mechanisms of Dutch disease and the natural resource curse at the disaggregated level in the literature. In this regard, we can formulate a set of testable hypotheses :

- Following the literature on Dutch Disease and the natural resources curse, a boom from the mining sector can result in a drop in the manufacturing sector. That means that manufacturing firms must see their performances reduced. So, when we test the relationship between mining booms and firms' performance, there must be a negative and significant relationship between the two variables.

- Our research recognizes the importance of considering the diverse characteristics of different types of firms and mines in understanding the relationship we are investigating. Factors such as a firm's size, age, and level of international engagement, as well as the type of mine, location, and production capacity, could significantly influence their response to mining booms. By incorporating these factors into our analysis, we aim to provide a comprehensive understanding of the dynamics at play.

5.3 Data and descriptive statistics

In this section, we first present the variables used in the study, followed by the descriptive statistics and stylized facts of these variables.

The final database from 2006 to 2022 merges two different sources: the World Bank Enterprise Survey (WBES) database (retrieved September 27, 2021) and the MinEx database. Firm-level variable comes from the WBES database [1] [2] that has been widely used to study firms' reactions to economic events (Bigsten and Söderbom, 2006; Xiao et al., 2022; Eifert et al., 2008). This database brings together representative firms from 154 countries including developing and developed countries. It contains some information on the firms themselves, such as their age and size, as well as indicators of firm competitiveness, such as the growth of sales, the quality of the workforce, the orientation of the market, and eventually, the level of innovation and technology of each firm. Since we are working on the Dutch disease mechanism, we have focused on manufacturing firms, excluding primary sector firms since their activity strongly correlates to the mining sector. Firms excluded represent approximately 6.34 percent of the original sample.

The MinEx database[3] gives information on the deposits discovered and mining activation information (Sosnick, 1970). This database gives the geolocalized position of each mine, the date of discovery of each mining deposit, and especially the date of the start of activity of the deposit and ts date of closure where applicable.

Considering the missing data in the various databases, we are left with 15,642 observations spanning 44 developing countries from 2006 to 2020. Since the WBES database does not geolocate firms, we consider the effect of mining activities on the performance of firms in the country experiencing a mining activity, regardless of their location. In addition, the WBES database does not allow us to create a panel, as a firm is not surveyed over time—the original database pools firms from 2006 to 2020.

[1] https://www.enterprisesurveys.org/en/data

[2] https://www.worldbank.org/content/dam/enterprisesurveys/documents/methodology/Enterprise%20Surveys_Manual%20and%20Guide.pdf

[3] https://minexconsulting.com

5.3.1 Definition of variables

Dependent variable

The dependent variable used in this study is firm performance. Profitability, growth, productivity, and sales are often used to measure a firm's performance (Chauvet and Jacolin, 2017; Chauvet and Ehrhart, 2018; Kouamé and Tapsoba, 2019; Bambe et al., 2022). WBES database provides annual sales, annual value-added, and the quality of each firm's workforce. The firms' sales allow us to capture their performance through sales growth. These sales can be made in the domestic or international market, which allows us to effectively capture the level of performance following a loss of competitiveness in the economy.

Sales growth ($Salesgrowth$) is our primary measure of firm performance. Following Iarossi et al. (2009) and Bambe et al. (2022), we computed the firms' performance as follows, with $Salesgrowth_{it}$ the sales growth of the firm i computed for the year t.

$$Salesgrowth_{it} = \frac{1}{2} * \frac{Sales_{t-1} - Sales_{t-3}}{\frac{Sales_{t-1}+Sales_{t-3}}{2}} \tag{5.1}$$

with $Sales_{t-1}$ the level of sales of firm i at period $t-1$ and $Sales_{t-3}$ the level of sales of firm i at period $t-3$.

We will use another measure of firm performance used in the literature (Kouamé and Tapsoba, 2019), labor productivity growth (LPG), in a robustness test. This variable is described as follows, with LPG_{iy} the labor productivity growth of the firm i computed for the year t.

$$LPG_{it} = \frac{1}{2} * \frac{LP_{t-1} - LP_{t-3}}{\frac{LP_{t-1}+LP_{t-3}}{2}} \tag{5.2}$$

with LP_{t-1} the level of labor productivity at period $t-1$ and LP_{t-3} the level of labor productivity at period $t-3$ obtained by the ratio between the sales and the number of workers.

Variable of interest

The variable of interest is the activation of the mine. Based on the MinEx database, we constructed our mine activation variable $Activity_{ic(t-3)}$, a binary variable with 1 for observations when at least a mine is activated in year $t-3$ in country c and 0 otherwise. For example, for a given country, $Activity$ is equal to zero until the year a mine is activated, and after that year, it returns to zero, until another mine is activated. This delay $t-3$ is explained by the need to adequately capture the performance dynamics due to the activation of mines. Thus, we match the activation of mines to the base period for measuring firm performance.

Variables of control

We controlled for the age (Age_{ict}), and size ($Size_{ict}$) of the firm, and its ability to access credit ($Creditline_{ict}$) following the literature (Chauvet and Jacolin, 2017; Chauvet and Ehrhart, 2018; Kouamé and Tapsoba, 2019; Bambe et al., 2022). These variables are critical to a firm's ability to adapt to shocks by having more access to credit or subsidies, for example. The firm's age (Age_{ict}) measures the years since the firm opened. The size ($Size_{ict}$) is a qualitative variable. It is equal to 1 if the firm has less than 20 employees; in that case, the firm is considered small.It is equal to 2 for medium firms with between 20 and 99 employees. Finally, the variable is equal to 3 for large firms with more than 99 employees. We also control for the participation in the capital of firms, since it is a factor that can influence a firm's ability to respond to shocks. We then added the share of national participation ($Domesticcapital_{ict}$) in the capital between our control variables, expressed in the percentage of the total capital. Also, to control for the firm human capital, which also impacts its response and adaptation to a shock, we use a variable that captures the level of skilled workers in the firm ($Ratioskill_{ict}$). It is computed as the share of workers of the firms that are skilled compared to the total number of workers in each firm. To capture the initial conditions of each firm, we added the level of sales in $t-3$, which is the variable $Sales3years$ since firms' performances are computed from $t-3$. Finally, we controlled for the local level of demand and the agglomeration effect[4] by considering the size of the city in which the firm is located (Kouamé and Tapsoba, 2019). The variable $Demand$ takes the unit value if the firm is located in a city with a population over one million and 0 otherwise.

In addition to these firm-level control variables, we also include three macroeconomic variables following Beck et al. (2005); Harrison et al. (2014); Chauvet and Jacolin (2017); Chauvet and Ehrhart (2018); Kouamé and Tapsoba (2019); Bambe et al. (2022). These variables are critical determinants of firms' performance since external factors also impact its performance (Hansen and Wernerfelt, 1989). The first variable is the manufacturing sector valued-added as part of GDP ($Manufact_{ct}$) to capture the economy's structure. The second variable we included is the country's

[4] See Allcott and Keniston (2018)

Table 5.1: Descriptive statistics table

	Description	Observations	Mean	Min	Max	SD
Firm-level variables						
Salesgrowth	Percentage	15,642	0.01	-1.00	1.00	0.32
LPG	Percentage	15,642	-0.03	-1.00	1.00	0.33
Age	Years	15,642	21.45	0.00	341.00	16.21
Firm Size	Ordinal	15,642	1.97	1.00	3.00	0.78
Creditline	Percentage	15,642	0.46	0.00	1.00	0.50
Domestic capital	% of total capital	15,642	88.59	0.00	100.00	29.47
Sales 3 years	Countinious	15,642	9.06	-9.73	21.54	2.88
Demand	Binary	15,642	0.40	0	1	0.49
Ratioskill	% of total workers	15,642	48.12	0.00	100	27.13
Country-level variables						
Manufact	% GDP	15,642	17.00	2.42	31.60	6.43
Growth	% GDP	15,642	5.00	-1.24	11.99	2.40
Institution	Continuous	15,642	6.72	1.17	10	2.39

level of growth ($Growth_{ct}$). This variable helps to consider the economic conditions in which the firms evolve. The last macroeconomic variable included in the analysis is the level of institutional quality ($Institution_{ct}$).

5.3.2 Descriptive statistics and stylized facts

The descriptive statistics (Table 5.1) give a first contact with the variables, and Table 5.7 gives complete information about all variables used in the analysis. Regarding the firm-level variables, firms have positive sales growth on average across the sample, while productivity growth is negative on average. They are, on average, 21 years old and of rather average size (1.97). Domestic investors own a large part of the firms in our sample, and around 48% of the workers in the firms in our sample are qualified. Macroeconomic variables at the country level show us that, on average, value-added from the manufacturing sector represents 17% of GDP in our sample countries. Also, growth is high enough (5%), thus confirming the growth dynamics of developing countries.

We can see the difference between the different performance indicators in the event of the activation of a mine in the table 5.2. At first glance, observations with mines activated have positive sales growth, which can be disconcerting since we expected an inverse relationship. This result can be explained by the agglomeration effect (Allcott and Keniston, 2018) induced by mining booms, which can be the source of a positive effect of mines on firms at the local level. However, when we look at this difference in the growth of labor productivity, it is lower in the event of

Table 5.2: Difference in performance variables

	Observations	Mean	Min	Max	SD
With mine activating					
Salesgrowth	7,124	0.02	-1.00	1.00	0.30
LPG	7,124	-0.03	-1.00	1.00	0.31
Without mine activating					
Salesgrowth	8,518	-0.01	-1.00	1.00	0.34
LPG	8,518	-0.02	-1.00	1.00	0.35

This table represents the difference in firm performance between firms that have experienced mine activation and those that have not.

the activation of a mine, which is more in line with our expectations. Therefore, it is vital to see whether the agglomeration effect overrides the mechanism of Dutch disease and the resource curse.

5.4 Methodology

Several papers have already questioned the effects of macroeconomic factors on firm performance (Chauvet and Jacolin, 2017; Chauvet and Ehrhart, 2018; Kouamé and Tapsoba, 2019; Bambe et al., 2022). They all agree on the challenge of capturing the real effects of such macroeconomic factors on the performance of individual agents such as firms. The first challenge comes from the data structure since macroeconomic and microeconomic data are combined. As Kouamé and Tapsoba (2019) pointed out, within a single country, firms share the same characteristics, such as the institutional environment, the macroeconomic framework, and economic policies that can affect firm productivity and performance. Thus, using classical econometric tools would lead to a downward bias in standard deviations.

The second challenge in this analysis relates to a potential endogeneity bias arising from the simultaneous relationship between firm performance and mine activation. Indeed, work such as Cust and Harding (2020) shows that exploration and exploitation depend highly on the institutional environment that conditions firm performance. Above all, efficient firms may lead to greater exploration and extraction of mineral deposits because of the need for minerals to finance this sustained economic activity. Mining activity can, in turn, impact firm performance through the Dutch disease and natural resources curse mechanisms.

We address these two challenges by using the multilevel mixed model. This approach introduced by **?** is used in social sciences as presented by **?** to account for the hierarchical data structures. Indeed, this model allows us to consider the clustering effect of firms belonging to the same country by allowing the intercept to vary between countries. Above all, in our estimations, we include both firm-level and country-level variables; this model allows for the simultaneous addition of these different-level variables. Concerning the question of endogeneity due to reverse causality, an adapted data matching method as used by Kouamé and Tapsoba (2019) limits the risk of firm performance impacting mine development. This is achieved by using mine activation at $t-3$. It ensures that the mine activation episodes correspond to the firm's performance benchmark. We further use the entropy balancing methodology in robustness to deal with this endogeneity problem.

The mixed two-level econometric model writes as follows:

$$Level1 : Salesgrowth_{ict} = \alpha_{0c} + \beta Activity_{c,(t-3)} + \eta X_{ict} + \gamma Y_{ct} + \varepsilon_{ict}\ ,\ \varepsilon_{ict} \sim N\left(0, \sigma^2\right) \tag{5.3}$$

$$Level2 : \alpha_{0ct} = \alpha_{00t} + \vartheta_{ct,}\ \vartheta_{ct}\ \sim N\left(0, \delta^2\right)\ ,\ \ \vartheta_{ct} \perp \varepsilon_{ict} \tag{5.4}$$

In this case, $Salesgrowth_{ict}$ is the measure of each firm's performance following the activation of a mine. $Activity_{c,(t-3)}$ refers to the activation of the mine as specified above. X_{ict} refers to the set of firm-level control variables and Y_{ct} refers to the country-level control variables. Finally, ε_{ict} represents the firm-level error term. Subscripts i refers to the firm, c refers to the country, and t refers to the year.

The final estimated model is the equation 5.5, which is a combination of equations 5.3 and 5.4.

$$Salesgrowth_{ict} = \alpha_{00t} + \beta Activity_{c,(t-3)} + \eta X_{ict} + \gamma Y_{ct} + \vartheta_{ct} + \varepsilon_{ict} \tag{5.5}$$

We have also included year, country, and sector fixed effects to control for possible factors that could influence firm performance and differences in survey waves. Standard deviations are clustered at the country level.

5.5 Results

Table 5.3: Main results and robustness analysis

	(1) Main	(2) Government	(3) International	(4) Inputs	(5) MCO	(6) Entropy	(7) LPG
Activity	-0.0603***	-0.0599***	-0.0576***	-0.0430**	-0.0603***	-0.0526***	-0.0768***
	(0.0167)	(0.0171)	(0.0173)	(0.0202)	(0.0167)	(0.0177)	(0.0180)
Age	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0001	0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Size	0.1451***	0.1451***	0.1431***	0.1443***	0.1451***	0.1410***	0.1139***
	(0.0110)	(0.0110)	(0.0102)	(0.0106)	(0.0110)	(0.0136)	(0.0114)
Credit line	0.0383***	0.0383***	0.0392***	0.0374***	0.0383***	0.0419***	0.0228***
	(0.0064)	(0.0064)	(0.0065)	(0.0065)	(0.0064)	(0.0066)	(0.0075)
Demand	0.0117	0.0117	0.0118	0.0089	0.0117	0.0162	0.0141*
	(0.0075)	(0.0075)	(0.0074)	(0.0069)	(0.0075)	(0.0107)	(0.0073)
Sales 3yrs	-0.0734***	-0.0734***	-0.0742***	-0.0739***	-0.0734***	-0.0743***	-0.0699***
	(0.0054)	(0.0054)	(0.0056)	(0.0052)	(0.0054)	(0.0055)	(0.0060)
Domestic capital	-0.0006***	-0.0006***	-0.0006***	-0.0005***	-0.0006***	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Ratioskill	-0.0003***	-0.0003***	-0.0003***	-0.0003**	-0.0003***	-0.0004***	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Growth	0.0353***	0.0352***	0.0347***	0.0340***	0.0353***	0.0334***	0.0428***
	(0.0032)	(0.0033)	(0.0033)	(0.0037)	(0.0032)	(0.0034)	(0.0035)
Institution	0.3154***	0.3153***	0.3244***	0.3255***	0.3154***	0.3232***	0.1952***
	(0.0388)	(0.0388)	(0.0407)	(0.0383)	(0.0389)	(0.0388)	(0.0456)
Manufact	-0.0855***	-0.0855***	-0.0865***	-0.0834***	-0.0855***	-0.0857***	-0.0673***
	(0.0052)	(0.0052)	(0.0054)	(0.0050)	(0.0052)	(0.0054)	(0.0056)
Government capital		-0.0001					
		(0.0003)					
Inter			0.0767***				
			(0.0279)				
National inputs				-0.0005***			
				(0.0001)			
Observations	15600	15599	15600	15439	15600	15600	15600
Countries	44	44	44	44	44	44	44
R^2	0.3703	0.3703	0.3717	0.3679	0.2950	0.3385	0.3287
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports main results and robustness analysis. The first column reports main result. The columns **[2]**-**[4]** show results of robustness by adding control variables. Column **[5]** reports the result when using simple FE estimator, and **[6]** presents it when using Entropy balancing methodology. Finally, the last column presents robustness when using labor productivity growth as the dependent variable. Robust standard errors are reported in parentheses. The constant is included, but not reported in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The main results are presented in column 1 of Table 5.3. The results show that the coefficient associated with the firm performance variable is negative and significant at the 1% level. According to this result, mines opening reduces firms' performance by 6.03 percentage points.

The above results are undoubtedly significant, but they do not give any information of economic significance, i.e., what the loss in firm performance following the activation of a mine represents. To do this, we will compare the loss of firm performance with the standard deviation of the firm performance variable. So, the coefficient -0.0603 corresponds to $18,84$ percent of the sample standard deviation, which is 0.32. Looking closely, we see that the performance indicator standard deviation is greater than the mean. This means there is a significant heterogeneity among firms hit by the mining boom. The result is reasonable since the economic effect must be significant to bring down a country's manufacturing sector, corroborating the literature.

5.6 Sensitivity analysis

We first test the robustness of our results. Then, we test their heterogeneity to see how they vary according to the characteristics of the firms or mines. This approach allows us to confirm our results and better understand the factors conditioning them.

5.6.1 Robustness analysis

The first series of sensitivity tests we carry out aims to demonstrate the robustness of our results.

Additional control variables: First, we want to show that our coefficients are stable. To do so, we introduced a series of control variables as a further test of the robustness of the results. We introduced a variable that captures the government's share of the firm's capital ($Government\,capital_{ict}$). The intuition behind adding this variable is that firms with significant government shareholding can access subsidies or additional capital more quickly than other firms. Also, firms with a significant government shareholding are often social-profit firms with high entry costs and, therefore, protected from competition. In line with our intuition, the results remain robust to the addition of the government equity variable (column [**2**] of Table 5.3). The second variable we have introduced captures the firm's openness to the rest of the world. The *Inter* variable shows whether the firm has international certification in terms of quality (column [**3**] of Table 5.3). The last variable we added is the firm's share of national inputs ($Nationalinputs$). Firms using mare national inputs can be differently touched by the mine opening since prices on the domestic market can be influenced by a mine activation. Our results remain stable when adding the share of national inputs for each firm (column [**4**] of Table 5.3).

Using a simple fixed-effects estimation: We use the mixed multilevel estimator as the primary model in our estimation. Although this model best suits our case, we re-estimated our first equation using a simple ordinary least squares model. The results are presented in the fifth column of the table 5.3. Chauvet and Ehrhart (2018) used this model as the primary model when trying to estimate the effect of aid on a firm's performance but took care to cluster the standard errors at the country level. Due to the potential clustering effect from firms in the same country, all the standard errors have been clustered at the country level. Results remain the same as the main ones using this model, showing their robustness. Moreover, our primary model better explains the firm's performance dynamic since the R^2 is more significant than this one of FE estimation.

Using the entropy balancing methodology: With this in mind, we set out to re-test our main results using an impact analysis methodology, in this case, entropy balancing. The choice of the entropy balancing method was motivated by several reasons described in works such as Hainmueller (2012), Neuenkirch and Neumeier (2016) and Bambe et al. (2022). First, this method is a non-parametric method, unlike classical matching methods. It reduces the risk of having biased estimates because this method does not require the specification of a functional form. Also, it allows us to have numerous characteristics before treatment among the different groups (treated and untreated), even with small samples or a limited number of untreated units. Therefore, the control group will comprise units as identical as possible to the treated group. Finally, this method allows us to control for fixed effects. It is essential to consider heterogeneity between countries, and over time, that does not depend on our treatment. In our case, the treatment variable is the mining activity variable. We, therefore, have the value 1 in the year when at least one mine comes into operation and 0 otherwise, and the study units are firms. The results of this methodology are presented in column [**6**] of Table 5.3 to support our main findings. Indeed, the coefficients are qualitatively similar to those of the main results, confirming the robustness of our findings.

Using Labor Productivity Growth (LPG) as firm performance

measure: Another robustness test we have undertaken concerns the measurement of firm performance. Indeed, there are several measures of firm performance. In our primary model, we used sales growth to measure performance. Here, we propose using labor productivity growth (LPG) to measure firm performance. The method of calculating the variable is given above in equation 5.2.

This robustness test allows us to see to what extent the activation of a mine impacts the productivity of firms. According to the literature, mining activity can be the origin of a structural change in the economy, and manufacturing firms can find themselves with an unskilled workforce due to their movement toward the booming sector: the mining sector, for example. Thus, activating a mine can negatively impact firms' productivity in our system. Again, the main results are corroborated, as we see in the last column of the table 5.3.

Replicating the main table with the Labor Productivity Growth variable: A last test of robustness we undertook is the re-estimation of all the first result tables, by using this time, the labor productivity growth (LPG) as the dependent variable. This choice can be explained by the fact that in the literature, some authors preferred using LPG as the firm performance measure (Kouamé and Tapsoba, 2019). The results are presented in table 5.8 and confirm the drop in the firm performance following mines' activation.

5.6.2 Conditioning factors at firm level

This section shows how our result varies depending on certain key variables. Columns [**1**] and [**2**] concern the heterogeneity concerning the age of the firm. Columns [**3**] and [**4**] are about the firm's size heterogeneity. Columns [**5**] and [**6**] are about the firm's openness to the rest of the world heterogeneity. Finally, [**7**] and [**8**] deal with heterogeneity about the local or foreign owner of the firm.

Table 5.4: Heterogeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Age		Size		Openness		Ownership	
	Young	Old	Small	Big	Not opened	Opened	Local	Foreign
Activity	0.0110	-0.2688***	0.1793***	-0.3620***	0.0942***	-0.2684***	-0.0559***	-0.2496**
	(0.0252)	(0.0181)	(0.0243)	(0.0299)	(0.0187)	(0.0275)	(0.0163)	(0.0979)
Age	-0.0021**	0.0004*	-0.0013***	0.0003*	-0.0003	0.0000	-0.0000	0.0002
	(0.0011)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0005)
Size	0.1410***	0.1445***	0.1033***	0.1116***	0.1466***	0.1234***	0.1459***	0.1381***
	(0.0114)	(0.0116)	(0.0072)	(0.0140)	(0.0103)	(0.0137)	(0.0113)	(0.0208)
Creditline	0.0562***	0.0199***	0.0346***	0.0363***	0.0414***	0.0321***	0.0422***	-0.0002
	(0.0086)	(0.0071)	(0.0095)	(0.0067)	(0.0081)	(0.0074)	(0.0067)	(0.0118)
Demand	0.0083	0.0143*	0.0145**	0.0046	0.0068	0.0259***	0.0109	0.0002
	(0.0112)	(0.0085)	(0.0073)	(0.0095)	(0.0082)	(0.0092)	(0.0083)	(0.0262)
Sales 3yrs	-0.0824***	-0.0634***	-0.0873***	-0.0671***	-0.0820***	-0.0611***	-0.0748***	-0.0606***
	(0.0054)	(0.0050)	(0.0049)	(0.0048)	(0.0052)	(0.0055)	(0.0056)	(0.0089)
Domestic capital	-0.0008***	-0.0004**	-0.0003	-0.0006***	-0.0004**	-0.0004**	-0.0004*	-0.0005
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0006)
Ratioskill	-0.0005***	-0.0001	-0.0005***	-0.0002	-0.0004***	-0.0002	-0.0003**	-0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Growth	0.0185***	0.0688***	0.0025	0.0836***	0.0033	0.0646***	0.0412***	-0.0326
	(0.0052)	(0.0035)	(0.0049)	(0.0066)	(0.0039)	(0.0050)	(0.0033)	(0.0228)
Institution	0.3329***	0.5571***	0.0607	0.6115***	0.3580***	0.3852***	0.3284***	1.1419***
	(0.0384)	(0.0473)	(0.0408)	(0.0518)	(0.0587)	(0.0452)	(0.0439)	(0.0980)
Manufact	-0.0911***	-0.0811***	-0.0923***	-0.0838***	-0.0959***	-0.0778***	-0.0849***	-0.1169***
	(0.0050)	(0.0052)	(0.0048)	(0.0053)	(0.0057)	(0.0065)	(0.0054)	(0.0102)
Observations	7990	8175	7796	7813	10863	4737	14394	1298
Countries	44	44	44	44	44	44	44	44
R^2	0.3832	0.3407	0.4132	0.3103	0.3844	0.3243	0.3716	0.3509
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports results to highlight the heterogeneity of our results. Columns **[1]** and **[2]** concern the heterogeneity in relation to the age of the firm. Columns **[3]** and **[4]** are about the firm's size. Columns **[5]** and **[6]** are about the firm's openness to the rest of the world. Finally, **[7]** and **[8]** deal with heterogeneity in relation to the local or foreign owner of the firm. Robust standard errors are reported in parentheses. The constant is included, but not reported in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Depending on the firm's age: Being an old firm can be an advantage or a disadvantage when adapting to shocks. Indeed, an old firm can have the experience to adapt to these shocks compared to a young one. However, the old firms can also have difficulties adapting to these shocks due to bureaucracy slowness, and particularly, due to their experience, they can have more chances to be oriented abroad, so they are affected by the competitiveness loss. We decided to test the heterogeneity of our results according to the firm's age. Old firms are those above the median firms' age, which is 17, and young ones are those below the median. Results presented in columns [**1**] and [**2**] of Table 5.4 show that old firms are the more affected.

Depending on the firm's size: We also test the sensitivity of our result as a function of firm size. The firms' size refers to the number of workers in these firms. Indeed, firm size plays a key role in a firm's ability to adapt to a shock since larger firms have more capital or easier access to credit. Small firms are those below the median firms' size, which is 36.25, and big ones are those above the median. The result is shown in columns [**3**] and [**4**] of the heterogeneity table (Table 5.4). Big firms are those that are hit by the mine's activation. Small firms see their performance increase following a mine activation. This last result can be explained by the fact that the small firms are mainly local.

Depending on the openness to the rest of the world: The level of openness of a firm to the rest of the world can seriously impact how it reacts to the domestic economy's competitiveness loss. Indeed, the loss of competitiveness mainly concerns firms that sell abroad since the exchange rate appreciation due to mining booms makes exportation more expensive. So, firms oriented abroad must be more affected by the mining boom effect. To confirm this intuition, we split the main sample into two: the first includes firms only oriented to the local market, while the second includes firms oriented abroad. The results are presented in columns [**5**] and [**6**] of Table 5.4. They meet our expectations since, as we can see, firms opened to the rest of the world are negatively affected by the booms in the mining sector.

Depending on the firm's ownership: The domestic or local ownership of the firm can also impact its ability to adapt to shocks. We tested this intuition, and results are presented in the two last columns ([**7**] **and** [**8**]) of table 5.4. Locally owned firms have less than 50% of their capital owned by foreign economic agents, contrary to foreign-owned firms. Nevertheless, we found no heterogeneity depending on the firm's domestic or foreign ownership. That means that the level of openness and not the ownership explains the ability to adapt to shocks.

5.7 Transmission channels

In this section, we aim to identify the crucial mechanisms that underpin our findings. As a reminder, our study revealed a significant drop in firm performance accompanying a mine activation. Drawing from the existing literature, we identify three key channels through which a mine activation can impact a firm's performance. The first channel is linked to the resource curse. The development of the mining sector can lead to a degradation of institutional quality, leading to uncertainty and an unfavorable business environment. From this point of view, the relation between mining or mine activation and a firm's performance is clear.

The second channel is the appreciation of the exchange rate, a phenomenon known as the Dutch disease. This leads to a decrease in export competitiveness, a crucial factor for firms' performance.

The third channel refers to the shift of the workforce from the manufacturing sector to the mining sector. The development of the mining sector leads to an increase in wages compared to the other sectors, so the workforce has moved from the manufacturing sector to the mining sector. The flight of labor, especially qualified workers, makes firms less efficient.

We tested these three channels, and the results are presented in Tables 5.5 and 5.9. The first channel tested is the institutional quality channel. We split the sample into two depending on the countries' institutional quality level at period t. So, we have two groups of firms: those in countries with low institutional qualities and those in countries with high levels of institutional quality. From $t-1$ to t, the effect of the mining boom on the institutions has time to occur, and we expect countries with low institutional quality to see their firms experience a performance drop. Results are presented in columns [**1**] and [**2**] of table 5.5, and they meet our expectations. The result in the first column of Table 5.9 confirms the institutional quality channel, as mining booms in $t-3$ lead to low levels of institutional quality in t.

The Table 5.9 in the appendix also shows an appreciation of the exchange rate in t following a mine activation in $t-3$. This conforms to the literature. Moreover, the columns [**3**] and [**4**] show that countries with high levels of exchange

Table 5.5: Transmission channels

	(1)	(2)	(3)	(4)
	Institution		Exchange rate	
	Below the median	Above the median	Below the median	Above the median
Activity	-0.1084***	0.0418*	0.0079	-0.2548***
	(0.0330)	(0.0251)	(0.0249)	(0.0633)
Age	-0.0001	-0.0000	-0.0001	0.0001
	(0.0004)	(0.0002)	(0.0002)	(0.0003)
Size	0.1476***	0.1383***	0.1232***	0.1644***
	(0.0121)	(0.0171)	(0.0141)	(0.0129)
Creditline	0.0446***	0.0335***	0.0373***	0.0383***
	(0.0076)	(0.0099)	(0.0068)	(0.0103)
Demand	0.0267**	-0.0010	0.0112	0.0113
	(0.0107)	(0.0101)	(0.0078)	(0.0130)
Sales 3yrs	-0.0791***	-0.0663***	-0.0664***	-0.0779***
	(0.0069)	(0.0060)	(0.0082)	(0.0060)
Domestic capital	-0.0008***	-0.0003**	-0.0006***	-0.0005**
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Ratioskill	-0.0003*	-0.0004***	-0.0005***	-0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Growth	-0.0163***	0.0124***	0.0872***	0.0785***
	(0.0040)	(0.0027)	(0.0022)	(0.0147)
Institution	-0.3074***	-0.2527***	-0.2124***	0.2078***
	(0.0253)	(0.0310)	(0.0138)	(0.0055)
Manufact	-0.1545***	-0.0137***	-0.0324***	-0.0603***
	(0.0119)	(0.0027)	(0.0049)	(0.0042)
Observations	7658	7942	8387	7213
Countries	22	22	22	22
R^2	0.4348	0.293	0.2361	0.4541
Sector FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports results to highlight the transmission channels of our results. Columns [**1**] and [**2**] concern the institutional quality channel. Columns [**3**] and [**4**] are about the exchange rate channel. Robust standard errors are reported in parentheses. The constant is included, but not reported in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

rates are those that see their firms lose performance following a mine activation. These two results confirm the exchange rate appreciation as a transmission channel of our result in the first column of Table 5.3.

According to the literature, booms from the mining sector lead to a shift of qualified workforce from the manufacturing sector to the booming mining sector. Already, we found that a drop in labor productivity growth accompanied the mining boom. This result can be explained by the fact that there is indeed a shift of qualified workforce toward the mining sector and the replacement of that shifted workforce by a less qualified one. The last column of Table 5.9 shows us a growth of the share of employment in the manufacturing sector following the mine opening. This can be explained by the need to compensate for the move of the qualified workforce.

5.8 Discussion and conclusion

A shock in the mining sector can lead to a change in the economy's structure, which in turn, leads to a loss of competitiveness in specific sectors and for the firms in those sectors. While work has been carried out at the macroeconomic level, with theoretical models developed for this purpose, studies have yet to be carried out at the firm level to understand the mechanism behind these results highlighted by the literature. This gap underscores the need for more disaggregated research in this area. Therefore, we propose to take our study to a more detailed level than that proposed by the literature by carrying out a study at the firm level. The mechanism of Dutch disease, for instance, originates at the level of firms, which are those that lose competitiveness due to exchange rate appreciation. In this way, using disaggregated data from 44 developing countries, we estimate the effect of booms in the mining sector (mine activations) on firm performance. Our results confirm the loss of firm performance following activation, further emphasizing the need for more detailed research in this area.

Our study's significance lies in the fact that we have tested, in a highly detailed and specific manner, the loss of competitiveness of countries following shocks in the mining sector. This detailed study has allowed us to better understand the factors that contribute to this loss. We have thus been able to highlight a direct relationship between mine start-ups and the loss of firm performance. This result, obtained using mixed multilevel levels as the primary methodology, was robust to the addition of further control variables and the use of an alternative measure of firm performance. Factors like firms' size, age, and openness level are factors conditioning our results. Another significant contribution is that we have been able to identify the mechanism underlying our result. Among the different channels proposed by the literature, exchange rate appreciation and workforce shift are the mechanisms that drive our results.

In line with Chauvet and Jacolin (2017) and Chauvet and Ehrhart (2018), working at a disaggregated level enables us to highlight better the mechanisms involved. We have thus been able to highlight the heterogeneity of the factors explaining these results. Firm-specific factors, more precisely, age, size, and openness to the rest of the world, condition the relationship we highlighted.

This study paves the way for several other questions linked to the impact of economic shocks on economies by going to a more disaggregated level to quantify better and capture the underlying mechanisms. In this way, several macroeconomic questions already visited at the macro level can be revisited with a focus on firms. Also, the geolocalized nature of the firms may enable us to study more precisely the interaction between the relationship between mine start-up and firm performance. Indeed, the natural resources curse can be neutralized locally by an effect of population agglomeration as pointed out by Allcott and Keniston (2018). The accuracy of the MinEx database in terms of mine activation dates makes it possible to study the impact of these shocks on the economy. Finally, a significant limitation of this paper is that the MinEx database does not include oil mines. However, this limitation allows us to focus on other types of natural resources. Much of the literature has focused on the impact of oil industry shocks on the economy. Future work could exploit this limitation, depending on the data available.

5.9 Appendix

Table 5.6: Countries representativity in the sample

Country	Freq.	Percent	Cum.	Country	Freq.	Percent	Cum.
Albania	47	0.30	0.30	Mali	34	0.22	50.70
Angola	81	0.52	0.82	Mexico	942	6.02	56.72
Argentina	578	3.70	4.51	Mongolia	218	1.39	58.11
Bangladesh	1.071	6.85	11.36	Morocco	116	0.74	58.85
Brazil	723	4.62	15.98	Namibia	47	0.30	59.15
Cameroon	106	0.68	16.66	Nicaragua	94	0.60	59.76
Chile	627	4.01	20.67	Nigeria	546	3.49	63.25
China	1.314	8.40	29.07	Panama	43	0.27	63.52
Colombia	610	3.90	32.97	Papua New Guinea	21	0.13	63.66
Costa Rica	144	0.92	33.89	Paraguay	82	0.52	64.18
Dominican Republic	84	0.54	34.43	Peru	605	3.87	68.05
Ecuador	97	0.62	35.05	Philippines	1.245	7.96	76.01
El Salvador	94	0.60	35.65	Poland	170	1.09	77.09
Ghana	248	1.59	37.23	Russian Federation	922	5.89	82.99
Honduras	89	0.57	37.80	Senegal	135	0.86	83.85
Hungary	136	0.87	38.67	Sri Lanka	278	1.78	85.63
Indonesia	874	5.59	44.26	Thailand	453	2.90	88.52
Jamaica	51	0.33	44.59	Tunisia	295	1.89	90.41
Jordan	236	1.51	46.09	Turkey	824	5.27	95.68
Kazakhstan	209	1.34	47.43	Uganda	189	1.21	96.89
Kenya	312	1.99	49.42	Ukraine	209	1.34	98.22
Lebanon	165	1.05	50.48	Zambia	278	1.78	100.00

This table reports countries representativeness in our sample. It gives for each country the number of firms present in the sample (in the column [**Freq**]).

Table 5.7: Variables and sources

Variable	Nature	Definition	Source
Firm-level			
Activity	Dummy	Mine activation variable	MinEx database and author's calculation
Salesgrowth	bounded between - 1 and 1	Firm's sales growth over last three years	Author' calculation
LPG	bounded between - 1 and 1	Firm's productivity growth over last three years	Author' calculation
Age	Continuous	Firm's age variable	World Bank Enterprise Survey
Size	Ordinal	Firm's size variable	World Bank Enterprise Survey
Creditline	Dummy	Firm's access to credit	World Bank Enterprise Survey
Domestic capital	Percentage	Share of capital owned by domestic private agents	World Bank Enterprise Survey
Foreign capital	Percentage	Share of capital owned by foreign private agents	World Bank Enterprise Survey
Ratioskill	Percentage	Share of workers that are skilled	World Bank Enterprise Survey
Government capital	Percentage	Share of capital owned by Government	World Bank Enterprise Survey
Inter	Dummy	Firm's level of openness to the world	Author' calculation
National Inputs	Percentage	Share of inputs having domestic origin	World Bank Enterprise Survey
Country-level			
Manufact	Continuous	Value added of Manufacture sector as part of GDP	World Development Indicator
Instit	Bounded continuous	Institutional quality variable	International Country Risk Guide
Growth	Continuous	Real GDP per Capita Growth	World Developement Indiacator

This table reports the sources our the different variables used. It gives the name of variables as used in the paper, the nature of these variables, a short explanation of the variables and their sources.

Table 5.8: Results using Labor Productivity Growth (LPG) as dependent variable

	(1) Main	(2) Government	(3) International	(4) Inputs	(5) MCO	(6) Entropy
Activity	-0.0768***	-0.0760***	-0.0743***	-0.0633***	-0.0768***	-0.0771***
	(0.0180)	(0.0175)	(0.0187)	(0.0212)	(0.0180)	(0.0254)
Age	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0013***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Size	0.1139***	0.1139***	0.1121***	0.1133***	0.1139***	0.1103***
	(0.0114)	(0.0114)	(0.0105)	(0.0111)	(0.0114)	(0.0124)
Credit line	0.0228***	0.0227***	0.0236***	0.0222***	0.0228***	0.0240**
	(0.0075)	(0.0074)	(0.0077)	(0.0075)	(0.0075)	(0.0099)
Demand	0.0141*	0.0141*	0.0142*	0.0121*	0.0141*	0.0119
	(0.0073)	(0.0073)	(0.0073)	(0.0069)	(0.0074)	(0.0073)
Sales 3yrs	-0.0699***	-0.0699***	-0.0706***	-0.0702***	-0.0699***	-0.0680***
	(0.0060)	(0.0060)	(0.0062)	(0.0058)	(0.0060)	(0.0064)
Domestic capital	-0.0007***	-0.0007***	-0.0007***	-0.0006***	-0.0007***	-0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Ratioskill	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Growth	0.0428***	0.0426***	0.0423***	0.0415***	0.0428***	0.0429***
	(0.0035)	(0.0034)	(0.0036)	(0.0040)	(0.0035)	(0.0051)
Institutions	0.1952***	0.1950***	0.2036***	0.2068***	0.1952***	0.1830***
	(0.0456)	(0.0455)	(0.0477)	(0.0452)	(0.0457)	(0.0506)
Manufact	-0.0673***	-0.0673***	-0.0682***	-0.0652***	-0.0673***	-0.0655***
	(0.0056)	(0.0056)	(0.0059)	(0.0054)	(0.0057)	(0.0062)
Government capital		-0.0001				
		(0.0004)				
Inter			0.0714**			
			(0.0295)			
National inputs				-0.0004***		
				(0.0001)		
Observations	15600	15599	15600	15439	15600	15600
Countries	44	44	44	44	44	44
R^2	.3287	.3287	.3299	.3253		
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports replication of main table test using labor poductivity growth as dependent variable. Robust standard errors are reported in parentheses. The constant is included, but not reported in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.9: Channels

	(1) Institution	(2) ER	(3) Workforce
Activity	-0.0911***	8.6573***	3.0991***
	(0.0289)	(0.3667)	(0.0863)
N	15642	15642	12657
R^2	.6212	.5031	.6311

Notes: N=12657, t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

6 General conclusion

This conclusion is organized as follows: the first section summarizes our analysis. The second section deals with the policy implications of our work. Finally, the last section presents possibilities for extending the studies carried out and avenues for future analysis.

6.1 Summary

Mineral and forest resources are essential to climate change adaptation and mitigation. This puts pressure on these resources and amplifies their possible effects on populations' welfare. At the same time, the efficient use of natural resources remains a challenge for all countries, particularly developing countries, because it could help improve the welfare of populations. Indeed, the resources curse still hurts most developing countries through political-budgetary cycles, for instance. Also, Dutch disease is still a reality since booms in the mining sector are at the origin of a contraction in economic activity, which can be seen through specialization towards less sophisticated products (raw materials) or the decline of firm performance. Finally, environmental protection policies could reduce environmental degradation due to extractive activity. Therefore, it is essential to continue to reflect on these questions to find solutions to improve the well-being of populations in these countries.

From this perspective, this dissertation analyzes how mining affects welfare by revisiting the relationship between mining and several determinants of the population's welfare, such as institutions, environment, and economic activity. Each of our four chapters contribute to enrich the reflection on the effects of exploiting forest and mineral resources to understand these effects better and elicit appropriate solutions. In order to cover the broadest possible field, the first two chapters deal with the institutional repercussions linked to the extractive industry, and the last two with economic repercussions.

Chapter 2 questions the capacity of environmental protection policies, namely protected areas, to protect forests from mining since mining is one of the primary drivers of deforestation after agriculture. This chapter contributes to the literature by linking mining, deforestation, and protected areas, questioning their role in the face of mining-driven deforestation, and considering complementarity between deforestation decision. We used a spatial econometrics methodology, the SAR method, on 2207 polygons in Sub-Saharan Africa from 2001 to 2019. Environmental protection policies could prove more effective since we have highlighted the inability of protected areas to contain deforestation induced by mining activity alone.

Chapter 3 of this dissertation analyzes the relationship between natural resources and institutions and, more precisely, the presence of political-budgetary cycles. The contribution of this chapter lies not only in the fact that it focuses on developing countries, which are often excluded from samples because of weak electoral competition but also in the particular case of forest rents. After using Nickell's bias-corrected ordinary least squares method on a sample of 83 developing countries between 1990 and 2018, it appears that forest resources can be used for re-election purposes in developing countries since we have highlighted the presence of these cycles.

Chapter 4 addresses the issue of Dutch disease by analyzing the structural change induced by mining through participation and positioning in the global value chain. This chapter adds to the literature by shedding light on mining as a determinant of participation in the global value chain. The method used is that of an event study on a sample of 74 developing countries between 1995 and 2018. This is how we demonstrated that mining booms are linked to specialization in industries placed at the beginning of chains, thus destroying the existing manufacturing sector.

Finally, in Chapter 5, we analyze this Dutch disease at the firm level since firms are affected by the loss of competitiveness. We studied the performance of 15,600 firms from 2006 to 2020 using a multilevel mixed model. Results suggest that firms, due to the loss of their competitiveness, experience a drop in performance. Therefore, this microeconomic result corroborates the presence of Dutch disease because we see a decline in firm performance due to mining booms.

6.2 Policy implications

Given the diversity of the issues addressed, several economic policy recommendations can be formulated on the institutional level. The political cycles of rents imply the manipulation by politicians. Setting up independent structures to manage these resources is essential in such a situation. In this case, supranational policies and structures are more than necessary since they escape the direct manipulation of politicians. So, supranational structures for managing countries' natural resources could thus help limit the mismanagement of these resources. Also, establishing supranational organizations and initiatives aimed at improving the management of natural resources could be beneficial. These include the Extractive Industries Transparency Initiative (EITI) and the Natural Resource Governance Institute (NRGI). At the national level, the solution is the development of strong institutions capable of sustainably managing natural resources. Building such institutions requires investment in human capital and the development of transparency and policy accountability initiatives. These strong institutions will also better protect forests from mining activity through greater rigor in managing protected areas, since our results show that protected areas alone are not enough to stop deforestation induced by mining activity. It is, therefore, a long-term policy. Finally, at the local level, a solution can be the inclusion of the local population in the mining decision-making process.

Then, on the economic level, national-level recommendations can also be made following our findings to allow each country to protect its economy from booms in the mining sector. Countries rich in natural resources must put in place policies to shield their economies from shocks coming from the mining sector. To this end, the first policy is the establishment of local mineral processing industries. This strategic move could significantly revitalize the economy and a more equitable redistribution of resources from natural resources. Also, in the event of shocks, protection policies for exposed sectors must be implemented to reduce the negative impact of these shocks. A final recommendation arising from neutralizing Dutch disease locally through the agglomeration effect could include developing a local market to reduce dependence on exportable goods.

6.3 Direction for future research

Following our analysis, several questions still deserve to be addressed to understand better the impact of extractive activity on the living conditions of the local population in developing countries. First, our various analyses could be extended depending on data availability. For instance, in Chapter 4, the MinEx database only considers the activation of minerals mines, not oil and gas mines. Some databases exist on oil and gas mine discoveries, but not activation. So, this analysis would be complete if a database on oil and gas mine activation were available. Also, in developing countries, informal firms represent a big part of functioning firms. However, these firms are not represented in the World Bank Enterprise Surveys database, reducing our ability to capture the effects of resource exploitation on local firms' performance in Chapter 5. Using the Informal Sector Enterprise Surveys database can solve this problem. In the same chapter, the survey methodology does not allow for capturing the dynamics since the survey does not study the same firms across survey waves.

Also, access to databases could improve the policy implications of our analysis. For instance, in Chapter 2, dealing with political cycles of forest rents, the availability of data on logging licenses and the rent received by states could make it possible to understand the phenomenon better. In Chapter 5, the various existing databases on mines only consider industrial mines. New databases, including artisanal mines, would make it possible to measure the full extent of the effect of mining activity on the environment. Finally, as far as the thesis is concerned, there is no information on public and private exploration spending, even if studies occasionally report continued spending on fossil fuels.

Finally, better measures of different concepts could help better understand the repercussions of forest and mineral exploitation. When analyzing the effectiveness of protected areas in reducing deforestation induced by mining activity in Chapter 2, it is necessary to address the endogeneity of the location of protected areas. For this, it is essential to have panel structure data on biodiversity, for example. However, the biodiversity data available to date do not allow us to have this variation over time to deal with endogeneity. There are methodologies to resolve this endogeneity issue; these are matching methods widely used in the literature. Nevertheless, these methods do not make it possible to decompose the direct effects of mines (nearby) from the indirect effects (distant). The recently developed AfrikENCA database may solve this problem if extended at the global level, as it enables biodiversity to be measured. This database will also enable us to study the impact of mining activity on biodiversity more directly, enabling us to protect biodiversity better, including forests.

Natural resources occupy a more important place since there are minerals; without them, the transition to greener economies would not be possible. These strategic minerals make manufacturing electronic components necessary to change towards more environmentally friendly economies possible. Thus, the pressure on these strategic minerals is increasing, which could also result in a more substantial effect on the well-being of populations and especially on the environment from exploiting these minerals. Future research could, therefore, analyze the relationship between the exploitation of these strategic minerals and the institutions, economy, or environment of the countries in which these coveted minerals are extracted.

Résumé extensif en français 7

Mines et bien-être dans les pays en développement

Les populations des pays en développement aspirent à de meilleures conditions de vie et les revenus tirés de l'exploitation des ressources naturelles peuvent être une source d'amélioration du bien-être de ces populations. En effet, les revenus issus de l'exploitation des ressources naturelles peuvent permettre de financer les politiques et projets de développement. Les ressources naturelles peuvent permettre aux pays d'accroître leur richesse et leur pouvoir d'achat sur les importations. Il peut donc en résulter une augmentation des investissements et de l'activité économique. En outre, l'exploitation des ressources naturelles peut conduire au développement d'infrastructures et d'industries, ainsi qu'au développement et au transfert de technologies. Cependant, force est de constater que le niveau développement et donc de bien-être dans la plupart des pays riches en ressources est inférieur à la moyenne. Ce contraste a été mis en lumière par la littérature économique qui présente les mécanismes du syndrome hollandais et de la malédiction des ressources naturelles.

Le syndrome hollandais est une notion popularisée par The Economist (1977) et qui explique le déclin du secteur industriel dans plusieurs pays suite à des chocs issus du secteur des ressources naturelles [1]. La notion de malédiction des ressources naturelles, quant à elle, a été introduite par Auty (2002). Sachs and Warner (1995) ont été parmi les premiers à mettre en lumière les effets néfastes de l'abondance en ressources naturelles sur l'activité économique. Mehlum et al. (2006a) précisent que l'effet néfaste de l'exploitation ressources naturelles dépend de la qualité institutionnelle des pays. Cependant, Couttenier (2008) précise que pour chaque pays, il existe un seuil de rentes au-dessus duquel naissent les comportements

[1] En 1960, les Pays-Bas ont connu la découverte de grands dépôts de gaz. Ce phénomène a eu comme répercussion une perte de la compétitivité des secteurs non-gaziers.

de recherche de la rente. L'effet est donc ambigu.

La question du changement climatique complexifie encore plus l'équation de l'utilisation bénéfique de ces ressources. La forêt constitue un rempart contre le changement climatique, car elle constitue un puits de carbone [2] et est source de biodiversité. Le changement climatique fragilise ces fonctions de la forêt. Les ressources minières fournissent les minéraux critiques à la réalisation de la transition énergétique [3]. Ainsi, l'exploitation des ressources forestières et minières, en plus des potentiels effets positifs et négatifs qu'on lui reconnait, pourrait avoir des effets sur l'adaptation et l'atténuation du changement climatique. Ce constat montre que les ressources minières et forestières méritent une attention particulière.

Une meilleure compréhension des effets de l'exploitation des ressources forestières et minières est donc nécessaire afin d'en tirer le meilleur parti. Dans cette optique, cette thèse analyse différentes facettes de l'effet de l'exploitation des ressources forestières et minières sur des déterminants des conditions de vie des populations que sont l'environnement, les institutions et les économies des pays en développement. Dans ce chapitre introduisant une telle analyse, la section 7.1 traite de la gestion forestière dans les pays en développement. La section 7.2 renvoie à la littérature analysant la relation entre l'activité minière et la performance économique tant au niveau macroéconomique qu'au niveau microéconomique. Enfin, la section 7.3 proposera un résumé des contributions à la littérature des quatre chapitres de la thèse.

7.1 La gestion des forêts dans les pays en développement

Une meilleure gestion des ressources forestières contribue à la lutte contre le changement climatique tout en améliorant le bien-être des populations. Cependant, la gestion des forêts est confrontée à de nombreux défis. Nous nous concentrons sur deux d'entre eux. Le premier est que le sous-sol des forêts est souvent riche en ressources minérales, ce qui met les forêts en danger. Il est donc important d'étudier

[2]Des auteurs montrent que la hausse du taux de CO2 de l'atmosphère est due à la destruction des forêts (Ke et al., 2024)

[3]Des analyses montrent que la transition énergétique accroit la demande en minéraux critiques du fait de leur nécessité. La demande en lithium, en cuivre et en cobalt pourrait être multiplié par quatre d'ici à six ans: https://unctad.org/fr/news/boom-des-mineraux-critiques-la-transition-energetique-mondiale-est-porteuse-dopportunites-et

comment les politiques de conservation peuvent atténuer les conséquences environnementales des activités minières dans les paysages forestiers. L'utilisation des rentes forestières constitue un deuxième défi majeur. Nous devons examiner comment les institutions démocratiques, par la compétition électorale sur laquelle elles reposent, affectent les rentes forestières.

7.1.1 Les effets de l'exploitation minière sur les forêts

Répercussions de l'activité minière sur l'environnement

L'installation et l'exploitation d'une mine impacte l'environnement puisqu'elles nécessitent la construction d'infrastructures pour l'extraction, le transport et la transformation du minerai. L'activité minière nécessite de déplacer de la terre, de construire des bâtiments et souvent de construire des routes. Douglas and Lawson (2002) montrent par exemple que l'exploitation minière est responsable du déplacement de 57 milliards de tonnes de terre par an et on pourrait s'attendre à des chiffres plus grands actuellement. Des études ont essayé de mettre en lumière la modification de la topographie suite à l'exploitation minière. C'est par exemple le cas de Schwantes (2000) qui a mis en lumière la modification de l'environnement physique aux États-Unis par les mines de l'entreprise Phelps Dodge Corporation.

En plus du changement physique de l'environnement qu'elle occasionne, l'activité minière est une grande source de pollution à travers les déchets qu'elle génère. Il faut dans ce cas faire la différence entre la pollution physique et la pollution chimique. La pollution physique renvoie au fait que les particules issues de l'extraction minière se répandent dans l'atmosphère, le sol, l'air et l'eau. La pollution chimique quant à elle renvoie à l'épandage dans l'environnement de réactifs utilisés lors du traitement des minerais ou à l'oxydation des minéraux suite à l'exposition à l'air. Ces différentes pollutions dépendent du type de minerai extrait, du mode d'extraction et de la taille de la mine. Aussi, les différents stades de l'exploitation minière correspondent à différents types de pollution.

Face à la question du changement climatique, l'activité minière est pointée du doigt, car étant l'une des causes de la déforestation et de pollution. Plusieurs travaux se sont penchés sur la relation entre l'activité minière et la déforestation. Une grande partie de ces travaux se concentre sur l'Amazonie en utilisant des données issues de l'imagerie satellitaire. Si l'agriculture est le principal moteur de la déforestation, la prospection et l'exploitation minières ont des effets sous-estimés sur la forêt (Giljum et al., 2022). Il est donc nécessaire d'évaluer dans quelle mesure l'exploitation minière impacte la forêt ainsi que l'efficacité des mesures de préservation.

Préserver les forêts dans les pays en développement

Face à la multitude d'activités humaines - dont l'activité minière - ayant des répercussions négatives sur l'environnement dans les pays en développement, des politiques de protection de l'environnement ont été mises en place dans plusieurs pays y compris ceux en développement. Les politiques environnementales peuvent être définies comme les mesures prises des gouvernements ou des organisations privées afin de réduire la trace de l'Homme sur l'environnement. Il existe plusieurs types de politiques de protection de l'environnement en fonction des sources de la pollution et de l'objectif de protection. Surtout, plusieurs instruments de politique environnementale, notamment les approches contraignantes, fondées sur les instruments de marché et les approches volontaires, peuvent être mises en place dans un cadre multilatéral et/ou national (Blowers, 1993; Fiorino, 2023; Jörgens, 2012; Runhaar, 2016).

Les aires protégées relèvent des instruments ordre et contrôle qui imposent des restrictions et des normes aux activités humaines dans les zones forestières. "Une aire protégée est un espace géographique clairement défini, reconnu, dédié et géré, par des moyens juridiques ou autres moyens efficaces, pour parvenir à la conservation à long terme de la nature avec les services écosystémiques et les valeurs culturelles associés." (Définition UICN 2008).[4]. En protégeant les forêts de façon générale, les aires protégées peuvent aider à réduire l'impact de l'activité minière sur l'environnement.

Plusieurs travaux se sont penchés sur l'efficacité des aires protégées (Joppa and Pfaff, 2011; Nelson and Chomitz, 2011). Différentes méthodologies ont été utilisées afin de faire face au biais de localisation des aires protégées (Cropper et al., 2001; Joppa and Pfaff, 2009) et l'interaction spatiale dans le phénomène de déforestation lié aux aires protégées (Angelsen, 2001; Oliveira et al., 2007; Schwartz et al., 2022). Les résultats montrent une grande hétérogénéité au niveau l'efficacité des aires protégées. Pfaff et al. (2015) montrent que les aires protégées sont plus

[4]Les différentes catégories sont les suivantes : réserve naturelle intégrale (Ia) ; zone de nature sauvage (Ib); parc national (II); monument naturel remarquable (III); zone de gestion de l'habitat/des espèces (IV); paysage/paysage marin protégé (V) ; zones protégées avec utilisation durable des ressources naturelles (VI). Les catégories les plus restrictives sont I, II et III. Les catégories IV, V et VI permettent une utilisation durable des ressources. Source : UICN disponible sur `https://www.iucn.org/theme/protected-areas/about`

efficaces aux abords des villes et des routes, pendant que Nolte et al. (2013) et Kere et al. (2017) montrent que les aires protégées les plus strictes protégeaient le mieux les forêts.

C'est suivant cette efficacité relative des aires protégées que l'objectif 11 de la convention d'Aichi sur la biodiversité[5] a proposé la conservation "d'au moins 17 % des zones terrestres et des eaux intérieures et de 10 % des zones côtières et marines". Cet objectif a besoin d'un engagement politique pour être atteint et surtout, d'une bonne qualité institutionnelle pour que les aires protégées effectivement mises en place soient réellement effectives.

7.1.2 L'activité minière et la sphère politique

L'une des explications du retard de développement des pays exploitant des ressources naturelles, y compris des ressources forestières, est la malédiction des ressources naturelles. Elle met en évidence le rôle de la qualité institutionnelle et a été largement discuté dans la littérature. Parmi les effets institutionnels potentiels de l'exploitation des ressources forestières, on peut citer les cycles électoraux dans les budgets des États. Nous parlerons donc d'abord de la malédiction des ressources, puis nous passerons en revue la littérature sur la façon dont les ressources forestières affectent la vie politique.

Le mécanisme de la malédiction des ressources naturelles

L'exploitation des ressources naturelles peut impulser le développement des infrastructures, des industries et le développement et le transfert de technologies. Cependant, cette vision positive de l'effet des ressources naturelles a été remise en question par l'exemple de certain pays. C'est dans l'esprit d'expliquer ce contraste que des travaux ont remis en question l'hypothèse de la croissance basée sur les ressources naturelles (Gelb, 1988). North (1991) souligne le déclin du royaume de Castille à partir du XVI siècle portant riche en ressources naturelles (Carbonnier, 2013). Ce paradoxe est connu sous le nom de la "Malédiction des ressources naturelles" (Auty, 2002). Dans la littérature traitant de cette question, Sachs and Warner (1995) ont été les premiers à explorer les mécanismes de la malédiction des ressources naturelles. Ainsi, sur la période 1971-1989, les deux auteurs établissent une corrélation négative entre le taux de croissance économique et le ratio

[5] https://www.cbd.int/sp/targets

exportations en ressources naturelles sur PIB sur un échantillon de 97 pays en développement.

Les différentes études traitant de la malédiction des ressources naturelles ont mis en lumière le rôle crucial des institutions (Mehlum et al., 2006a). En effet, Mehlum et al. (2006b) notent que la littérature sur la relation entre qualité institutionnelle et les ressources naturelles est peu concluantes et peut être subdivisée en trois. La première littérature montre que les effets des ressources naturelles, dont les ressources minières et forestières sur la croissance et le développement, dépendent de la qualité institutionnelle. La deuxième littérature montre que les institutions ne jouent pas de rôle important dans les effets de la dotation en ressources naturelles sur l'économie. Enfin, dans la troisième littérature, les institutions sont affectées par la richesse en ressources naturelles, dont les ressources minières et forestières. Les institutions, en déterminant les horizons de décision des agents économiques, est un intermédiaire par lequel la malédiction des ressources naturelles peut arriver, notamment sous la forme cycles politiques.

Les cycles politiques au niveau des rentes forestières

L'une des manifestations de la malédiction des ressources naturelles est la présence de cycles politico budgétaires des rentes de ces ressources dans les pays concernés. Un cycle politico budgétaire est un cycle dans une composante spécifique du budget du gouvernement du fait du calendrier électoral. Plusieurs travaux théoriques ont essayé d'expliquer ces cycles (Nordhaus, 1975; MacRae, 1977). Ces travaux pionniers ont développé des modèles dans lesquels le candidat au pouvoir crée de l'inflation en période électorale afin de tirer profit de la courbe de Philips dans le court terme pour se faire réélire. Ces premiers modèles ont été améliorés par Rogoff and Sibert (1988); Rogoff (1990) qui développent des modèles dans lesquels le candidat au pouvoir essaie d'envoyer un signal de sa compétence en manipulant les variables macroéconomiques. Cependant, tous ces modèles ont la limite d'être des modèles de résultats dans lesquels l'hypothèse implicite est que le candidat au pouvoir peut directement manipuler les grandeurs macroéconomiques. Une nouvelle série de modèles dans lesquels les cycles politiques sont rendus possibles par la manipulation faite au niveau des composantes du budget ont alors été développés (Brender, 2003; Brender and Drazen, 2005; Shi and Svensson, 2006).

À la suite des travaux théoriques, des travaux ont économétriquement testé la présence des cycles politiques. Tufte (1978) est un exemple pionnier portant sur les élections américaines. Depuis lors, la littérature économétrique s'est largement développée. Cependant, les résultats restent contrastés. Comme le soulignaient Akhmedov and Zhuravskaya (2004), les résultats portant sur les économies en développement sont encore peu probants. Cela peut être imputé à deux facteurs principaux : le premier facteur est celui de la conformité des hypothèses des modèles théoriques aux caractéristiques des pays en développement. En effet, d'après les modèles théoriques, les élections se déroulent de façon compétitive. Ce qui n'est pas forcément le cas dans la plupart des élections dans les pays en développement en particulier en Afrique. Il faut donc prendre en compte cette différence lors des études en prenant en compte le niveau de compétition des élections et le niveau de la qualité institutionnelle dans toute étude portant sur la présence de cycles politiques au niveau des rentes dans les pays en développement. Ensuite, le second problème et qui est récurrent au niveau des études portant sur les pays en développement est la disponibilité des données sur les différents pays.

Pour palier au premier problème, les auteurs tentent de prendre en compte le niveau de compétition électoral en tenant compte du niveau de démocratie dans les pays. C'est ainsi que Gonzalez (2000) et Shi and Svensson (2002) mettent en exergue le rôle important de la qualité institutionnelle quant à ces résultats contre-intuitifs concernant la présence de cycles politico budgétaire dans les pays en développement. D'autres travaux se sont exclusivement concentrés au cas des pays en développement (Block, 2002; Block et al., 2003; Akhmedov and Zhuravskaya, 2004; Sáez and Sinha, 2010; Mosley and Chiripanhura, 2016; Iddrisu and Bokpin, 2018). Par ailleurs, d'autres auteurs ont aussi mis en évidence que les décideurs politiques pouvaient aussi manipuler la qualité de l'environnement à des fins électorales (Boly et al., 2023).

Les rentes générées par les ressources naturelles sont potentiellement sujettes aux cycles électoraux, car les élites politiques peuvent y avoir facilement accès. On peut s'attendre à ce que ces élites poursuivent leurs propres objectifs et utilisent ces rentes pour favoriser leur réélection. Ainsi, les élections peuvent agir sur l'extraction de la rente, mais aussi sur la déforestation. Une littérature s'est donc développée autour de la question de la présence de cycles politiques au niveau des rentes en ressources naturelles au niveau national (Klopp, 2012; Klomp and de Haan, 2016) et au niveau local (Pailler, 2018). Les pays en développement étant caractérisés par une faiblesse institutionnelle et une forte dépendance par rapport aux ressources naturelles, on pourrait s'attendre une présence de cycles politiques au niveau des rentes dans ces pays.

7.2 L'activité minière et la performance économique

Outre la relation entre l'activité minière et la déforestation, la littérature s'est également intéressée à la relation entre l'activité minière et l'activité économique. En effet, le secteur minier peut initier des changements structurels qui affectent la performance macroéconomique et microéconomique.

7.2.1 L'effet de l'activité minière au niveau macroéconomique

Le changement structurel induit par l'activité minière

L'expansion minière peut avoir des résultats contrastés sur les économies. Elle peut être source de croissance économique en accroissant les exportations et en attirant les investissements étrangers. Cependant, en cas de mauvaise qualité institutionnelle, cette expansion se transforme en une malédiction.

Les répercussions économiques négatives de l'exploitation des ressources naturelles revoient au syndrome hollandais. La notion de syndrome hollandais fut introduite par The Economist (1977)) et fait allusion au déclin du secteur industriel du fait des chocs issus du secteur pétrolier et gazier. Corden and Neary (1982) montrent que suite à un choc positif dans le secteur d'exploitation des ressources primaires, le secteur primaire et le secteur des biens non échangeables évincent le secteur des biens échangeables. Cette notion de syndrome hollandais s'est ensuite généralisée pour faire référence à un choc conduisant à un afflux massif de devises étrangères, ayant pour effet l'appréciation du taux de change réel et par la suite à une perte en compétitivité de l'économie. Ces chocs peuvent survenir dans différents domaines comme les investissements directs étrangers, les envois de fonds de migrants, l'aide publique au développement, les activités illicites (narcotrafic).

Ainsi, à l'exemple des chocs issus du secteur des ressources naturelles, les chocs issus du secteur minier (expansion du secteur minier) peuvent impacter l'économie et donner naissance au syndrome hollandais (Dagys et al., 2020; Olvera, 2024). La découverte de gisement minier et surtout sa mise en activité entraine une hausse des exportations, ce qui crée un afflux de devises étrangères dans le pays. Cet afflux engendre une appréciation du taux de change réel, ce qui nuit à la compétitivité de l'économie, c'est l'effet de dépense des chocs miniers. À côté de l'effet de dépense se trouve l'effet de mouvement des ressources qui se traduit par un déplacement des ressources productives des secteurs des biens échangeables vers les secteurs des biens non échangeables et le secteur ayant connu le choc positif : le secteur minier dans notre cas. Aussi, les effets de cette expansion sur l'économie peuvent être appréhendés à différents niveaux de l'activité économique et par différents indicateurs dont la participation et le positionnement dans la chaine mondiale des valeurs.

Les effets de l'exploitation des ressources naturelles sur la participation à la chaine mondiale des valeurs

L'activité minière impacte la compétitivité économique, qui en retour a des répercussions sur la compétitivité du secteur manufacturier. En effet, une forte croissance de l'activité minière conduit dans un premier temps à une appréciation du taux de change, ce qui réduit la compétitivité de l'économie. Ensuite, cette activité conduit aussi à un déplacement de la main d'œuvre du secteur manufacturier vers les secteurs primaires. Et enfin dans le plus long terme, la détérioration de la qualité institutionnelle conduit aussi à une détérioration de l'environnement dans lequel évoluent les différents agents économiques. Cette détérioration peut concerner la protection des droits de propriété, la stabilité politique et sécuritaire.

Plusieurs travaux montrent comment les chocs issus du secteur minier impactent l'activité économique (Corden and Neary, 1982; Corden, 1984; Krugman, 1987; Aizenman and Lee, 2010). En effet, les chocs positifs tels que les découvertes ou les mises en activité des mines peuvent influencer l'activité économie par une perte de la compétitivité des firmes des pays concernés. Cela passe soit par des pressions inflationnistes, soit par un déplacement de la main d'œuvre vers les secteurs primaires, désavantageant ainsi le secteur manufacturier.

Cet effet sur l'activité économique être appréhendé par le changement dans la participation des pays à la chaîne de valeur mondiale. En plus d'influencer la participation des pays à la chaîne de valeur mondiale en leur donnant un avantage comparatif qu'est la disponibilité des matières premières, l'activité minière peut également être une source de syndrome hollandais, qui modifie la structure de production des économies. Ce syndrome hollandais peut, à son tour, être un mécanisme par lequel l'activité minière influence la participation des pays à la chaîne de valeur mondiale (Corden and Neary, 1982; Corden, 1984). Ainsi, à travers le changement de la structure de l'économie, la production change et les pays tendent à se spécialiser vers des industries de début de chaîne. L'activité minière a donc un impact sur la participation et le positionnement dans la chaîne de valeur mondiale.

7.2.2 L'activité minière et les firmes

L'effet de l'activité minière à l'échelle locale

Les effets de l'activité minière au niveau local sont particulièrement intéressants à étudier puisqu'ils permettent d'appréhender pleinement l'effet de l'activité minière sur le bien-être des populations locales. En effet, d'une part, l'implantation de sites d'extraction peut entraîner le déplacement de la population, des changements dans l'utilisation des terres, au détriment de l'agriculture ou de la conservation d'espaces naturels. D'autre part, cette activité est source d'essor économique au niveau local. Que ce soit au niveau industriel ou artisanal, l'activité minière est source d'emplois pour les populations locales. De plus, les investissements locaux et les revenus de la population stimulent l'activité économique.

Des travaux ont été menés pour confirmer ou infirmer la thèse selon laquelle l'activité minière peut être une source de développement au niveau local. C'est ainsi que Al Rawashdeh et al. (2016) montrent qu'en Jordanie, les régions minières sont plus prospères que les autres régions en utilisant des indicateurs socio-économiques tels que le chômage, l'indice de développement humain, la pauvreté, l'éducation, la santé et l'éducation. Parallèlement, en Australie, le développement local n'a pas été nécessairement promu en raison de l'emploi de non-résidents dans les mines et de la fuite des capitaux vers les grands centres urbains (Sincovich et al., 2018; Chuhan-Pole et al., 2017; Veiga et al., 2001). Enfin, en Indonésie, les effets de l'activité minière sur l'économie locale dépendent fortement du niveau d'intensité des facteurs de production (capital ou travail). Dans les districts avec une activité minière est intensive en capital, il n'y a pas de pression sur les salaires, contrairement à ceux avec une activité minière intensive en main d'œuvre (Pelzl and Poelhekke, 2021).

Comme le montre la littérature, l'activité minière peut être une source de développement local. Des travaux récents expliquent un mécanisme à l'origine des bonnes performances économiques locales dues à l'activité minière. En effet, aux États-Unis, l'activité minière a contribué au développement local des communautés. Les auteurs ont montré la présence d'un phénomène d'agglomération expliquant cet effet positif au niveau local. Ils ont constaté que les niveaux de salaires affectent positivement l'activité économique (Allcott and Keniston, 2018). Cela s'explique d'abord par le fait que les booms miniers dans certaines localités augmentent les salaires, la population et l'emploi. Cette augmentation des revenus peut entraîner une croissance de l'industrie manufacturière en raison de la présence d'un sous-secteur soumis au commerce local ou lié au secteur minier. Ce sous-secteur n'est donc pas affecté négativement comme les sous-secteurs des biens exportables, mais plutôt positivement. Ainsi, ces sous-secteurs de biens faisant l'objet d'un commerce local ou liés au secteur minier connaissent un essor lors des booms miniers en raison de l'augmentation des revenus et de l'emploi. Le sous-secteur des biens exportables se contracte bien sûr pendant les booms miniers, mais sa productivité totale des facteurs ne diminue pas. Ainsi, lors d'un boom temporaire, les effets positifs l'emportent sur les effets négatifs, et le mécanisme du syndrome hollandais disparaît au profit de l'effet d'agglomération. En d'autres termes, la mobilité du travail à l'intérieur du pays neutralise l'appréciation du taux de change réel : l'offre répond à l'augmentation de la demande.

L'activité minière et la performance des firmes manufacturières

Selon Taouab and Issor (2019), la notion de performance d'une entreprise peut être appréhendée de plusieurs manières. Ainsi, la définition de la performance d'une entreprise a évolué au cours du temps. Au départ, elle faisait référence à l'efficacité organisationnelle (Bartoli and Blatrix, 2015). Ensuite, la performance faisait référence à la capacité de l'entreprise à être efficace et efficiente (Georgopoulos and Tannenbaum, 1957). Enfin, la dernière définition donnée à la notion de performance est la croissance, la rentabilité, la productivité et l'efficacité (Siminică et al., 2008).

Plusieurs facteurs expliquent le niveau de performance d'une entreprise et peuvent être des facteurs internes et externes. Des modèles théoriques ont été développés pour expliquer le niveau performance des firmes (Hansen and Wernerfelt, 1989; Sosnick, 1970). Des travaux économétriques ont également cherché à comprendre les sources de la performance des entreprises. Il en ressort que des facteurs tels que la localisation géographique de l'entreprise, sa taille, son âge, et les caractéristiques de ses dirigeants sont des facteurs explicatifs du niveau de performance (Bigsten et al., 2000; Fafchamps, 2001; Mazumdar and Mazaheri, 2003; Söderbom and Teal, 2004; Van Biesebroeck, 2005; Smith et al., 2006; Bhagat et al., 2010).

L'activité minière peut affecter la compétitivité des entreprises de plusieurs manières. Déjà, le syndrome hollandais rend également les entreprises moins compétitives. Ensuite, la migration des facteurs de production vers le secteur minier fragilise des entreprises manufacturières. Par ailleurs, l'évolution de l'environnement des affaires dû à l'activité minière a un impact sur la compétitivité des entreprises locales. En effet, la littérature montre un effet négatif de la richesse en ressources naturelles sur les institutions qui sont censées promouvoir un bon climat des affaires. Cet effet sur les entreprises peut être compris à travers la baisse des performances des entreprises due à l'activité minière. Enfin, la main-d'œuvre minière acquerra un niveau de formation inférieur à celui des travailleurs d'autres secteurs. Il en résultera des retombées moindres, réduisant l'effet que les booms miniers pourraient avoir sur les économies.(Choi and Pyun, 2020; Yasar et al., 2011; Aron, 2000; Loayza et al., 2005; Dixit, 2009; North, 1990; Wright et al., 2005).

7.3 Les objectifs et les résultats de la thèse

L'analyse de la littérature présentée précédemment a mis en lumière les effets spécifiques de l'exploitation des ressources minière et forestières sur les conditions de vie dans les pays en développement. Bien que la littérature soit assez bien fournie, des questions méritent encore d'être traitées. Cette thèse rassemble quatre essais sur deux facteurs essentiels du bien-être des populations dans les pays en développement : la qualité des institutions et l'activité économique. Ainsi, les chapitres 2 et 3 portent sur les ressources forestières. Le chapitre 2 explore les conséquences environnementales (perte de forêts) de l'activité minière, tandis que le chapitre 3 questionne la présence de cycles électoraux dans les rentes forestières. Les deux derniers chapitres explorent les impacts socio-économiques des activités minières. Le chapitre 4 traite de l'effet des activités minières sur la participation et le positionnement des pays dans la chaîne de valeur mondiale. En revanche, le chapitre 5 adopte une perspective microéconomique et évalue dans quelle mesure les activités minières dans les pays affectent les performances de l'entreprise dans les pays en développement.

7.3.1 Les aires protégées protègent-elles la forêt des activités minières en Afrique Sub-Saharienne ?

Alors que des études antérieures ont exploré séparément la corrélation entre l'exploitation minière d'une part et la déforestation(Sonter et al., 2017; González-González et al., 2021; Azomahou and Ouédraogo, 2021) et l'efficacité des aires protégées dans la réduction de la déforestation d'autre part (Joppa and Pfaff, 2011; Nelson and Chomitz, 2011; Pfaff et al., 2015; Nolte et al., 2013; Kere et al., 2017), nous nous proposons dans cette analyse de faire le lien entre ces deux littératures. Ainsi, nous nous penchons sur la relation spécifique entre l'exploitation minière, la déforestation qu'elle provoque et le rôle des aires protégées dans l'atténuation de cette déforestation en Afrique Sub-Saharienne puisque cette partie du monde bien que riche en ressources minières (Philippe et al., 2024), est bien souvent exclue de la littérature.

L'activité minière est l'une des principles source de la déforestation, aussi ses effets sur la déforestation sont potentiellement sous-estimés par la non prise en compte des effets indirects (Giljum et al., 2022) et les aires protégées se sont avérées efficaces pour protéger les forêts sous certaines conditions. Ainsi, une question qui pourrait émerger des résultats de la littérature est la suivante : « Quelle est l'efficacité des aires protégées face à la déforestation ? Quelle est l'efficacité des zones protégées face à la déforestation induite par l'activité minière ?

En répondant à cette question, nous contribuons à la littérature économique de deux manières. D'abord, nous estimons dans quelle mesure les activités minières contribuent à la déforestation. Ensuite, nous évaluons si les aires protégées (AP) peuvent efficacement contrecarrer les effets délétères des activités minières sur les forêts.

Nous utilisons une stratégie d'identification basée sur l'économétrie spatiale, à savoir le modèle autorégressif spatial (SAR), en prenant comme unités d'étude 926 polygones forestiers sur les 2207 couvrant notre zone d'étude. Grâce aux différentes bases de données, nous sommes allés à un niveau très fin dans cette étude. En effet, la variable d'intérêt nous vient de la base de données de Hansen[6] sur la déforestation. La variable d'intérêt, à savoir la présence d'une mine active au niveau d'un polygone, nous est fournie par la base de données géolocalisée MinEx[7]. Enfin, la variable conditionnelle, la surface de la zone protégée, provient de la base de données mondiale sur les aires protégées (WDPA)[8]. Les autres variables de contrôle sont des déterminants du niveau de la déforestation tels que le niveau de population, la pluviométrie, la température, l'activité économique, ce qui nous permet de les analyser à un niveau fin.

Nos résultats montrent que, directement et indirectement, une mine supplémentaire dans un polygone entraîne une augmentation de la déforestation d'environ

[6] Cette base de données permet d'observer, à l'aide d'images satellitaires, l'évolution du couvert forestier à partir de 2000(Hansen et al., 2013)

[7] La base de données MinEx répertorie les mines en donnant leurs dates de découverte, de mise en activité, de fermeture et leur géolocalisation.

[8] Cette base de données répertorie les aires protégées et les autres mesures de conservation des surfaces (UNEP-WCMC, 2019)

155 kilomètres carrés. En revanche, une réduction de la perte de forêt de 9,7 kilomètres carrés peut être obtenue en protégeant 100 kilomètres carrés de terres. Il faudrait donc le doublement de ces aires protégées pour contrecarrer les effets négatifs de l'exploitation minière sur la perte de forêts. Cela est hautement improbable, car d'une part, il s'agit d'une augmentation irréaliste et d'autre part, elle repose sur l'hypothèse forte de rendements constants dans la conservation. Il est donc essentiel de renforcer la qualité de la gestion des aires protégées pour les rendre plus efficaces et de promouvoir des pratiques minières moins dangereuses pour l'environnement, telles que l'exploitation minière intelligente, encore appelée "smart-mining".

7.3.2 Existe-t-il des cycles politiques au niveau des rentes forestières dans les pays en développement ?

Une littérature fournie s'est développée sur la présence de cycles politiques au sein de la politique économique des pays (Nordhaus, 1975; MacRae, 1977; Rogoff and Sibert, 1988; Rogoff, 1990; Brender, 2003; Brender and Drazen, 2005; Shi and Svensson, 2006). Une partie de cette littérature s'est également concentrée sur la présence possible de cycles politiques dans les recettes publiques, en particulier au niveau des rentes provenant des ressources naturelles(Klopp, 2012; Klomp and de Haan, 2016; Pailler, 2018). En effet, les rentes permettraient au gouvernement de financer sa réélection sans enregistrer de déficit, ce que les électeurs sanctionnent.

Cependant, de nombreux modèles développés pour expliquer les cycles politico-budgétaires supposent une démocratie bien établie au niveau du pays, ce qui limite les études économétriques à des échantillons de pays développés dotés d'une démocratie. Dans le Chapitre 3 de cette thèse, nous cherchons à mettre en évidence la présence de cycles politiques dans les rentes forestières des pays en développement. La question à laquelle nous voulons répondre est la suivante : y a-t-il une augmentation ou une diminution des rentes forestières au cours de la période préélectorale dans les pays en développement ?

La réponse à cette question présentée dans ce chapitre enrichit la littérature puisque les études existantes se sont principalement concentrées sur les rentes des combustibles fossiles et de ressources minières, négligeant les ressources forestières portant cruciales dans la lutte contre le changement climatique. De plus, les études existantes ne concernent que des pays ayant une bonne qualité institutionnelle, conduisant à une moindre attention portée aux pays en voie de développement.

Nous optons pour une spécification dynamique nous permettant de prendre en compte l'inertie du niveau des rentes et surtout, l'état régulier vers lequel convergeraient les économies. Cette approche nous conduit à opter pour la méthodologie des moindres carrés corrigés du biais de Nickell. La variable d'intérêt, le niveau des rentes forestières en pourcentage du PIB, et de nombreuses variables de contrôle sont extraites de la base de données World Development Indicators (WDI)[9]. La variable de la période préélectorale, l'une des variables d'intérêt, a été construite en suivant une méthodologie recommandée dans la littérature et basée sur la base de données des élections nationales (NELDA) [10]. Enfin, la variable de la concurrence électorale, l'autre variable d'intérêt, provient de la base de données Political Constraint Index (POLCON) [11].

Les résultats montrent qu'il existe effectivement des cycles politiques au niveau des rentes forestières dans les pays en développement. En effet, une plus grande compétition électorale s'accompagne de cycles positifs au niveau des rentes forestières pendant qu'une faible compétition électorale est accompagnée par des cycles négatifs. Cependant, de façon générale, en tenant compte du niveau moyen de compétition électorale de notre échantillon, les cycles négatifs l'emportent sur ceux positifs. Nous avons testé la robustesse de nos résultats à l'aide d'une série de tests. Le niveau de compétition électorale, le niveau de corruption et, enfin, la représentation ou non du candidat influencent la présence de ces cycles. Il est donc essentiel de mettre en place des structures indépendantes de gestion de la rente (fonds souverains) tout en encourageant la mise en place d'initiatives nationales et internationales de transparence pour gérer ces rentes.

7.3.3 Activité minière et chaine mondiale des valeurs

Le secteur minier en expansion peut concurrencer les autres secteurs de l'économie pour les facteurs de production ; il affecte la composition des biens importés et exportés par le pays ainsi que les flux de capitaux, et par conséquent sa balance des paiements. Cette modification de la balance commerciale correspond à une modification de la participation au commerce international qui peut être positive ou négative. En effet, elle peut entraîner une augmentation de la participation au commerce international par une augmentation des exportations de matières

[9] https://databank.worldbank.org/source/world-development-indicators

[10] https://nelda.co

[11] https://mgmt.wharton.upenn.edu/faculty/heniszpolcon/polcondataset/

premières ou un accroissement des investissements directs étrangers, améliorant le bien-être des populations (Van der Ploeg, 2011). Cependant, elle peut aussi s'accompagner d'un affaiblissement du secteur industriel et d'une détérioration de l'environnement et du content politique (Corden and Neary, 1982; Corden, 1984). Cette dernière situation pourrait conduire à un faible participation à la chaine mondiale des valeurs ou à un glissement du secteur industriel vers les activités de début de chaine. C'est donc dans la logique de faire la lumière sur ces potentiels effets que nous avons étudié la relation entre l'activité minière et la participation et le positionnement dans la chaîne de valeur mondiale dans le Chapitre 4 de cette thèse. Face aux différents éléments fournis par la littérature, on peut légitimement se poser la question suivante : Quel est l'effet de ces booms miniers sur la participation et le positionnement des pays dans la chaîne de valeur mondiale ?

De nombreuses études ont été menées dans le but de mettre en lumière le lien entre l'expansion du secteur des ressources naturelles et les changements structurels de l'économie. En outre, ce chapitre est l'un des premiers à mettre la lumière sur les booms miniers en tant que déterminants de la participation à la chaîne de valeur mondiale en combinant des indices de participation et de positionnement dans la chaîne de valeur mondiale (construits à l'aide de la base de données EORA[12]) à une variable d'activité minière.

La méthodologie que nous avons choisie pour répondre à cette question est celle de l'étude d'événement encore appelé "event study" avec un horizon d'étude de cinq ans. Cette approche permet d'observer, année après année, les effets d'entraînement de l'activation des mines sur la participation et le positionnement dans la chaîne de valeur mondiale. En d'autres termes, elle nous permet de saisir les effets dynamiques de l'exploitation minière sur la participation et le positionnement dans la chaîne de valeur mondiale. Nous avons construit trois variables dépendantes en utilisant la base de données CNUCED-Eora pour mesurer la participation et le positionnement dans la chaîne de valeur mondiale. La variable d'intérêt, l'activation d'une mine, provient de la base de données MinEx. Les autres variables que sont l'ouverture commerciale, la valeur ajoutée du secteur manufacturier en pourcentage du PIB, le niveau d'activité économique et enfin le taux d'urbanisation, proviennent de la base de données World Development Indicators.

Les principaux résultats, qui se sont montrées robustes à une série de

[12] https://www.worldmrio.com

tests, révèlent que l'activation des mines a un impact négatif sur le positionnement d'un pays dans la chaîne de valeur mondiale. Ainsi, l'activité minière a un effet négatif sur le positionnement dans la chaîne de valeur mondiale par le biais d'une spécialisation vers les industries de début de chaîne. Ces résultats, montrant une grande hétérogénéité, sont influencés par des facteurs tels que la méthode d'extraction du minerai et la position géographique du pays.

Par conséquent, les pays dépendant des ressources naturelles doivent protéger les autres secteurs en cas de chocs par le biais d'investissements ou d'une meilleure planification de la reconversion des sites miniers. Cette protection peut également être assurée par la transformation locale des minerais, ce qui accroît l'effet positif de l'activité minière sur les économies.

7.3.4 L'expansion minière et la performance des firmes

Le changement structurel induit par les booms du secteur des ressources naturelles, dont les mines, peut être observé à un niveau plus désagrégé, c'est-à-dire au niveau de la performance des firmes (Paldam, 2013; Nülle and Davis, 2018; Mien and Goujon, 2021). En effet, selon la littérature, les chocs positifs sur les ressources naturelles pourraient entraîner une perte de compétitivité de l'économie et une détérioration de la qualité des institutions, autant d'éléments qui se répercutent sur la performance des entreprises (Sachs and Warner, 1995, 2001; Kretzmann and Nooruddin, 2005; Ross, 2004, 2006; Collier and Hoeffler, 2005). La migration de la main-d'œuvre du secteur manufacturier vers le secteur minier est un autre canal par lequel ces chocs peuvent influencer les entreprises manufacturières.

Dans cette logique, nous cherchons à mettre en évidence et à quantifier l'effet des booms miniers sur la performance de l'entreprise dans le chapitre 5. Nous répondons ainsi à la question suivante : Comment les booms miniers affectent-ils la performance des entreprises dans le secteur minier ?

Ce chapitre contribue à la littérature de plusieurs manières. D'abord, alors que la littérature sur le syndrome hollandais et la malédiction des ressources naturelles se concentre généralement sur les indicateurs macroéconomiques, nous adoptons un point de vue microéconomique, au niveau des entreprises. À cette fin, nous fusionnons des données au niveau des firmes provenant des enquêtes de la Banque mondiale sur les entreprises (WBES)[13] avec les données minières par la base de

[13] https://www.enterprisesurveys.org/en/data

données MinEx[14]. Cette fusion nous permet de mener l'analyse sur 15,642 firmes dans 44 pays en développement entre 2006 et 2020.

Nous avons construit une mesure de la performance des entreprises en suivant la littérature. La performance d'une firme est mesurée par la croissance des ventes ou de la productivité de la main d'œuvre. La méthodologie utilisée est le modèle mixte multiniveaux du fait de l'utilisation simultanée de variables au niveau firmes et au niveau pays. La variable d'activation de la mine et les caractéristiques de la mine proviennent de la base de données MinEx. Des variables de contrôle macroéconomiques issues de la base de données WDI[15] ont été ajoutées à notre analyse.

Les résultats suggèrent une détérioration de la performance des firmes manufacturières à la suite de l'expansion minière, ce qui est cohérent avec la littérature sur le syndrome hollandais. Le mécanisme expliquant ce résultat est la perte de compétitivité suite à l'appréciation du taux de change et la baisse de la qualité institutionnelle.

7.4 Conclusion

7.4.1 Principales recommandations

Compte tenu de la diversité des questions abordées, plusieurs recommandations de politique économique peuvent être formulées au niveau institutionnel. Les cycles politiques au niveau des rentes impliquent la manipulation par les politiciens. La mise en place de structures indépendantes pour gérer ces ressources est essentielle dans une telle situation. Dans ce cas, les politiques et les structures supranationales semblent être une solution à prioriser puisqu'elles échappent à la manipulation directe des politiciens locaux. Ainsi, les structures supranationales de gestion des ressources naturelles des pays pourraient donc contribuer à limiter la mauvaise gestion de ces ressources. La mise en place d'organisations et d'initiatives supranationales visant à améliorer la gestion des ressources naturelles pourrait également être bénéfique. Il s'agit notamment de l'Initiative pour la transparence des industries extractives

[14] https://minexconsulting.com

[15] https://databank.worldbank.org/source/world-development-indicators

(ITIE) [16] et de l'Institut de gouvernance des ressources naturelles (NRGI) [17]. Au niveau national, la mise en place d'institutions perméables à la corruption nécessite un investissement dans le capital humain et le développement d'initiatives en matière de transparence et de responsabilité politique. Ces institutions fortes permettront également de mieux protéger les forêts de l'activité minière grâce à une plus grande rigueur dans la gestion des zones protégées, puisque nos résultats montrent que les zones protégées ne suffisent pas à elles seules à stopper la déforestation induite par l'activité minière. Il s'agit donc d'une politique à long terme. Enfin, au niveau local, une solution peut consister à inclure la population locale dans le processus de prise de décision en matière d'exploitation minière.

Ensuite, au niveau économique, des recommandations peuvent également être faites au niveau national à la suite de nos résultats afin de protéger l'économie des booms du secteur minier. Les pays riches en ressources naturelles doivent mettre en place des politiques pour protéger leur économie des chocs provenant du secteur minier. À cette fin, la première politique est l'établissement d'industries locales de traitement des minerais. Ce mouvement stratégique pourrait conduire à une revitalisation significative de l'économie et à une redistribution plus équitable des ressources issues des ressources naturelles. Par ailleurs, en cas de chocs, des politiques de protection des secteurs exposés doivent être mises en œuvre pour réduire l'impact négatif de ces chocs. Une dernière recommandation découlant de la neutralisation du syndrome hollandais au niveau local grâce à l'effet d'agglomération pourrait inclure le développement d'un marché local afin de réduire la dépendance à l'égard des biens exportables.

7.4.2 Limites et développements futurs

À la suite de notre contribution à la littérature, plusieurs questions méritent encore d'être abordées pour mieux comprendre l'impact de l'activité extractive sur le bien-être des populations locales dans les pays en développement. En effet, en fonction de la disponibilité des données, certaines questions déjà abordées pourraient être revisitées, ou encore, de nouvelles questions restent à explorer. Dans le Chapitre 2 analysant l'efficacité des aires protégées dans la réduction de la déforestation induite par l'activité minière, il est nécessaire d'aborder l'endogénéité de la localisation des aires protégées. Pour ce faire, il est essentiel de disposer de données de structure de

[16] https://eiti.org/our-mission

[17] https://resourcegovernance.org/about-us

panel sur la biodiversité, par exemple, comme instrument. Les données disponibles à ce jour ne nous permettent pas d'avoir cette variation dans le temps pour traiter l'endogénéité. Il existe des méthodologies pour résoudre ce problème d'endogénéité ; il s'agit des méthodes d'appariement largement utilisées dans la littérature. Cependant, ces méthodes ne permettent pas de décomposer les effets directs des mines (proches) des effets indirects (lointains). Dans le Chapitre 3 traitant de la présence de cycles politiques au niveau de la rente forestière, la disponibilité de données sur les permis d'exploitation et sur la rente perçue par les États pourrait permettre de mieux comprendre le phénomène. Aussi, le Chapitre 4 qui ne tient compte que des ressources minérales, pourrait être étendu en analysant l'effet de la mise en activité des gisements miniers, pétroliers et gaziers sur la participation à la chaine mondiale des valeurs, mais aussi sur d'autres déterminants plus directs du bien-être des populations comme les inégalités. Enfin, dans le Chapitre 5, la base de données World Bank Enterprises Survey ne permet pas une analyse en panel et une géolocalisation des entreprises, ce qui limite la portée des études pourrait. Aussi, ce dernier chapitre pourrait être repris en tenant compte des entreprises informelles, qui constituent une grande partie du tissu industriel dans les pays en développement.

De manière générale, dans la problématique du changement climatique, les ressources naturelles occupent une place plus qu'importante puisqu'il existe des minerais sans lesquels la transition vers des économies plus vertes ne serait pas possible. Ces minéraux dits stratégiques rendent possible la fabrication des composants électroniques nécessaires à l'évolution vers des économies plus respectueuses de l'environnement. Ainsi, la pression sur ces minéraux stratégiques augmente, ce qui pourrait également se traduire par un effet plus substantiel sur le bien-être des populations et surtout sur l'environnement du fait de l'exploitation de ces minéraux. Les recherches futures pourraient donc analyser la relation entre l'exploitation de ces minerais stratégiques et les institutions, l'économie ou l'environnement des pays dans lesquels ces minerais convoités sont extraits. Il pourrait s'agir d'analyser la relation entre l'activité minière et la liberté de la presse. De façon générale, des études pourraient aussi être menées afin de mesurer directement l'effet de l'activité minière sur la biodiversité de façon directe en se basant sur les nouvelles données disponibles sur la biodiversité, notamment la base de données AfrikENCA [18].

[18] https://oss-online.org/sites/default/files/2023-05/ArfikENCA.pdf

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