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FOUR ESSAYS ON GIANT NATURAL RESOURCES DISCOVERIES, SOVEREIGN DEBT RATINGS, AND INTERGENERATIONAL MOBILITY

Thèse présentée et soutenue publiquement le **31 Mars 2023**

pour l'obtention du titre de Docteur (ès) en Sciences Economiques

par

Regina Stéphanie SERI

sous la direction de :

Pr. Théophile T. AZOMAHOU et M. Samuel GUERINEAU

Membres du Jury

Eugénie W. H. MAIGA	Professeur, Directrice de l'UFR en Sciences Economiques et de Gestion, Université Norbert Zongo, Burkina-Faso	Rapporteur
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Four Essays on Giant Natural Resources Discoveries, Sovereign Debt Ratings, and Intergenerational Mobility

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Declaration

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Résumé

Cette thèse vise à étudier les impacts macroéconomiques et microéconomiques des découvertes géantes de ressources naturelles. D'un point de vue macroéconomique, cette thèse analyse les effets différenciés des découvertes géantes sur l'accès aux marchés financiers internationaux mesuré par la notation de la dette souveraine dans les pays en développement et émergents. D'un point de vue microéconomique, elle se concentre exclusivement sur l'Afrique et étudie les effets microéconomiques des découvertes et des productions minières sur la mobilité intergénérationnelle en matière d'éducation et de profession. En couvrant les aspects macroéconomiques et microéconomiques des découvertes géantes de ressources naturelles, cette thèse fournit un aperçu général de leurs effets potentiels tout en contribuant au débat actuel sur la question de savoir si les pays sont bénis ou maudits d'être riches en ressources naturelles. Tout au long de ses quatre principaux chapitres, cette thèse révèle que l'impact dépend de plusieurs facteurs.

D'un point de vue macroéconomique, le chapitre 2 utilise un échantillon de 28 pays en développement et émergents et emploie un modèle probit ordonné à effet aléatoires sur la période 1990-2014. Il analyse l'impact des découvertes géantes de pétrole, de gaz et de minéraux sur la notation de la dette souveraine à court, moyen et long terme. Il met en évidence des effets différenciés des découvertes géantes sur les notations, car certains pays connaissent une amélioration de la notation de leur dette souveraine tandis que d'autres connaissent une détérioration des conditions financières à la suite des découvertes. Pour un groupe de 13 pays de l'échantillon, les découvertes géantes sont associées à une baisse des notations à court terme mais à une hausse des notations à moyen et long terme. Pour un autre groupe de 15 pays, l'effet est non significatif à court terme mais négatif à moyen et long terme. Ce chapitre a également trouvé des preuves d'effets d'apprentissage dans les pays dont la notation de la dette souveraine s'améliore, car l'historique des découvertes passées est positivement associé à la notation de la dette souveraine. En outre, les découvertes géantes s'avèrent être de bons prédicteurs de l'accès aux marchés financiers, affectant positivement ou négativement les notations, dont les effets différenciés dépendent du comportement de plusieurs variables macroéconomiques et d'indicateurs politiques, notamment les recettes fiscales, la dette publique, le développement des marchés financiers, les investissements et la qualité des institutions. Ce qui semble compter,

ce ne sont pas seulement les ressources, mais aussi la manière dont les gouvernements réagissent à la nouvelle de la découverte.

Le chapitre 3 étudie l'impact du pic des découvertes géantes plutôt que des découvertes géantes ou des dotations en ressources naturelles. En effet, le pic des découvertes semble être plus exogène et pourrait également être associé à des effets plus importants et amplifiés sur les notations de la dette souveraine. Ce chapitre étudie empiriquement les effets du pic des découvertes géantes de pétrole et de minerais sur le Institutional Investor's Country Credit Rating (ICR) en utilisant la méthode de Synthetic Control Method (SCM). Il considère cinq pays en développement, dont l'Angola, le Kazakhstan, la Roumanie, le Gabon et le Cameroun sur la période 1985-2014. Ce chapitre confirme les effets hétérogènes des découvertes de ressources naturelles sur les notations des pays, tels qu'ils ont été constatés dans le chapitre précédent, avec une amélioration des notations observée dans les années suivant le pic des découvertes en Angola, au Kazakhstan et en Roumanie, tandis qu'une détérioration des notations a été constatée au Gabon et au Cameroun au lendemain du pic des découvertes. La description des études de cas révèle que des facteurs tels que la diversification, des politiques macroéconomiques et d'emprunt saines, une gouvernance solide, une gestion transparente des ressources, des investissements adéquats dans les biens publics et les infrastructures, ainsi que l'amélioration du climat des affaires, jouent un rôle important pour que les découvertes de ressources naturelles soient une bénédiction pour ces pays.

D'un point de vue microéconomique, les chapitres 4 et 5 soulignent des effets positifs des découvertes et des productions minières sur la mobilité intergénérationnelle dans l'éducation et la profession en Afrique. Le chapitre 4 utilise un vaste ensemble de données portant sur 14 millions d'individus dans 28 pays africains et 2890 districts et examine la relation entre les activités minières et la mobilité intergénérationnelle dans l'éducation. Tout d'abord, il calcule des mesures absolues de la mobilité intergénérationnelle en matière d'éducation et fournit quelques faits stylisés sur la dynamique de la mobilité intergénérationnelle en matière d'éducation dans les pays et régions d'Afrique. Les faits stylisés montrent que la mobilité de l'enseignement primaire et secondaire/tertiaire s'est améliorée en Afrique au fil du temps, avec une augmentation plus significative de la mobilité de l'enseignement primaire. En outre, l'écart entre les genres en faveur des hommes s'est réduit, les femmes obtenant de meilleurs résultats que les hommes au cours des dernières décennies ; toutefois, l'écart de résidence en faveur des personnes vivant dans les zones urbaines par rapport à celles vivant dans les zones rurales reste important. Deuxièmement, il emploie empiriquement un modèle Generalized Difference-In-Differences dans une expérience quasi-naturelle pour analyser la relation entre les activités minières et la mobilité éducative intergénérationnelle. Dans l'ensemble, cet article a trouvé des effets positifs des découvertes et productions de minéraux sur la mobilité intergénérationnelle éducative au niveau primaire. Cependant, aucune preuve significative de la mobilité intergénérationnelle n'est identifiée pour l'enseignement secondaire et supérieur. En outre, il dévoile deux canaux de transmission par lesquels les effets positifs des découvertes et des productions minières sur la mobilité de l'éducation primaire opèrent, notamment l'effet de revenu représenté par les parents travaillant dans le secteur minier et les niveaux élevés de rendements de l'éducation.

Le chapitre 5 étudie la relation entre les activités minières et la mobilité professionnelle intergénérationnelle à l'aide d'un échantillon d'environ 1,5 million d'individus répartis dans 27 pays africains et 2690 districts. Comme le chapitre 4, il utilise un modèle Generalized Difference-In-Differences et constate que les découvertes et les productions minières ont un impact positif sur la mobilité des cols bleus et blancs pour les personnes exposées et vivant dans des districts où se trouvent des découvertes et des productions minières, contribuant ainsi à l'amélioration des conditions du marché du travail en Afrique. En outre, deux canaux de transmission potentiels sont observés. Premièrement, le canal de la demande de travailleurs qualifiés (facteur lié à la demande) montre que la transformation structurelle et la création d'emplois dans les zones minières augmenteront la demande de travailleurs qualifiés dans les régions où se trouvent des découvertes. Deuxièmement, le canal de l'éducation (facteur lié à l'offre) révèle que les individus exposés aux découvertes ont tendance à augmenter leur niveau d'éducation afin d'obtenir un meilleur rendement de l'éducation et parce que les activités minières génèrent des revenus accrus pour que leurs parents puissent investir dans leur éducation.

Les analyses et les résultats de cette thèse peuvent être utilisés pour concevoir plusieurs recommandations politiques. Tout d'abord, au niveau macroéconomique, la première partie révèle que les effets des découvertes géantes sur la notation de la dette souveraine des pays en développement et émergents peuvent être positifs ou négatifs, cet effet dépendant des caractéristiques du pays et des mesures de politiques prises par les autorités à la suite des nouvelles de la découverte. Afin d'éviter la malédiction des ressources naturelles et de bénéficier positivement de ces ressources, les autorités pourraient augmenter leurs recettes fiscales, réaliser des investissements solides et à haut rendement, améliorer l'intégration de leur marché financier, renforcer la stabilité de leur gouvernement et accroître la transparence institutionnelle. En outre, elles doivent préserver la viabilité de leur dette, veiller à ce qu'elle n'augmente pas rapidement et lutter contre la corruption. Par conséquent, il est essentiel de disposer d'un cadre macroéconomique et institutionnel solide pour tirer parti des découvertes de ressources naturelles et les rendre plus rentables. Ensuite, au niveau microéconomique, la deuxième partie montre que les découvertes géantes de ressources naturelles favorisent la mobilité intergénérationnelle en matière d'éducation et de profession pour les personnes vivant dans les zones minières en Afrique. Cependant, ces effets positifs favorisent les hommes et les personnes vivant dans les zones urbaines. Pour que ces opportunités soient saisies, les gouvernements devraient investir dans les infrastructures scolaires et prendre des mesures pour améliorer la qualité de l'enseignement. Ensuite, ils pourraient également implémenter des politiques visant à renforcer les collaborations entre les entreprises minières internationales et les Petites et Moyennes Entreprises locale de sorte à davantage soutenir la création d'emplois pour les populations. De plus, pour adresser les inégalités de genre et localisation (urbain-rural), les autorités pourraient instaurer des programmes favorisant un meilleur accès aux niveaux d'éducation et de profession supérieurs pour les femmes et les personnes vivant dans les zones rurales. Enfin, il serait judicieux de réunir dans un fond souverain l'ensemble des revenues miniers et opter pour des politiques de redistribution entre les districts en vue de réduire les disparités régionales.

Comme pistes de recherches futures, trois analyses principales pourraient être menées. Premièrement, une analyse pourrait évaluer l'importance relative des différents facteurs identifiés comme conditionnant l'impact de la découverte de ressources naturelles sur la notation de la dette souveraine. Par exemple, il s'agirait de déterminer si les facteurs institutionnels comptent davantage que la dynamique de la dette et l'intégration financière lorsqu'il s'agit de réduire les risques pour un pays de subir une malédiction liée aux ressources naturelles. Nous pourrions également mener d'autres études de cas par pays afin de mieux connaître les expériences des pays qui gèrent avec succès leurs ressources naturelles et les transforment en une richesse équitable partagée entre la population. Deuxièmement, nos analyses dans la deuxième partie de cette thèse se concentrent sur l'exploitation minière industrielle. Il pourrait être intéressant d'explorer les effets des activités minières artisanales sur la mobilité intergénérationnelle en Afrique car il y a de bonnes raisons de penser que les mines artisanales pourraient avoir moins d'effets positifs sur la mobilité intergénérationnelle en matière d'éducation et de profession. Troisièmement, étant donné la richesse de l'ensemble de données au niveau géolocalisé, une analyse pourrait aller au-delà de la portée de cette thèse pour évaluer les effets environnementaux potentiels des découvertes de minéraux au niveau des districts.

Mots clés: Découvertes géantes, Ressources Naturelles, Notations de dette souveraines, Mobilité Intergénérationnelle, Pays en développement, Afrique, Modèles à effet aléatoire ordonnés, Synthetic Control Method, Generalized Difference-in-Differences, Expérience naturelle

JEL Codes: C23, C32, C55, G15, I21, I25, I26, J62, N9, O10, O55, Q32, Q33

Summary

This dissertation aims at investigating the macroeconomic and microeconomic impacts of the giant discoveries of natural resources. From a macro standpoint, this dissertation analyzes the differentiated effects of giant discoveries on access to international financial markets proxied by sovereign debt ratings in developing and emerging countries. From a micro standpoint, it focuses exclusively on Africa and studies the microeconomic effects of mining discoveries and productions on intergenerational mobility in education and occupation. By covering the macroeconomic and microeconomic aspects of giant discoveries, this dissertation provides a general overview of the potential effects of giant discoveries while contributing to the ongoing debate on whether countries are blessed or cursed to be rich in natural resources. Throughout its four chapters, this thesis reveals that the impact depends on several factors.

From a macroeconomic standpoint, chapter 2 uses a sample of 28 developing and emerging countries and employs a random effect ordered probit model over the period 1990-2014 to analyze the impact of giant discoveries of oil, gas, and mineral on the sovereign debt ratings in the short, medium and long term. It finds evidence of differentiated effects of giant discoveries in which some countries experience an improvement of their sovereign debt ratings while others experience a deterioration of financial conditions in the aftermath of discoveries. For a group of 13 countries in the sample, giant discoveries are associated with decreased ratings in the short term but increased ratings in the medium to long term. For another group of 15 countries, the effect is non-significant in the short term but is negative in the medium to long term. This paper also found evidence of learning effects in countries with improving sovereign debt ratings, as the history of past discoveries is positively associated with sovereign debt ratings. In addition, giant discoveries are found to be good predictors of access to financial markets, affecting both positively or negatively the ratings, which differentiated effects depend on the behavior of several macroeconomic variables and political indicators, including tax resources, public debt, development of financial markets, investments and quality of institutions. What seems to matter is not only the resources but also how governments respond to the news of the discovery.

Chapter 3 investigates the impact of the peak of giant discoveries rather than any giant discoveries or natural resources endowments. Indeed, the peak of discoveries appears to be more

exogenous and could also be associated with more significant and amplified effects on sovereign debt ratings. This chapter empirically studies the effects of the peak of oil and mineral giant discoveries on the Institutional Investor's Country Credit Rating (ICR) using a Synthetic Control Method. It considers five developing countries, including Angola, Kazakhstan, Romania, Gabon, and Cameroon over the period 1985-2014. This chapter confirms the heterogeneous effects of natural resources discoveries on country ratings as found in the previous chapter, with improved ratings observed in the years following the peak of discoveries in Angola, Kazakhstan, and Romania, while deteriorated ratings have been found in Gabon and Cameroon in the aftermath of the peak of discoveries. The description of the case studies reveals that factors like diversification, sound macroeconomic and borrowing policies, strong governance, transparent resource management, adequate investments in public goods and infrastructures, and improvements of the business climate matter for natural resource discoveries to be a blessing.

From a microeconomic standpoint, chapters 4 and 5 point out to some positive effects of mineral discoveries and productions on intergenerational mobility in education and occupation in Africa. Chapter 4 uses a large dataset of 14 million individuals across 28 African countries and 2890 districts and examines the relationship between mining activities and intergenerational mobility in education. First, it computes absolute measures of intergenerational educational mobility and provides some stylized facts on the dynamics of intergenerational educational mobility across African countries and regions. It shows that primary and secondary/tertiary educational mobility have improved in Africa over time, with a more significant increase in primary educational mobility. Moreover, the gender gap in favor of males has been reduced, with females doing better than males in recent decades; however, the residency gap in favor of people living in urban areas compared to those in rural areas remains significant. Second, it empirically employs a generalized difference-in-differences model in a quasi-natural experiment to analyze the relationship between mining activities and intergenerational educational mobility. Overall, this paper found positive effects of mineral discoveries on primary educational mobility. However, no significant evidence of intergenerational mobility for higher education, including both secondary and tertiary education, has been found. In addition, it unveils two transmission channels through which the positive effects of mineral discoveries and productions on primary educational mobility operate, including the income effect proxied by parents working in the mining sector and the returns to education.

Chapter 5 investigates the relationship between mining activities and intergenerational occupational mobility using a sample of around 1.5 million individuals across 27 African countries and 2690 districts. Like chapter 4, it employs a generalized difference-in-differences model and finds positive impacts of mineral discoveries and productions on blue- and white-collar mobility for individuals exposed to and living in districts with mining discoveries and productions, therefore contributing to an improvement of the labor market conditions in Africa. Furthermore, two potential transmission channels are analyzed. First, the demand for skilled workers channel (demand-side factor) shows that the structural transformation and the creation of jobs in mining zones will increase the demand for skilled workers in the regions with discoveries. Second, the educational channel (supply-side factor) reveals that individuals exposed to the discoveries tend to increase their education to obtain higher returns to education and because mining activities will generate increased income for their parents to invest in their education.

The analyses and results of this thesis can be used to design several policy recommendations. First, at the macroeconomic level, the first part reveals that the effects of giant discoveries on the sovereign debt ratings of developing and emerging countries can be positive or negative, with this effect depending on the characteristics of the country and the policy measures taken by the authorities following the news of the discovery. To avoid the natural resource curse and positively benefit from these resources, authorities could increase tax revenues, make sound, high-return investments, improve financial market integration, enhance government stability, and increase institutional transparency. In addition, they need to maintain debt sustainability, ensure that debt does not increase rapidly, and fight corruption. Therefore, a sound macroeconomic and institutional framework is essential to take advantage of natural resource discoveries and make them more profitable. Second, at the micro level, Part II shows that giant natural resource discoveries promote intergenerational mobility in education and occupation for people living in African mining areas. However, these positive effects favor men and people living in urban areas. For these opportunities to be seized, governments should invest in school infrastructure and take steps to improve the quality of education. Second, they could also implement policies to strengthen collaborations between international mining companies and local Small and Medium Enterprises (SMEs) to support job creation for the population. In addition, to address gender and location (urban-rural) inequalities, authorities could implement programs that promote greater access to higher levels of education and employment for women and people living in rural areas. Finally, it would be worth collecting all mining revenues in a sovereign fund and opting for redistribution policies among the districts to reduce regional disparities.

As avenues of future research, three main analyses could be conducted. First, an analysis could weigh the relative importance of the different factors that are identified as conditioning the impact of natural resource discoveries on sovereign debt ratings. For instance, whether institutional factors matter more than debt dynamics and financial integration when it comes to reducing the risks for a country to experience a natural resource curse. We could also conduct further country case studies to learn better the experiences of countries that successfully manage their natural resources and turn them into equitable wealth shared among the population. Second, our analyses in the second part of this thesis focus on industrial mining. It could be interesting to explore the effects of artisanal mining activities on intergenerational mobility in Africa since there are good reasons to believe that artisanal mines could have fewer positive effects on intergenerational mobility in education and occupation. Third, given the richness of the dataset at the geolocalized level, one analysis could go beyond this thesis's scope to assess the potential environmental effects of mineral discoveries at district levels.

Keywords: Giant discoveries, Natural resources, Sovereign debt ratings, Intergenerational Mobility, Developing countries, Africa, Random effect ordered response models, Synthetic Control Method, Generalized Difference-in-Differences, Natural experiment

JEL Codes: C23, C32, C55, G15, I21, I25, I26, J62, N9, O10, O55, Q32, Q33

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CHAPTER 1

General introduction

Are countries blessed or cursed to be rich in natural resources? Are the windfalls from the resources a blessing that brings prosperity or a curse that brings despair? These questions have occupied a central place in the academic literature, but today again, the answers are ambiguous and inconclusive. In this dissertation, we attempt to provide a response and contribute to the ongoing debate on the effects of natural resource discoveries by demonstrating in four essays that the global impact depends on diverse factors. For several countries in the world, and particularly in Africa, the discovery and exploitation of natural resources is a great opportunity, but this opportunity comes with risks. Indeed, history has shown that many resource-rich countries with a large endowment in oil, gas, and mining, have experienced prolonged episodes of negative growth and weaker potential growth, higher unemployment, higher rates of poverty, greater income inequality, acute conflicts, and political instability, several episodes of financial crises, more often than in less resource-dependent economies (Page and Tarp 2020). Fortunately, there are also countries with success stories with those resource-rich countries that succeeded in their economic diversification and transformation; and have enjoyed higher growth and prosperity, well-developed educational and health systems, and stable political systems thanks to natural resources.

To set up the scene of this thesis, this chapter, relative to the general introduction, is structured in four main sections. First, it presents the literature on resource curse and discusses the limits of the measures used to study the impact of natural resources. Second, it elaborates on the use of giant natural resource discoveries in the literature, its advantages over previous measures, its macroeconomic and microeconomic impacts, and presents some stylized facts - e.g., on its evolution worldwide. Third, it describes some country case studies. Lastly, it presents the four chapters of this dissertation and their respective contributions to the literature.

1.1 The resource curse literature and the critics

1.1.1 The resource curse literature

Since Adam Smith and David Ricardo (before the 1980s), natural resource fields, including oil, gas, and mining, have been considered as an excellent opportunity for countries to improve their economic and social situation. They are perceived as a way for the economy to move from under-development to industrialization, as was the case for Britain, Australia, and the United States (Viner 1952; Rostow 1959). However, the pioneering papers on the links between natural resources and economic development have argued that natural resources are more a curse than a blessing. This is the well-known "resource curse" literature. The idea of the resource curse, firstly employed by Auty (1993), is defined as the paradox that resource-rich countries experience an absence of sustained or high economic growth relative to less-resources-dependent countries. A growing literature describing the resource curse in resource-rich countries has emerged following the seminal empirical study of Sachs and Warner (1995), who found that countries with a high ratio of natural resource exports to GDP experienced lower growth rates. Among them, e.g.,Corden and Neary (1982); Ross (2004, 2006); Kretzmann and Nooruddin (2005); Collier and Hoeffler (2005); Van Der Ploeg (2011); Keen (2012); Van Der Ploeg and Poelhekke (2017) show that natural resources have generally been associated with the deterioration of economic and institutional conditions, the occurrence of conflicts, as well as with weak fiscal policy stance and unsustainable debt accumulation. Moreover, this literature revealed that resource-rich countries are characterized by lagging human and physical capital accumulation, de-industrialization, low savings, and stagnating or declining productivity (see, e.g., Budina et al. 2007; Mien and Goujon 2021). A common explanation of the negative effects of natural resources is provided by Corden and Neary (1982) in their analysis of the "Dutch disease". They find that a manufacturing recession in the Netherlands was prompted by an appreciation of the real exchange rate caused by the natural gas discoveries during the 1960s, which compressed employment in the tradable sectors, inducing a de-industrialization of the economy and a loss of competitiveness. Another explanation is elaborated by Torvik (2002). He shows in his model that natural resource abundance increases the number of entrepreneurs involved in rent-seeking and reduces the number of entrepreneurs running productive firms. Thus, natural resources lead to lower welfare because the drop in income due to rent-seeking is higher than the increase in income from the resources.

1.1.2 The critics of the resource curse literature

Far from being a consensus, the resource curse literature has been extensively criticized. Among the recent papers reviewing the literature on natural resources,[1] Badeeb et al. (2017) concluded that "there is currently no consensus regarding the existence of a natural resource curse. If the curse is a relevant concern, the disparate literature indicates that its ubiquity should not be exaggerated". Indeed, they revealed that several papers falling into this resource curse literature have some empirical shortcomings. They focused on average effects, and the variables they used to capture resource abundance, intensity, or dependence are likely to be endogenous (Brunnschweiler and Bulte 2008; Van der Ploeg and Poelhekke 2009; James 2015). Specifically, Brunnschweiler and Bulte (2008) find that the most used measures in the previous literature (e.g., natural resource exports to GDP, export share of resource in total exports, natural resource rents to GDP) capture "resource dependence" rather than "resource abundance" and are endogenous to underlying structural factors. Indeed, they point out that these measures using GDP in the denominator are not independent of economic policies and institutions (see also on the same conclusion, Alexeev and Conrad (2009)). As such, the papers finding a negative effect of natural resource abundance on economic activity and institutions are biased. To overcome this issue, they propose using subsoil assets as a proxy of resource abundance, which leads to a positive effect on natural resources rather than a curse. However, this new measure suggested by the authors is also not exogenous due to its strong correlation with resource rents, as shown by several authors, including Van der Ploeg and Poelhekke (2010).

Against this debate, a positive effect of natural resources has emerged in more recent analyses focusing on African countries or other developing countries. They show that natural resources reduce inequality and poverty and increase living standards, income, and welfare. In fact, Goderis and Malone (2011) find that resource exploitation booms reduce income inequality in resource-rich countries, while Fisher et al. (2009) show evidence of the reduction of poverty in the mineworkers' population in Tanzanian artisanal mines of gold and diamond. Zabsonré et al. (2018) reveal for Burkina Faso that gold exploitation led to better living standards, increased per capita household expenditures, and reduced poverty in the mining areas. Marlet (2020), using mining exploitation in Ghana, finds that mining activities tend to increase migration flows up to 200 km from the treated district by reducing migration costs through the construction of roads and infrastructures. Moreover, they also induce an increase in income and welfare improvement by 1.3 percent.[2]

[1] For recent literature reviews of the debate on the effects of natural resources, please see, e.g., Frankel (2010), Venables (2016), Van Der Ploeg and Poelhekke (2017), Badeeb et al. (2017), Mien and Goujon (2021).

[2] In contrast, some papers find that mining activities can create some environmental issues by increasing pollution and metal toxicity (Hausermann et al. 2018; von der Goltz and Barnwal 2019).

1.2 New approaches to measure natural resource abundance

To address the shortcomings of the literature presented in the previous section, recent studies on natural resources have used giant discoveries of oil, gas, and minerals. Indeed, giant discoveries of natural resources exhibit three essential features: the relatively significant size, the production lag, and the plausible exogenous timing of discoveries (Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019). First, giant discoveries represent a substantial amount of natural resource revenues for a specific country; therefore, they can significantly impact countries' socio-economic development. By representing a significant economic shock, they can transform some macroeconomic outcomes or change social conditions related to the habit of individuals and their expectations about their own and children's future. Second, giant discoveries do not immediately translate into production. Indeed, there is a significant delay between the discovery announcement and the start of the production, around four to six years after the discovery, depending on the resources, which require considerable investments. This allows for studying the differentiated effects of giant discoveries and subsequent productions. Third, the timing of giant discoveries is plausibly exogenous and unpredictable due to the uncertain nature of natural resource exploration. Specifically, while the technology used for exploration has improved over time, it is still highly improbable to predict the timing and success likelihood of finding a mineral field in a particular region (Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019). Moreover, the exact location of mineral resources discoveries is somehow exogenous as it depends on random geographical factors of the area. Therefore, while some regions may be endowed with mineral resources, it is improbable to find any resources in others. Given that, it is more plausible to treat giant discoveries as quasi-natural experiments. Therefore, they can be considered as exogenous shocks with huge macroeconomic and political implications for countries.

1.2.1 Data sources on giant discoveries and stylized facts

Three types of giant discoveries have been considered in the literature: oil, gas, and minerals. First, giant oil and gas discoveries are provided by Horn (2011). They define giant discoveries of oil and gas as discoveries with a recoverable volume of at least 500 million barrels of ultimately recoverable oil equivalent (boe). This data covers a very long period from 1868 to 2010. It has comprehensive coverage of countries accounting for 40 to 60 percent of world petroleum reserves, according to Mann et al. (2007). It builds upon the initial investigation by Halbouty et al. (1970). It provides very detailed information, including the oil and gas field trends, the size (giant, mega-giant, supergiant), the type of drilling (onshore/ offshore), the exact geographical location (latitude, longitude), the discovery year, and many others. Second, giant discoveries of minerals are provided by MinexConsultingDataset (2019). It defines as giant discoveries that generate an amount of at least US$500 million of revenue per annum for 20 years or more. It also encompasses major and moderate discoveries, generating an annual revenue stream superior or equal to US$50 million (for major discoveries) over a shorter lifetime (Bhattacharyya and Mamo 2021). Moreover, this database covers around 85 percent of all actual discoveries between 1950 and 2019, 90 percent for non-bulk deposits, and around 70 percent for bulk ones. It also provides very detailed information on the type and the class of primary metal (bulk and non-bulk metals), the status of the mine (operating, closed, feasibility, advanced exploration, underdeveloped, etc.), the discovery year, the start and end of production (mine startup year, mine shutdown year), the geo-localization, and the type of exploratory companies.

In Figure D.1 to Figure D.3, I present some stylized facts on giant discoveries of oil, gas, and minerals. First, Figure D.1 depicts the number of giant discoveries by type of natural resources and by decades from 1950 to 2019. Overall, giant discoveries are not rare phenomena since they occurred across all the decades, with rising occurrence for mineral discoveries compared to oil and gas discoveries that have decreased over time. Second, in Figure D.2 and Figure D.3, I present the geography of the mineral discoveries. It reveals that all types of giant discoveries occurred in all regions. However, there are some disparities: around 39 percent of giant oil discoveries occurred in the Middle East and North Africa region, 31 percent of gas discoveries in Europe and Central Asia, and 24.8 and 22.6 percent of mineral discoveries in Eat Asia and Pacific and Sub-Saharan Africa, respectively.

1.2.2 The literature on the effects of giant natural resources discoveries

Giant discoveries have had both macroeconomic and microeconomic impacts. Regarding the effects of discoveries at the country level on macroeconomic variables and policies, institutions, and conflicts, studies generally point out negative impacts. For example, giant discoveries of natural resources could deteriorate the conduct of fiscal policy and increase debt levels and therefore are associated with a rising likelihood of crises Kretzmann and Nooruddin (2005). Similarly, Ruzzante and Sobrinho (2022) show that the "fiscal presource curse" of natural resources discoveries (mainly oil and gas) on government debt sustainability lead to permanent higher government debt and debt distress episodes before the "first drop of oil is pumped". Moreover, other papers find that giant discoveries are associated with an overvaluation of the exchange rate Harding et al. (2020), an increase in the incidence of armed conflicts and a change of institutional framework toward autocracy (Tsui 2011; Lei and Michaels 2014), an increase in corruption (Vicente 2010) and an increase in both poverty and inequality (Smith and Wills

2018). Contrarily, few papers point out to positive or ambiguous effects of giant discoveries. For example, Toews and Vezina (2017) find that giant oil and gas discoveries favor an increase of more stable funds like foreign direct investments in non-resource sectors. In the aftermath of discoveries, Arezki et al. (2017) find evidence of a significant "anticipation effect". They show that the current account and saving rate decline for the first five years before turning positive sharply during the following years; investment rises robustly soon after the news arrives, GDP does not increase until the fifth year, and employment rates fall slightly for a sustained period.

On the microeconomic and local impacts, the literature shows that natural resource discoveries have contributed to improving local economic development, governance, the provisions of public goods, and welfare and reducing the likelihood of conflicts. Indeed, Cavalcanti et al. (2019) find evidence of a positive impact of oil and gas discoveries on local development and urbanization in Brazil. Cust and Mensah (2020) reveal that oil, gas, and mineral discoveries positively impact the citizen's expectations, which is materialized by a decrease in outward migration and an increase in fertility in the short term. Bhattacharyya and Mamo (2021) show that oil and mineral discoveries reduce the likelihood of conflict in 48 African countries, mainly driven by improved economic development and efficient political distribution patronage in districts with discoveries.

Taken together, the impacts of giant discoveries, or more broadly natural resources, are mixed and inconclusive. Against this background, the following section describes some country case studies to present how countries have reacted (e.g., changes in economic policies) to giant discoveries of natural resources and explore the effects on socio-economic indicators and mechanisms.

1.3 Country case studies

Understanding how countries and governments react to natural resource discovery news is critical. In general, the size of an anticipated boom is overestimated, and the delay in receiving revenues is underestimated (Page and Tarp 2020). While most countries will unsustainably increase their borrowings and face debt sustainability issues, choose projects with lower returns, and not build a strong governance framework for the management of the resources; others contrarily will prudently start investments in projects with high returns to diversify their economy, to increase their human capital and productivity, and save the windfalls for the future generation.

1.3.1 Mozambique

The giant discoveries of gas in 2012 in the Cabo Delgado province in Mozambique have raised much hope from the government and local communities. However, the country has faced many issues before extracting the resource (Roe 2018). First, a foreign direct investment (FDI) surge in the extractive sector was associated with an FDI boom in non-extractive sectors. Specifically, in the aftermath of the discoveries, investments have risen by more than 20 percentage points of GDP. This big change in investments was due to a surge in non-extractive FDI, which grew by 58 percent in the two years following the discovery. Also, the number of FDI projects increased by 30 percent, and the number of jobs created rose by 54 percent (Toews and Vezina 2017). Second, the various governments have contracted huge external loans to finance public investments, which also boomed, assuming that Mozambique will become a key gas exporter. These loans were contracted in disregard of good practices in public financial management since they were significant concerns around the selection of the projects and the terms of the loan contracts. Contrary to the findings in Alfaro and Charlton (2013), and Roe (2018), which show that FDI surge in non-extractive sectors (mainly services and manufacturing) is associated with higher economic activity, Mozambique has experienced weaker growth in the years following discoveries.

Why did Mozambique not fly as expected by the authorities and population? First, the discoveries of natural resources in Cabo Verde, in particular, have been followed by a terrorist insurgency in 2017, allowing terrorists to secure a steady revenue stream through illicit trade and taxation (Langa 2021). Then, the national security issues generated by this insurrection prevented the government from benefiting from the natural resources revenues through investments in sound public infrastructures. It also impeded the population from enjoying themselves because of the fear of their security. Second, Roe (2018) shows, among other reasons, that the behavior of government borrowing and its implication for debt sustainability is a crucial factor. Indeed, the borrowing plan should have better incorporated the estimation of the resources' proceeds and the duration between the discovery and the start of production. For instance, the EMATUM bond issue of 2013 expired in 2020 before the government would have collected the first dollar revenue from the resource. Thus, the debt service of this bond relied on pre-existing government revenues. At the same time, donor funding, particularly grants, have declined following the suspension of the IMF program in April 2016, which has not helped improve the debt trajectory. As a result, the debt to GDP ratio increased from 40 percent in 2012 to around 130 percent in 2020. The behavior of the government, by contracting heavy international and domestic borrowing and, starting in 2013, issuing public guarantees of loans amounting to US$2.3 billion (around 20 percent of GDP) have worsened the macroeconomic framework creating a situation of debt distress (IMF 2016; Khan et al. 2016; Page and Tarp 2020).

In addition, the authorities have not included delays in the projects conducing to the production. Initially planned for 2021, new projections show that the productions are unlikely to start before 2024 and 2025. In other words, production would start when the fiscal situation has significantly deteriorated, and expenditure prioritization will be needed despite the windfalls from the resources used to ensure debt sustainability. In a different context, the anticipated revenues would have been used to fill the education gap (4 percent of GDP annually) and the health gap (over 50 percent of GDP). But now, a significant share of these resources would go to debt servicing, leaving the social welfare deficits unaddressed. The sad reality is that Mozambique's bondholders should be paid portions of Mozambique's future natural gas revenues as part of the 2018 debt restructuring of the country's Eurobonds.

1.3.2 Ghana

Similarly to the case of Mozambique, Ghana is also a good illustration of the "presource curse" in the years following discoveries, as discussed by Ruzzante and Sobrinho (2022). Indeed, Ghana had two giant oil discoveries in 2007 and 2010, summing up to 2 billion barrels of oil equivalent (boe). At this time, governments and citizens alike were jubilant, anticipating the prosperity these discoveries herald, and the former Ghanaian President, John Kufuor, proclaimed in 2007, "Even without oil we are doing well ... With oil as a shot in the arm, we are going to fly". Unfortunately, today, Ghana is not flying (Cust and Mihalyi 2017). The predictions of the World Bank estimate the earnings from the production around US$20 billion in the period 2012-30. However, sound economic predictions have failed to materialize. Growth dropped below 4 percent between 2014 and 2016, the lowest in 20 years, and the contribution of oil to government revenues was less than 10 percent, averaging about 7.5 percent for the first five years of oil production (Benkenstein 2016). The external debt to GDP ratio rose from 37 percent to 50 percent between 2009 and 2016. Financial conditions quickly deteriorated, as illustrated by the $1 billion emergency loan as part of an IMF-supported program requested in 2015 by the Ghanaian authorities. The jubilation ends because of economic imprudence and bad luck: profligate spending, heavy borrowing (over this period, Ghana borrowed $4.5 billion on international markets and only saved $484 million in oil revenues for a rainy day), and the oil price bust of 2014 (Bawumia and Halland 2017; Page and Tarp 2020) (IMF, 2017).[3] While Ghana has learned from the experience of other countries and devoted efforts to creating a sound framework

[3]Other countries like Sierra Leone with the discovery of iron-ore deposits in 2009 or Uganda with those of oil in 2006, experienced a deterioration of their financial conditions, and growth falls in the aftermath of the giant discoveries because of miscalculated anticipations and disastrous decisions related to off-budget government borrowing (Khan et al. 2016).

for oil resource governance and management; the authorities have not properly implemented the good international standards in terms of accountability, the collection of revenues, including surface rentals, and the equitable distribution of the windfalls from the resources.

1.3.3 Botswana

Fortunately, the picture appears nuanced with some success stories that give hope to countries dealing with giant discoveries of natural resources. In Africa, Botswana is one of the most prosperous countries that has built its economy based on the windfalls from diamond extraction. Since the discoveries of diamonds in the late 1960s and early 1980s, Botswana has rapidly improved its economic, social, and institutional environment and has become a middle-income country. Since then, Botswana has benefited from good financial conditions and permanent access to the international market. As an illustration, the sovereign rating on Botswana's long-term debt has always been classified in the upper-medium investment grade by Standard and Poor since 2001. Despite consistent access to the international market, Botswana has developed a domestic capital market since 1989, becoming the Botswana Stock Exchange in 1995. Over the years, the domestic stock market has grown tremendously. As the regulatory environment has improved, new products have been introduced, and various outreach programs have been implemented to attract issuers and investors. Botswana overcame the resource curse's threat primarily through government investment in public goods and infrastructures, measures taken to boost productivity, the establishment of savings funds to smooth the economy during financial turmoil, and the excellent governance pursued by the authorities. For instance, in 1994, the Pula Fund was established under the Bank of Botswana Act as a sovereign wealth fund to hold a long-term investment with the objective to build reserves and preserve part of the windfalls from the diamond exports for future generations.[4] As shown by Dixon (2016), the Pula Fund is Africa's oldest and third-largest fund, and it stood at US$5.4 billion in 2016. Botswana has been able to reinvest in improving health and education through a lack of unnecessary public spending, low inflation, or an increase in foreign reserves while avoiding over-indebtedness issues (Acemoglu et al. 2003; Leith 2005).

1.3.4 Malaysia

Out of Africa, Malaysia has successfully converted natural resource discoveries into a critical driver of its sustainable and inclusive growth. The oil and gas sector has yielded a lot of benefits. Since the discovery of oil and gas, thanks to technology in the 1970s, Malaysia has

[4]Please follow this link for more details on the Pula Fund: https://www.bankofbotswana.bw/content/pula-fund.

relied on oil and gas revenues to narrow economic inequalities and build sustainable economic growth. Indeed, following the ethnic riots in 1969, the Malaysian government committed to using economic development to narrow racial and economic inequalities (Yusof 2011). The growing nationalism in Malaysia and the idea that it is essential to maintain sovereign control over natural resources led the government to secure greater control over the oil and gas sector and renegotiate production agreements with the international oil majors. Moreover, the governments have also pursued diversification strategies by using revenues to support investment sectors not directly linked to resources. They multiplied the investment programs in the agriculture, manufacturing, and service sectors thanks to sound resource management. Within agriculture, investment programs raised productivity and implemented a transition from rubber to palm oil production. In manufacturing, the economy was open to trade and foreign direct investment. An industrial policy was pursued (including infrastructure development, particularly in special economic zones) that succeeded in developing a range of labor-intensive activities, including the electronics sector. In addition, macroeconomic stability was maintained by fiscal prudence and some elements of luck, as when rapidly increasing oil volumes offset the price fall of the 1980s (Venables 2016). Malaysia's national oil company also conducted this diversification strategy, which began investing inroad in emerging ASEAN economies, including Myanmar, Cambodia, Thailand, and Vietnam.

1.3.5 Key takeaways

The striking contrast offered by the country case studies between Ghana and Mozambique (the boom-and-bust stories), and Botswana and Malaysia (success stories reside) could reside in six aspects according to Page and Tarp (2020):

- the experiences (duration) in managing natural resources;
- the Warner's five common features of decision-making on public investment following the discovery (Warner 2014; Roe 2018), including:
  - a failure to select public investments by reference to sound economic criteria;
  - a systematic tendency to use over-optimistic predictions of prices, cost, and impacts;
  - a lack of information at the time of implementation to identify the likely (true) rates of return on investments;
  - inertia in investment programs: investments once started is likely to continue to command finance even when the conditions needed for success deteriorate;

- a high degree of vulnerability of public investment decisions to abuse for personal or political motives.

Indeed, the exposition time in managing natural resources is critical to understand how they affect socio-economic development trajectory and people's lives. This is well illustrated in Cust and Mihalyi (2017) and Ruzzante and Sobrinho (2022), who used the term "presource curse" and distinguished it from the "resource curse". Indeed, the "presource curse" deals with the period that is typically relatively short (but uncertain) between the discovery and the start of production. Cust and Mihalyi (2017) show mixed results depending on the quality of institutions. They find that countries with weaker political institutions experienced lower growth during the "presource" period, below IMF forecasts and pre-discovery growth, while those with solid institutions see at least growth in line with IMF forecasts and pre-discovery growth. Similarly, Ruzzante and Sobrinho (2022) find evidence of a "fiscal presource curse", i.e., natural resources can jeopardize fiscal sustainability even before "the first drop of oil is pumped". Specifically, they show that giant oil and gas discoveries lead to permanently higher government debt and, eventually, debt distress episodes, especially in countries with weaker political institutions and governance. Altogether, these findings show that it is important to dissociate the discovery announcement and the start of production. It is generally the reactions of government to discovery and exuberance from the population, also presented in Warner's five common features of decision-making, rather than the beginning of the production, that give rise to the likelihood of a resource curse. This evidence suggests that the curse can be mitigated and even prevented by pursuing prudent fiscal policies and borrowing strategies, strengthening governance, implementing transparent and robust fiscal frameworks for resource management, saving through sovereign funds for future generations, and investing in sound projects in education, health, and infrastructures to improve the human capital and productivity.

1.4 The value-added of this thesis and contributions

To summarize, the empirical literature on the effects of natural resources is mixed and inconclusive. At the macroeconomic level, studies have generally found negative effects, while positive effects have emerged at the microeconomic or local level. Some analyses have shown that the methodology and the variables used to measure natural resources play a key role in capturing the "true" effects of natural resources. This leads many papers to consider giant discoveries as a good proxy of natural resources, given their relatively significant size, the production lag, and the plausible exogenous timing of discoveries. On the other hand, country case studies have shown that what matters for the effects of natural resources is how the governments and population react to the news of the discoveries. The good actions lead to prosperity while bad ones lead to desperation. Consequently, average effects captured in most analyses are less likely to provide a clear picture of the effects of natural resources and the mechanisms.

While there is extensive literature on the benefits or adverse consequences of natural resources, my interest is to contribute to the debate and further investigate the effects of giant discoveries at both i) the macroeconomic level on sovereign debt ratings and access to financial markets and ii) the microeconomic-level on educational and occupational intergenerational mobility. Also, this dissertation aims to formulate policy recommendations to help countries better use their resources.

This dissertation presents the research results, structured into two parts and four chapters. The first part, divided into two chapters, investigates the relationship between giant discoveries of natural resources (oil, gas, minerals) and access to financial markets. In chapter 2, I shed light on the effects of giant discoveries of natural resources (oil, natural gas, minerals) on sovereign debt ratings in the short and long run. To do so, I use 28 developing and emerging countries over the period 1990-2014. I apply a random effect ordered probit model on two different sets of samples. I find evidence of the differentiated effects (positive and negative) of giant discoveries on ratings. Specifically, for 13 countries, I find that giant discoveries are associated with a deterioration of sovereign debt ratings in the short-term but an increase of those ratings in the medium- and long-term. For the other 15 countries, I show that giant discoveries have no effect in the short-term but reduce ratings in the medium- to long-term. These differentiated effects depend on the behavior of macroeconomic and political indicators resulting from the actions and policies taken in the aftermath of the discoveries. I also reveal that there are some learning effects of giant discoveries in countries with increasing sovereign debt ratings. Countries with a history of giant discoveries tend to experience higher ratings. What seems to matter is not only the resources but also how governments respond to the news of the discovery. Indeed, I show that in countries with increasing ratings, on average, giant discoveries are associated with increased tax revenues to GDP, investments, decreased public debt to GDP, and improved government stability. Contrasting this finding, I find that in countries with decreasing ratings, giant discoveries are associated with a reduction in investments and an increase in corruption. These findings call for a careful assessment of governments' decisions in the aftermath of giant discoveries. Indeed, taking the right actions and policies will help countries to prevent a deterioration of their financial conditions.

In chapter 3, a companion paper to chapter 2, I examine the causal effects of the peak of giant oil and mineral discoveries on investor country credit rating (ICR). I used a synthetic control method (SCM) and applied it to five developing countries, including Angola, Kazakhstan, Romania, Gabon, and Cameroon, from 1985 to 2014. The SCM allows to capture the country-specific causal effect of the peak of giant discoveries and is more appropriate for comparative case studies. We focus on the peak of giant discoveries rather than giant discoveries, as in chapter 2. The reason is that the peak of giant discoveries is more likely to be exogenous and could induce amplified effects on financial conditions (Tsui 2011; Masi and Ricciuti 2019). We find that the peak of discoveries both positively and negatively impacts the investor country credit ratings, depending on the specific characteristics of the governments. Therefore, we confirm the heterogeneous effects of (the peak of) giant discoveries on access to financial conditions, as found in chapter 2. Specifically, we find that investor country credit ratings have significantly improved in Angola, Kazakhstan, and Romania following the peak of the discoveries. In contrast, investor country credit ratings have significantly deteriorated in Gabon and Cameroon following the peak of giant discoveries. These findings confirm that the average effects of giant discoveries presented in the literature may hide the real development in countries that may differ from one to another.

The second part looks at more granular effects of mineral discoveries and focuses on Africa, home to abundant mineral resources. It studies the relationship between mineral discoveries and intergenerational mobility in education and occupation. In chapter 4, we adopt an innovative approach by exploring the effects of mineral discoveries and productions on intergenerational educational mobility, linking parents to their children's education levels for more than 14 million individuals across 28 African countries and 2,890 districts. We employ a generalized difference-in-differences method in a quasi-natural experiment. Our quasi-natural experiment relies on the plausible exogeneity of mineral discoveries that revert specific characteristics, specifically the unpredicted time of discoveries, the unpredicted geographical location, and the lag between the natural resources discoveries and the beginning of production (Horn 2011; Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019). We find that mineral discoveries and productions positively affect educational mobility for primary education in Africa for individuals exposed to the mineral sites and living in districts with discoveries. Specifically, the probability of upward primary educational mobility, i.e., the probability for a child born from uneducated parents or parents with less than primary educational attainment to achieve at least primary education, increases by 2.7 percentage points (pp.) following mineral discoveries and 6.7 pp. following mineral productions. The probability of downward primary educational IM, i.e., the probability for a child born from parents with at least primary education attainment to be uneducated or have less than primary education attainment, decreases by 1.2 pp. following both mineral discoveries and productions. These positive effects are increasing for individuals born later after discoveries and productions, males, and individuals living in urban areas. However, we find no significant evidence of intergenerational mobility for higher education, including secondary and tertiary education. In addition, we discuss two transmission channels through which the positive effects of mineral discoveries and productions on primary educational mobility operate, including the income effect proxied by parents working in the mining sector and the returns to education. First, our results show that the mining sector creates new job and income opportunities for parents, allowing them to invest more in their child's education attainment (Becker and Tomes 1979). Second, we uncover that the economic dynamism and creation of new jobs following the discoveries of mineral resources lead to an increase in the demand for skilled workers, thereby boosting the returns to education (Torche 2014).

The chapter 5, a companion paper to chapter 4, investigates the relationship between mineral discoveries and productions and intergenerational occupational mobility. Specifically, we consider 1.5 million individuals across 2,690 districts from 27 African countries. Our main findings show that mineral discoveries and productions increase both blue- and white-collar occupational mobility; therefore, they have contributed to improving African labor market conditions. Specifically, the probability of upward blue-collar mobility increases by up to to 2.3 pp. following mineral activities. Downward blue-collar mobility decreases by around 4 pp. Likewise, the likelihood of upward white-collar mobility increases by up to 1.6 pp. following mining activities. Downward mobility decreases by up to 13.3 pp. These positive effects are also found for individuals aged 16–20 years old entering the labor market at the time of discovery or production, but interestingly, these effects are higher for those born after discoveries and productions. Moreover, our results show some heterogeneous effects depending on the African region's location, the mineral discoveries's size, gender, and the urban-rural divide. In addition, we explore the demand for skilled workers channel (demand-side factor) and the educational channel (supply-side factor) through which mineral discoveries and productions affect occupational mobility. Furthermore, two potential transmission channels, including the demand for skilled workers (demand-side facto) and the educational channel (supply-side factor) are observed. First, we uncover that the creation of new jobs following the discoveries of mineral resources will increase the demand for skilled workers, thereby boosting the likelihood of intergenerational occupational mobility. Second, we find that children exposed to mineral activities tend to have higher educational mobility driven by higher return to education and new and higher income of their parents is invested in their education.

In the following chapters, we discuss our findings, the methodology employed, the data used, and main policy recommendations, hoping that it will help policymakers turn natural resources into a blessing rather than a curse.

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Part I:

The Macroeconomic Impacts of Giant discoveries on Sovereign Debt Ratings in Developing Countries

CHAPTER 2

How giant discoveries of natural resources impact sovereign debt ratings in developing and emerging countries?

Abstract

This paper sheds light on the effects of giant discoveries of natural resources (oil, natural gas, minerals) on sovereign debt ratings in the short and long run. To do so, it employs 28 developing and emerging countries over the period 1990-2014 and applies a random-effects ordered probit model on different sets of samples. It shows evidence of the differentiated effects (positive and negative) of giant discoveries on ratings. These differentiated effects are linked to the behavior of macroeconomic and political indicators resulting from the actions and policies taken in the aftermath of the discoveries. It also finds evidence of the learning effects of giant discoveries in countries with increasing sovereign debt ratings. What seems to matter is not only the resources but also how governments respond to the news of the discovery of those resources. Therefore, taking the right actions and policies will help countries to prevent a deterioration of their financial conditions.

Keywords: Giant discoveries; Natural resources; Sovereign debt ratings; Developing countries; Random effect ordered response models
C23; G15; Q32; Q33

2.1 Introduction

Giant natural resources discoveries worldwide have generally led first to jubilation, and more often turned into disappointments after that, in line with the so-called "Dutch Disease" .[1] The exuberance duration is generally linked to the actions and policies that the country authorities will undertake in the aftermath of the discovery. Still, they may also depend on the country's structural and institutional characteristics. Although relevant for growth, institutional factors, exchange rate, and industrialization, giant discoveries also matter for the terms under which countries have access to international capital markets. Indeed, there are regularly giant discoveries of natural resources worldwide, and many of the resources-rich countries have encountered periods of access to international markets and periods of financial turmoil. However, the existing literature on giant discoveries has overlooked their effects on the financial conditions, especially on the long-term sovereign debt ratings. Should we expect an improvement or a deterioration in financial conditions in the years following the discoveries? This paper provides an answer to

[1] The papers supporting the Dutch disease include, among others, Sachs and Warner (1995, 2001); Kretzmann and Nooruddin (2005); Ross (2004, 2006); Van Der Ploeg (2011); Keen (2012); Van Der Ploeg and Poelhekke (2017); Corden and Neary (1982); Collier and Hoeffler (2005). They show that natural resources are generally associated with the deterioration of economic and institutional conditions, the occurrence of conflicts, an appreciation of real exchange rate which induces a loss of competitiveness and a de-industrialization of the economy, as well as with weak fiscal policy stance and unsustainable debt accumulation.

this question. It shows that while some countries could improve their financial conditions in the aftermath of giant discoveries, others could experience a deterioration. These differentiated effects depend on the behavior of many macroeconomic and political indicators resulting from the actions and policies taken in the discoveries' aftermath. What seems to matter is not only the resources but also how authorities respond to the news of the discovery of those resources.

Some case studies drive my assumptions. The case of Ghana illustrates the failures. Indeed, Ghana had two giant discoveries in 2007 and 2010, summing up to 2 billion barrels of oil equivalent (boe). At this time, governments and citizens alike were jubilant, anticipating the prosperity these discoveries herald, and the former Ghanaian President, John Kufuor, proclaimed in 2007, "Even without oil we are doing well ... With oil as a shot in the arm, we are going to fly". Unfortunately, fast-forward to today, Ghana is not flying. Growth dropped below 4% between 2014 and 2016, the lowest in 20 years; debt increased by 14 percentage points (pp.) of GDP in 2014 and remained above 70% of GDP since then, and financial conditions quickly deteriorated, as illustrated by the $1 billion emergency loan as part of an IMF-supported program requested in 2015 by the Ghanaian's authorities. The jubilation ends because of economic imprudence and bad luck: profligate spending, heavy borrowing (over this period, Ghana borrowed $4.5 billion on international markets and saved $484 million in oil revenues for a rainy day), and oil price bust of 2014 (Bawumia and Halland 2017). Other countries like Mozambique, Sierra-Leone, and Uganda experienced a deterioration of their financial conditions, and growth falls in the aftermath of the giant discoveries because of miscalculated anticipations and disastrous decisions related to off-budget government borrowing (Khan et al. 2016).

Fortunately, the picture also appears bifurcated. Some success stories give hope to countries in which giant discoveries are found. Botswana is one of the successful countries reliant on natural resources. Since the discoveries of diamond in the late 1960s and early 1980s, Botswana has rapidly improved its economic, social, and institutional environment and has become a middle-income country. Since then, Botswana has benefited from good financial conditions and permanent access to the international market. As an illustration, the sovereign rating on Botswana's long-term debt has always been classified in the upper-medium investment grade by Standard and Poor since 2001. Despite consistent access to the international market, Botswana has developed a domestic capital market since 1989, becoming the Botswana Stock Exchange in 1995. Over the years, the domestic stock market has grown tremendously. As the regulatory environment has improved, new products have been introduced, and various outreach programs have been implemented to attract issuers and investors. Botswana overcame the resource curse's threat mostly by government investment in public goods and infrastructures, by measures taken to boost productivity, by establishing savings funds to smooth the economy during financial turmoil, and because of the good governance pursued by the authorities. It has been able to reinvest in improving health and education through a lack of unnecessary public spending, low inflation, or an increase in foreign reserves while avoiding over-indebtedness issues (Acemoglu et al. 2003; Leith 2005). Taking stock of these case studies, I assume that giant discoveries of natural discoveries may have a dual effect on countries' financial conditions, and their effects depend on how authorities respond to the news of the discovery of those resources.

Then, this paper is related to two strands of literature. The first strand of papers describes the effects of giant discoveries on several macroeconomic indicators and policies, institutions, and conflicts. They generally point out to negative impacts of giant discoveries, notably a deterioration of the fiscal policy and increase in debt level associated with the rising likelihood of crises (Kretzmann and Nooruddin 2005), an overvaluation of exchange rate (Harding et al. 2020), an increase of the incidence of armed conflicts and change of institutional framework towards autocracy (Lei and Michaels 2014; Tsui 2011), and an increase in both poverty and inequality (Smith and Wills 2018). Few papers point out to positive or ambiguous effects of giant discoveries. They find that oil and gas giant discoveries favor an increase of more stable funds like foreign direct investments in non-resource sectors (Toews and Vezina 2017). Also, after discoveries, the current account and saving rate decline for the first five years and then rise sharply during the ensuing years; investment rises robustly soon after the news arrives, while GDP does not increase until the fifth year; employment rates fall slightly for a sustained period (Arezki et al. 2017). This literature on giant discoveries does not directly analyze their effects on the financial conditions of countries.

The second strand of papers looks at the determinants of financial conditions proxied by either sovereign spreads of interest rates or sovereign debt ratings.[2] In this literature, Hooper (2015) is the paper closely related to my analysis; however, it studies how oil and gas reserves affect sovereign spreads instead of giant discoveries. It finds that oil reserves increase sovereign spreads while gas reserves lower them and that financial markets' reactions also depend on institutional quality. The paper sustains that oil and gas reserves may facilitate access to international financial markets since they can be used as collaterals. An argument that is also shared by Manzano and Rigobon (2001) and Melina et al. (2016).

Three categories of determinants of sovereign debt ratings are identified in the existing literature. The first category includes the macroeconomic factors: higher income per capita, lower inflation, higher GDP growth, higher fiscal base, lower external debt and higher investment are positively associated with financial conditions(see, e.g. Cantor and Packer 2011; Larraín et al. 1997; Bissoondoyal-Bheenick 2005; Mellios and Paget-Blanc 2006; Depken et al. 2011;

[2]According to Cantor and Packer (2011) and Chen et al. (2016), sovereign debt ratings are defined as an assessment of the relative likelihood that a borrower will default on its obligation. They incorporate a combination of economic, social, and political factors to assess a country's capacity and willingness to honor its current and future debt obligations in full and on time.

Afonso et al. 2011; Jaramillo and Tejada 2011; Erdem and Varli 2014). The second category includes institutional factors: greater political stability, lower corruption, absence of violence and terrorism and no default history are positively associated with financial conditions (see, e.g. Cantor and Packer 2011; Afonso et al. 2011; Mellios and Paget-Blanc 2006; Teixeira et al. 2018; Depken et al. 2011; Erdem and Varli 2014; Andreasen and Valenzuela 2016). The third category includes external factors: good terms of trade and sustained exports are positively associated with financial conditions (see, e.g. Mellios and Paget-Blanc 2006; Hilscher and Nosbusch 2010; Erdem and Varli 2014).

My paper reconciles the two strands of literature by looking at the effects of giant discoveries on countries' sovereign debt ratings. Giant discoveries are included as a critical determinant of sovereign debt ratings. I assume that natural resources discoveries could favor access to international markets, on one side, and lead to excessive debt, borrowing, and off-budget activities on the other side. Consequently, the effects of giant discoveries on financial conditions may be ambiguous. I assume that the effects will depend on the country's authorities' actions and policies in the aftermath of discoveries. To answer these research questions, I use a sample of 28 developing and emerging countries from 1990 to 2014.[3] I divide these countries into two groups of countries in which sovereign ratings tend to improve or deteriorate in the aftermath of giant discoveries, based on the stylized facts.[4] I then estimate on the different samples, a random-effects ordered Probit model following Afonso et al. (2009) and Teixeira et al. (2018), where the dependent variable is the foreign currency long term sovereign debt rating (from Kose et al. 2018), the variable of interest is giant discoveries of natural resources (from Horn 2011, and MinExConsultingDatasets (2014)), and the control variables are some macroeconomic, institutional, and external determinants in line with the literature. Following Arezki et al. (2017), I consider different time horizons that allow me to differentiate the effects of giant discoveries in the short, medium, and long term.

After controlling for the variables on the determinants of sovereign debt ratings, I find that giant discoveries lead to differentiated effects. Some countries experience an improvement in their sovereign ratings while others experience a deterioration. This finding reveals that the outcome of giant discoveries on ratings is sensitive to the group of countries studied. My results show that, when considering the full sample, giant discoveries of natural resources deteriorate sovereign debt ratings over the medium and long term. In the set of countries with

[3]The size of the sample is constrained by the availability of data on both sovereign debt ratings and giant discoveries.

[4]I further discuss more extensively the subdivision of the sample in the Section 2.2. Countries with increasing sovereign ratings that I qualify as "up" sample include Bolivia, Brazil, China, Ecuador, India, Indonesia, Kazakhstan, Mongolia, Pakistan, Peru, Philippines, Romania, Turkey. Countries with decreasing sovereign ratings that I qualify as "down" sample include Argentina, Azerbaijan, Colombia, Egypt, Ghana, Guatemala, Mexico, Mozambique, Malaysia, Russia, South Africa, Thailand, Venezuela, Vietnam.

increasing ratings (Up sample) of 13 countries, I find that giant discoveries are associated with a deterioration of sovereign debt ratings in the short-term while they improve them in the medium and long term. In the set of decreasing ratings (Down sample) of 15 countries, I show that giant discoveries have no effect in the short term but have significant negative impacts in the medium and long term. These results point out to the differentiated effects of giant discoveries. These findings are robust to changing control variables and dropping the extreme values of ratings. Moreover, when including the history of past-giant discoveries, I find the evidence of possible learning effects of giant discoveries in countries with increasing sovereign debt ratings. Indeed, past-discoveries' history is positively associated with sovereign debt ratings, which is not the case for countries with decreasing ratings. This result suggests that while some countries have learned from the past, others have remained at least identical, taking the same actions and policies following discoveries.

More interestingly, I analyze why giant discoveries may have differentiated effects on countries. Then, I investigate the effects of giant discoveries on several macroeconomic and institutional variables in the two sets of countries. I show that in countries with improving sovereign debt ratings, on average, over ten years following giant discoveries, giant discoveries are also associated with an increase of tax revenues in percent of GDP, a decrease of public debt, an improvement of financial markets development and total investments, and an enhancement of the government stability index. In contrast, in countries with decreasing ratings following giant discoveries, giant discoveries are associated with a a reduction of total investments, and a deterioration of the institutional quality through a worsening of the corruption's level. My findings call for a careful assessment of the macroeconomic conditions and decisions that governments may undertake in the aftermath of giant discoveries. What seems to matter is not only the resources but also how governments respond to the news of the discovery of those resources. Many countries are about to find giant discoveries; then, if they want to enjoy the benefits of good luck for many years, they need to take the right actions and policies.

The rest of the paper is organized as follows. Section 2.2 describes data and stylized facts. In Section 2.3, I present the methodology. Section 2.4 displays the benchmark results. In Section 2.5, I describe whether my results are robust. Section 2.6 discusses the main transmission channels, and Section 2.7 concludes.

2.2 Data and Stylized facts

2.2.1 Data

This study covers 28 developing and emerging countries over the period 1990-2014.[5][6] This sample is obtained given the availability of data, including in the regression analysis. I use as dependent variable the foreign currency long-term sovereign debt ratings from Kose et al. (2018). This variable captures the market perception of a government's creditworthiness, as established by credit rating agencies, including Standard & Poor's, Moody's, and Fitch Ratings (Afonso et al. 2011; Reusens and Croux 2017). According to Cantor and Packer (2011) and Chen et al. (2016), sovereign debt ratings are defined as an assessment of the relative likelihood that a borrower will default on its obligation. They incorporate a combination of economic, social, and political factors to assess a country's capacity and willingness to honor its current and future debt obligations in full and on time. Its values range from 1, reflecting the worst financial conditions, to 21, reflecting the best financial conditions.[7]

The variable of interest is giant discoveries of oil, natural gas, and minerals. Giant discoveries of oil and gas are from Horn (2011). They define them as a discovery with a recoverable volume of at least 500 million barrels of ultimately recoverable oil equivalent (boe). Giant discoveries of minerals are from Minex Consulting Datasets and encompass the giant and super-giant discoveries, following their definition and criteria.[8] Besides, giant discoveries of natural resources exhibit three essential features worth noting: the relatively significant size, the production lag, and the plausible exogenous timing of discoveries. First, giant discoveries represent a substantial amount of natural resources revenues for a specific country; therefore, they can significantly impact countries' behavior and trajectory. Second, giant oil discoveries do not immediately translate into production. Indeed, there is a significant delay between the announcement of the discovery and the start of the production, four to six years after the discovery, which requires considerable investments. Third, the timing of giant oil discoveries is plausibly exogenous and unpredictable due to the uncertain nature of oil exploration (see, Arezki et al. 2017; Khan et al. 2016). Given that, it is reliable to treat giant discoveries as quasi-natural experience. They can be considered as exogenous shocks with huge macroeconomic and political implications for countries, notably for sovereign debt ratings.

[5] I drop all developed countries from the analysis as they exhibit strong governments' ratings. Moreover, this allows me to increase the homogeneity of the sample. Giant discoveries data are used since 1970 to also account for their long-run effects.

[6] As we will see in the next section, this set of 28 countries can be divided into two groups: (i) countries with increasing ratings following giant discoveries, and (ii) countries with decreasing ratings following giant discoveries.

[7] The different rating categories are reported in table A.2.

[8] The different value of minerals discoveries are reported in table A.3

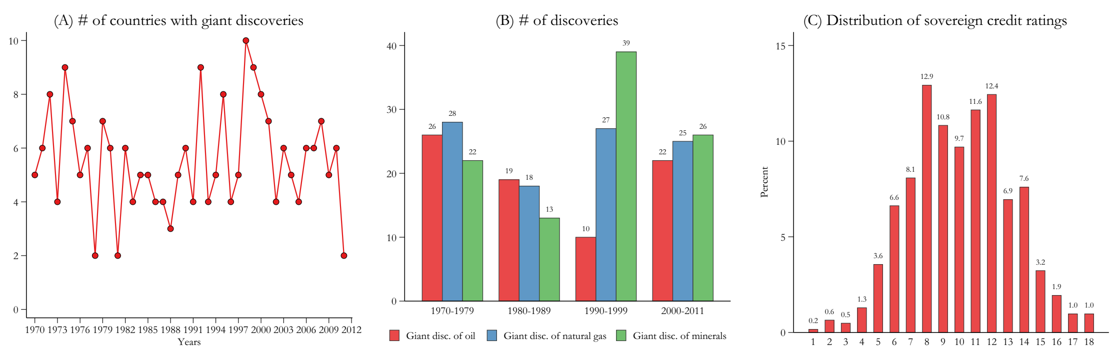
The set of control variables used include macroeconomic, external, and institutional variables critical for sovereign ratings, in line with the literature. All the data and their sources are reported in table A.1, and tables A.4 and A.5 present the summary statistics.

2.2.2 Stylized facts

2.2.2.1 Evolution of giant discoveries and distribution of sovereign debt ratings

I present in fig. D.1 some statistics on giant discoveries and sovereign debt ratings in the set of 28 countries. First, fig. D.1 (A) shows the evolution over time of the number of countries in which giant discoveries were found. In all years, giant discoveries were found in at least two countries. The years where giant discoveries were found in many countries include 1998 (10 countries), 1974, 1992, 1999 (9 countries), and in few countries include 1978, 1981, 2011 (2 countries). Overall, the number of countries where giant discoveries were found follows a downward trend from 1970 to 1988 and 1998 to 2011, and an upward trend from 1988 to 1998. Second, fig. D.1 (B) presents the number of giant discoveries by types of natural resources and by decades. It shows that giant discoveries of oil, natural gas, and minerals have been widespread over decades, concentrated in the 1970s, the 1990s (except for oil), and the 2000s. During the 1980s, they were relatively few discoveries of oil, natural gas, and minerals. Third, fig. D.1 (C) presents the distribution of sovereign debt ratings over the period 1990-2016. It shows that few country-year observations had a rating located in the tails of the distribution, namely the categories of default (1-2), high default risk (3-5), strong payment capacity (15-17), and high credit quality (18). They were concentrated in the middle categories, namely high speculative (6-8), speculative (9-11), and adequate payment capacity (12-14).

Figure 2.1: Giant discoveries and sovereign debt ratings



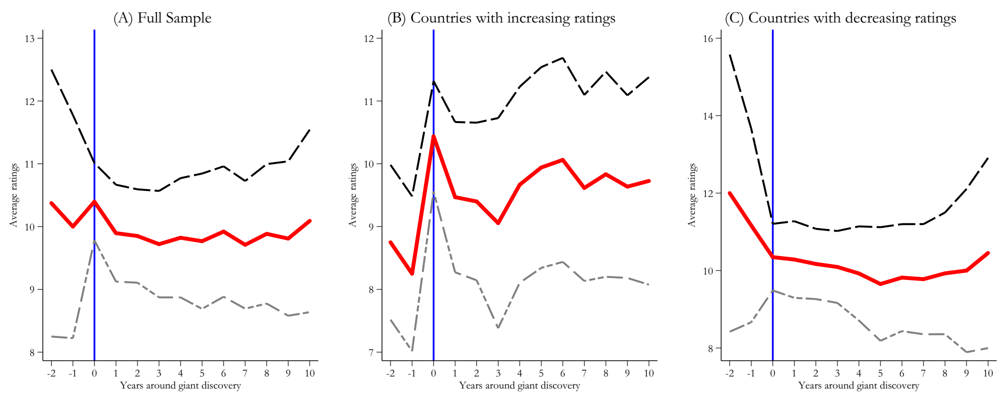
Notes: Panel (A) shows the evolution of countries in which giant discoveries were found over time. Panel (B) presents the number of giant discoveries by types of natural resources and by decades. Panel (C) plots the distribution of sovereign debt ratings over the period 1990-2010.

2.2.2.2 Evolution of sovereign debt ratings following giant discoveries, and justification of sample's subdivision

As noted in section 2.1, giant discoveries can have both a positive and negative effect on sovereign debt ratings. Therefore, I look at the evolution of sovereign debt ratings following giant discoveries for each of the 28 countries. I report the findings for eight countries in fig. A.1 as an illustration. One can notice that sovereign debt ratings increase in the aftermath of giant discoveries for India, Peru, the Philippines, and Romania (Panel A) while they decrease for Egypt, Colombia, South Africa, and Venezuela (Panel B). This sustains that giant discoveries may have differentiated effects in different countries. Based on the graphical analysis, I identify two groups of countries: (i) 13 countries with increasing sovereign debt ratings following giant discoveries (Bolivia, Brazil, China, Ecuador, India, Indonesia, Kazakhstan, Mongolia, Pakistan, Peru, Philippines, Romania, Turkey), denominated hereafter as "Up sample"; and (ii) 15 countries with decreasing sovereign debt ratings following giant discoveries (Argentina, Azerbaijan, Colombia, Egypt, Ghana, Guatemala, Mexico, Mozambique, Malaysia, Russia, South Africa, Thailand, Turkmenistan, Venezuela, Vietnam), denominated hereafter as "Down sample ".[9] In fig. D.2, I plot the average dynamics of sovereign debt ratings from 2 years before giant discoveries to up to 10 years after the discoveries for the full sample (Panel A), the Up sample (Panel B), and the Down sample (Panel C). In the full sample, sovereign debt ratings tend to moderately decrease in the aftermath of giant discoveries and remain around 10. In the up sample, sovereign debt ratings are around 8 the year before the giant discoveries, jump to more than 10 and remains close to this level in the aftermath of giant discoveries. In the Down sample, sovereign debt ratings are around 12 before giant discoveries, fall to approximately 10, and remain close to this level in the aftermath of giant discoveries. Given that, I employ in the next section a more comprehensive methodology to explain the effects of giant discoveries on sovereign debt ratings after controlling for other determinants. Throughout the paper, I will present the results for the full sample and the two sets of up and down samples.

[9]This subdivision is also supported by empirical tests. First, I include a dummy Updown taking the value of one if the country belongs to the set of Up countries and zero if it belongs to the set of Down countries. This dummy is significant, which shows that the level of sovereign ratings is different across the two subsamples. Second and more importantly, I interact this dummy Updown with the dummy of giant discoveries. I also include these dummies in the regressions. Here also, the interactive term is significant, which supports the differentiated effects of giant discoveries across the two subsamples. The results are available upon request. In the rest of the paper, I apply my model on the two subsamples Up and Down to account for not only for the differentiated effects of giant discoveries, but also for the differentiated effects of covariates, between the two subsamples.

Figure 2.2: Evolution path of rating around the moment of giant discoveries



Notes: This figure shows the dynamics of sovereign debt ratings from 2 years before giant discoveries to up to 10 years after for the full sample (Panel A), the up sample (Panel B, countries with increasing ratings), and the Down sample (Panel C, countries with decreasing ratings).

2.2.3 Differences in characteristics between countries in up and down samples

In table A.5, I report the difference in characteristics between countries in the up and down samples. First, it reveals that these two countries' groups have no significant differences in terms of giant discoveries, history of giant discoveries, history of default, reserves, current account balance, exchange rate, and financial openness. Second, sovereign debt ratings, natural resources rents, the volatility of growth, and quality of institutions (ICRG index, political rights index, internal conflicts index) are, on average lower in the up sample than in the down sample. Third, the level of development (real GDP), total investments, and public debt are higher in the up sample compared to the down sample. These findings suggest that while the two sets of countries have some common characteristics, they are also different for many other variables. Therefore, I control for all these characteristics in the regression analysis.

2.3 Methodology

My empirical strategy follows closely Afonso et al. (2009); Depken et al. (2011); Erdem and Varli (2014) and Teixeira et al. (2018). Given the nature of the sovereign debt ratings used as a dependent, I employ a random effects ordered probit model and assume that rating agencies make a continuous evaluation of a country's creditworthiness, embodied in an unobserved latent variable $R^*_{i,t}$. Therefore, the model can be specified as follows

$$R^*_{i,t} = \alpha_0 + \beta^T D_i^T + X_{i,t-1}\theta + \sigma_t + \alpha_i + \varepsilon_{i,t} \tag{2.1}$$

where, $R_{i,t}$ is sovereign debt ratings with different cut-off points μ_i. Indeed, while random effects assume that the disturbances μ_i are independent across time, and are not correlated with the explanatory variables, fixed-effects contrarily assume possible correlation with explanatory variables. However, the latter model presents some issues since it fails estimating time-invariant covariates coefficients, and also is limited by the incidental parameters problem. (Wooldridge 2019). In this context, I apply the Hausman test to choose the more appropriate model between fixed effect and random effect models. I obtain a negative statistic, [10] and I follow Greene (2005) chap.9 to interpret this result. He shows that in the presence of a negative statistic, we cannot reject the random effects model. Consequently, I use in this paper the random effects ordered Probit model, which seems to be the most convenient way to make this analysis, and which is also the most widely used in the literature on the analysis of the determinants of sovereign debt ratings.

D_i^T is a dummy that takes the value one over a specified horizon T following the giant discoveries and zero otherwise. I consider five different horizons to capture the effects in the short-, medium-, and long-run: (i) from the year of discovery to up to 2 years after, (ii) between 3 and 5 years after the discovery, (iii) from the year of discovery to up to 5 years after, (iv) between 6 and 10 years after the discovery, and (v) from the year of discovery to up to 10 years after. Therefore, the effects of giant discoveries on sovereign debt ratings over the different horizons T is captured by the coefficients β^T. I expect β^T to vary over the different horizons T, in line with Arezki et al. (2017); Khan et al. (2016), and across the different sets of samples (full, up, and down samples). $X_{i,t-1}$ is a set of control variables comprising macroeconomic, external, and institutional determinants of sovereign debt ratings, included with a one-year lag to limit reverse causality issues. σ_t describes time fixed effects capturing the common shocks affecting countries like the global financial crisis of 2008-09. α_i is the country-specific effect and $\varepsilon_{i,t}$ is the idiosyncratic error term.[11] [12] α_0 is an intercept. Given the specification, I assume that the probabilities for each level of sovereign debt ratings follow a normal distribution, which allows calculating the different cut-off points μ_i of the latent variables $R^*_{i,t}$ described as follows

[10] which could be due to the small sample of our study, according to Mora (2006)

[11] α_i and $\varepsilon_{i,t}$ constitute the random effects.

[12] To capture the possible differences in terms of ratings across regions, I also include regional dummies (Africa, Asia, Latin America) in the analysis. These dummies are not significant; hence they are excluded from the analysis.

$$R_{i,t} = \begin{cases} 1 & \text{if } R^*_{i,t} \leq \mu_1 \\ 2 & \text{if } \mu_1 < R^*_{i,t} \leq \mu_2 \\ 3 & \text{if } \mu_2 < R^*_{i,t} \leq \mu_3 \\ \vdots & \\ 18 & \text{if } \mu_{17} < R^*_{i,t} \end{cases} \tag{2.2}$$

I use log-likelihood maximization to estimate the parameters and cut-off points of the item i). Following Cantor and Packer (2011); Bissoondoyal-Bheenick (2005); Mellios and Paget-Blanc (2006); Depken et al. (2011); Afonso et al. (2011); Hilscher and Nosbusch (2010) and Erdem and Varli (2014), I use a set of control variables $X_{i,t-1}$, macroeconomic variables: (i) natural resources rents, (ii) log of real GDP, (iii) volatility of growth, (iv) total investments, (v) public debt, and (vi) history of default; external variables: (vi) international reserves, (vii) current account balance, (viii) log. of exchange rate, and (ix) financial openness index; and an institutional variable: (xi) ICRG index.

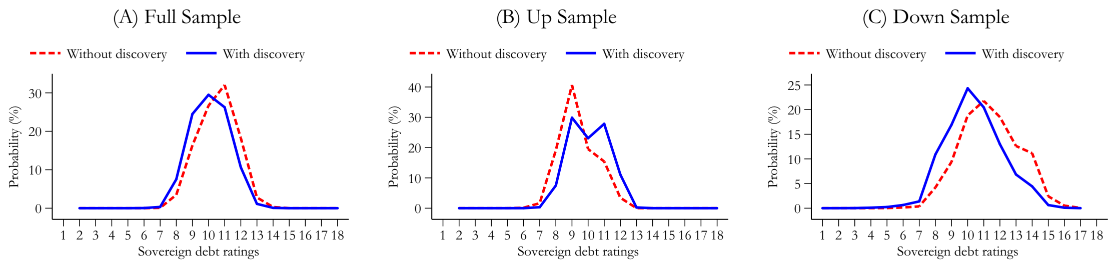
2.4 Results

In this section, I discuss the benchmark results. I first discuss the effects of giant discoveries on sovereign debt ratings for the full sample (see, table 2.1) before turning to the differentiated effects in the up (see, table 2.2) and down (see, table 2.3) samples. For each sample of countries, I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: from the year of discovery to up to 2 years after (column 1), between 3 and 5 years after the discovery (column 2), from the year of discovery to up to 5 years after (column 3), between 6 and 10 years after the discovery (column 4), and from the year of discovery to up to 10 years after (column 5). I also report for each sample, the predicted probabilities for each level of sovereign ratings over the 10 years following giant discoveries and periods with no giant discoveries in table A.7, in order to quantify the results. The fig. D.3 displays them graphically. [13] [14]

[13] The following results show that the information criteria (AIC, BIC) are lower in the up and down samples compared to the full sample, and the log-likelihoods for regressions are higher in the up and down samples compared to the full sample. These findings show that the choice of splitting the results across the up and down samples instead of the full sample is improving the specifications and the results.

[14] In table A.6, the results without control variables are reported. It generally leads to similar results than the results found when control are added.

Figure 2.3: Predicted probabilities of sovereign debt ratings



Notes: This figures plots the predicted probabilities for each level of sovereign ratings in the 10 years following giant discoveries (blue and solid lines) and in periods with no giant discoveries (dashed and red lines), based on columns 5 of table 2.1 (Panel A), table 2.2 (Panel B) table 2.3 (Panel C).

2.4.1 Effects of giant discoveries in the full sample

In the full sample of 28 countries (see, table 2.1), I find that giant discoveries have no significant effect on sovereign debt ratings over the 2 years (column 1), from the year 3 to up to 5 years (column 2), and the year 6 to up to 10 years (column 4), following the discoveries. However, this effect is negative and significant over the 5 (column 3) and 10 (column 5) years following the discoveries. As found by Arezki et al. (2017) and Khan et al. (2016) for other variables, this finding suggests that it may take some time to have significant effects of giant discoveries on sovereign debt ratings, in line with the delay in the production of the resources. Moreover, this could reflect that the financial markets fail to anticipate the effects of giant discoveries on sovereign ratings in the short run.

As the coefficients cannot be interpreted, I plot the probabilities associated with each level of sovereign debt ratings in the 10 years following discoveries and periods without discoveries in fig. D.3 (A), based on column 5 of table 2.1. It reveals that the probability of having a rating inferior or equal to 10 (bad ratings) is higher when countries have giant discoveries than do not. In contrast, the likelihood of having a rating superior or equal to 11 (good ratings) is lower when countries have giant discoveries than do not. For instance, the probability of having a rating of 9 (speculative) is 24.5% in countries with giant discoveries, while it is 16.3% in countries without giant discoveries. The probability of having a rating of 12 (adequate payment capacity) is 10.7% in countries with giant discoveries, while it is 18.3% in countries without giant discoveries. This shows that having a giant discovery downgrades the probabilities of having relatively good ratings in the 10 years following the discoveries.

Table 2.1: Benchmark results for Full sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.067	-0.122	-0.205*	-0.040	-0.389***
	(0.112)	(0.111)	(0.116)	(0.119)	(0.147)
Natural ressources rents, one-year lag	-0.038***	-0.037***	-0.038***	-0.037***	-0.036**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log of real GDP, one-year lag	0.571***	0.567***	0.585***	0.563***	0.582***
	(0.200)	(0.201)	(0.202)	(0.200)	(0.202)
Volatility of growth, one-year lag	-0.105**	-0.105**	-0.099**	-0.107**	-0.093**
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Total investments, one-year lag	0.067***	0.067***	0.069***	0.067***	0.073***
	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)
Public debt, one-year lag	-0.025***	-0.025***	-0.025***	-0.026***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
History of default, one-year lag	-0.794***	-0.769***	-0.796***	-0.783***	-0.811***
	(0.205)	(0.205)	(0.205)	(0.204)	(0.205)
Reserves, one-year lag	0.055***	0.054***	0.055***	0.054***	0.054***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Current account balance, one-year lag	0.004	0.005	0.004	0.005	0.006
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Log of exchange rate (LCU / $US), one-year lag	0.216***	0.219***	0.222***	0.215***	0.223***
	(0.042)	(0.042)	(0.043)	(0.042)	(0.043)
Financial openness index, one-year lag	1.979***	1.999***	2.014***	1.972***	1.979***
	(0.270)	(0.270)	(0.271)	(0.270)	(0.270)
ICRG index, one-year lag	4.192***	4.233***	4.336***	4.174***	4.503***
	(0.720)	(0.722)	(0.726)	(0.719)	(0.731)
Constant	2.793***	2.837***	2.853***	2.794***	2.870***
	(0.862)	(0.875)	(0.878)	(0.863)	(0.883)
Observations	567	567	567	567	567
AIC	1900.4	1899.6	1897.6	1900.7	1893.7
BIC	2139.1	2138.3	2136.3	2139.4	2132.5
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-895.2	-894.8	-893.8	-895.3	-891.9

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the availability of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

2.4.2 Effects of giant discoveries in the up sample

In the up sample of 13 countries (see, table 2.2), I find that giant discoveries are negatively associated with sovereign debt ratings the first two years following discoveries and have no significant effects from the year 3 to up to 5 years, and over the five years, following the discoveries. From year 6 to up to 10 years and over the 10 years following the discoveries, the effects are positive and significant, confirming the stylized facts in section 2.2.2. This finding shows that after controlling for other determinants of sovereign ratings, giant discoveries significantly increase sovereign debt ratings in the long run for some countries.

Table 2.2: Benchmark results for Up sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.447**	0.264	-0.119	0.539***	0.609***
	(0.200)	(0.181)	(0.196)	(0.191)	(0.228)
Natural ressources rents, one-year lag	-0.062***	-0.063***	-0.063***	-0.068***	-0.070***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Log of real GDP, one-year lag	1.131***	1.071***	1.084***	1.159***	1.089***
	(0.353)	(0.350)	(0.355)	(0.363)	(0.358)
Volatility of growth, one-year lag	-0.276***	-0.317***	-0.309***	-0.298***	-0.349***
	(0.074)	(0.071)	(0.073)	(0.072)	(0.072)
Total investments, one-year lag	0.066**	0.060*	0.066**	0.051	0.038
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
Public debt, one-year lag	-0.025***	-0.025***	-0.024***	-0.023***	-0.024***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
History of default, one-year lag	-0.571	-0.521	-0.457	-0.457	-0.450
	(0.362)	(0.361)	(0.359)	(0.363)	(0.364)
Reserves, one-year lag	0.023	0.025*	0.023	0.023	0.026*
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Current account balance, one-year lag	-0.012	-0.016	-0.013	-0.013	-0.020
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Log of exchange rate (LCU / $US), one-year lag	0.332***	0.318***	0.334***	0.341***	0.313***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.058)
Financial openness index, one-year lag	2.050***	2.005***	1.912***	2.174***	2.232***
	(0.509)	(0.508)	(0.505)	(0.516)	(0.520)
ICRG index, one-year lag	5.707***	5.452***	5.613***	5.621***	5.213***
	(0.921)	(0.917)	(0.925)	(0.919)	(0.924)
Constant	4.890**	4.818**	4.962**	5.209**	5.097**
	(2.155)	(2.127)	(2.188)	(2.296)	(2.249)
Observations	274	274	274	274	274
AIC	876.4	879.3	881.1	873.4	874.3
BIC	1071.6	1074.4	1076.2	1068.5	1069.4
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-384.2	-385.7	-386.5	-382.7	-383.1

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

The probabilities associated with each level of sovereign debt ratings in the 10 years following discoveries and periods without discoveries in fig. D.3 (B), based on column 5 of table 2.2. This chart shows that the probability of having a rating inferior or equal to 10 (bad ratings) is lower when countries have giant discoveries than do not. However, the likelihood of having a rating superior or equal to 11 (good ratings) is higher when countries have giant discoveries than do not. For instance, the probability of having a rating of 9 (speculative) is 29.9% in countries with giant discoveries, while it is 40.7% in countries without giant discoveries. The probability of having a rating of 12 (adequate payment capacity) is 11.1% in countries with giant discoveries, while it is 3.4% in countries without giant discoveries. This finding is opposite to what I found in the full sample, which falls short of capturing the differentiated effects. Next, I further investigate the effects of giant discoveries in the sample of down countries.

2.4.3 Effects of giant discoveries in the down sample

In the down sample of 15 countries (see, table 2.3), I find that giant discoveries have no significant effect on sovereign debt ratings over the 2 and 5 years following the discoveries. However, the effect is significant and negative for the horizons, from the year 3 to up to 5 years, from the year 6 to up to 10 years, and over the 10 years, following the discoveries. Therefore, the long-run results are like what is found in the full sample and contrary to what is found in the up sample, in line with the stylized facts in section 2.2.2. This finding shows that after controlling for other determinants of sovereign ratings, giant discoveries significantly decrease sovereign debt ratings in the long run for some countries.

The probabilities associated with each level of sovereign debt ratings in the 10 years following discoveries and periods without discoveries in fig. D.3 (C), based on column 5 of table 2.3. This figure shows that the probability of having a rating inferior or equal to 10 (bad ratings) is higher when countries have giant discoveries than do not. However, the likelihood of having a rating superior or equal to 11 (good ratings) is lower when countries have giant discoveries than do not. For instance, the probability of having a rating of 9 (speculative) is 16.9% in countries with giant discoveries, while it is 9.4% in countries without giant discoveries. The probability of having a rating of 12 (adequate payment capacity) is 13% in countries with giant discoveries, while it is 18.5% in countries without giant discoveries.

2.4.4 Effects of control variables

Besides, I provide some interpretations of the control variables. I find that total investments, international reserves, financial openness, and ICRG are consistently positively associated with sovereign debt ratings across all samples. Also, the log. of real GDP and the log. of the exchange rate (+ means depreciation) are positively associated with ratings in the full and up samples. The current account has a positive effect on the down sample. However, public debt has a significant and negative effect on ratings, which is consistent across samples, natural resource rents and volatility of growth are negatively associated with ratings in the full and up samples, and history of default has a significant and negative effect on ratings in the full and down sample. In sum, these findings confirm the results found in the literature (Cantor and Packer 2011; Bissoondoyal-Bheenick 2005; Mellios and Paget-Blanc 2006; Depken et al. 2011; Afonso et al. 2011; Hilscher and Nosbusch 2010; Erdem and Varli 2014).

Table 2.3: Benchmark results for Down sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	0.231	-0.458***	-0.259	-0.292*	-1.037***
	(0.154)	(0.155)	(0.166)	(0.174)	(0.236)
Natural ressources rents, one-year lag	-0.002	0.001	-0.004	-0.006	-0.004
	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Log of real GDP, one-year lag	0.320	0.330	0.341	0.310	0.287
	(0.309)	(0.318)	(0.310)	(0.309)	(0.336)
Volatility of growth, one-year lag	0.056	0.069	0.052	0.055	0.084
	(0.059)	(0.059)	(0.059)	(0.058)	(0.060)
Total investments, one-year lag	0.121***	0.126***	0.126***	0.121***	0.132***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Public debt, one-year lag	-0.025***	-0.024***	-0.025***	-0.026***	-0.026***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
History of default, one-year lag	-1.064***	-1.054***	-1.085***	-1.091***	-1.135***
	(0.301)	(0.304)	(0.302)	(0.300)	(0.308)
Reserves, one-year lag	0.093***	0.097***	0.097***	0.091***	0.097***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Current account balance, one-year lag	0.025*	0.024*	0.023*	0.026*	0.027**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
Log of exchange rate (LCU / $US), one-year lag	0.125	0.127	0.108	0.122	0.126
	(0.121)	(0.124)	(0.122)	(0.121)	(0.129)
Financial openness index, one-year lag	1.967***	2.128***	2.052***	1.959***	2.306***
	(0.363)	(0.370)	(0.368)	(0.363)	(0.375)
ICRG index, one-year lag	2.816*	3.017*	2.592	2.704	2.931*
	(1.654)	(1.659)	(1.644)	(1.647)	(1.664)
Constant	2.113**	2.291**	2.168**	2.082**	2.491**
	(0.989)	(1.067)	(1.010)	(0.980)	(1.183)
Observations	293	293	293	293	293
AIC	982.6	976.2	982.4	982.1	965.3
BIC	1181.4	1174.9	1181.2	1180.8	1164.0
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-437.3	-434.1	-437.2	-437.0	-428.6

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

Overall, our benchmark findings reveal that the effects of giant discoveries on sovereign debt ratings are neither systemically positive nor negative. They show that many countries will experience a deterioration of their financial conditions in the years following giant discoveries while others will enjoy an improvement. As we will see in section 2.6, what matters for the effects of giant discoveries is the responses of governments to the news of giant discoveries.

2.5 Robustness checks

In this section, I check the robustness of my benchmark findings. First, I use an alternative methodology, the correlated random effects, which is a model that unifies the traditional random and fixed effects estimators and overcome each of their limits. Second, I include as regressors the history of giant discoveries. It is the sum of past discoveries since 1970 at a time of a new discovery. This variable will capture the learning effects. I assume that countries with a past history of giant discoveries have learned how to use and manage them better. Then, it will also explain the differentiated effects of giant discoveries on sovereign debt ratings. Third, I use other institutional and conflict variables, including political rights and internal conflicts, instead of the ICRG index, to capture the effects of institutions' quality and, more importantly, of conflicts. Indeed, as pointed out by Lei and Michaels (2014) and Tsui (2011), giant discoveries are associated with an increase of armed conflicts and a change of institutional framework towards autocracy. Fourth, I check the sensitivity of my results by dropping extreme values in sovereign debt ratings.

2.5.1 Alternative methodology: Correlated Random Effects

As we described in the methodology section, both random effects and fixed-effects models present some limits, including respectively the strong assumption of the independence between error terms and regressors for the former, and the incidental parameters problem, and the failing in estimating time-invariant covariates coefficients for the latter. In order to solve this issue, we follow Mundlak (1978), Allison (2009), and Wooldridge (2010) who propose the Correlated Random Effects (CRE). CRE unifies the traditional random and fixed effect models, and consists firstly to add time-average of the independent variable as additional time-invariant regressors, in order to deal with possible problem of correlation between errors terms and regressors; and secondly to add the average of the explanatory or control variables as supplementary variables.

$$R^*_{i,t} = \alpha_0 + \beta^T D_i^T + \overline{D_i} + X_{i,t-1}\theta + \overline{X_{i,t-1}} + \sigma_t + \alpha_i + \varepsilon_{i,t} \tag{2.3}$$

By using this alternative methodology, the results reported in table A.8 are still qualitatively and quantitatively robust [15].

[15] For the Correlated Random Effects' methodology, only results for the full sample are reported. The results for the "Up" and "Down" samples are available upon request.

2.5.2 History of giant discoveries

The results when the history of giant discoveries is included as additional covariate in the model in tables A.9 to A.11, for the full, up, and down samples, respectively. They show that the history of giant discoveries has a positive and significant effect on sovereign debt ratings in full and up samples. In contrast, it has no significant impact on the down sample. This finding sustains the presence of learning effects in the full and up samples. Giant natural resources discoveries worldwide have generally led first to jubilation, and more often turned into disappointments. The jubilation ends because of economic imprudence and bad luck: profligate spending, heavy borrowing, oil price bust. Countries that have gone through this process often have learned how to manage their resources well to prevent them from losing access to capital markets. Nevertheless, the learning effects are not a panacea since I find that in countries with decreasing ratings, the history of giant discoveries has no significant impact on sovereign debt ratings. Moreover, our benchmark findings on the effects of new giant discoveries remain valid. They have negative and significant effects on sovereign debt ratings in the full and down samples, and a positive effect in the up sample.

2.5.3 Controlling for political rights and internal conflicts

The results where the ICRG index is substituted by the political rights index and internal conflicts index are reported in tables A.12 to A.14, for the full, up, and down samples, respectively. They indicate the robustness of the benchmark findings. Giant discoveries induce a decrease of sovereign debt ratings in the full and down samples over the long run, sometimes over the medium-term. In contrast, they have a positive effect on the up sample over the long run. Besides, I find that internal conflicts are positively associated with sovereign ratings in the full and up samples, showing that the absence of internal conflicts favors an increase of sovereign debt ratings. However, political rights have no significant effects on ratings.

2.5.4 Dropping country-year observations in the top 5% and bottom 5% of sovereign debt ratings

The results where country-year observations in the top 5% and bottom 5% of sovereign debt ratings are dropped out in the analysis are reported in tables A.15 to A.17, for the full, up, and down samples, respectively. I do so to reduce the influence of outliers with very high and low sovereign ratings. Extreme values of sovereign debt ratings do not drive the results; they are quite robust both qualitatively and quantitatively.

2.6 Transmission channels

I have shown that giant discoveries have a differentiated effect on sovereign debt ratings in different sets of countries. While some countries may experience an improvement in their financial conditions in the aftermath of giant discoveries, others may experience a deterioration. These differentiated effects depend on the behavior of many macroeconomic and political indicators resulting from the actions and policies taken in the discoveries' aftermath. What seems to matter is not only the resources but also how authorities respond to the news of the discovery of those resources. Therefore, I employ several intermediary variables, also known as critical for sovereign debt ratings.

The differentiated effects could come from differences in the reaction of tax resources, public debt, development of financial markets, total investment (private and public), and quality of institutions including high government stability and low level of corruption. These variables will allow me to capture the indirect effects of giant discoveries going through other determinants of sovereign debt ratings, consequently, highlighting possible transmissions channels. To shed light on the transmission channels, I estimate for each sample (full, up, and down), a panel fixed-effects model described as follows.[16]

$$X_{i,t} = \alpha_0 + \beta^T D_i^T + Z_{i,t}\theta + \alpha_i + \sigma_t + time_i + \varepsilon_{i,t} \tag{2.4}$$

where $X_{i,t}$ represents the dependent variable used as a channel, including tax resources, public debt, development of financial markets index, the total investment (private and public), and quality of institutions including high government stability and low level of corruption. D_i^T is a dummy that takes the value one over a specified horizon T following the giant discoveries and zero otherwise. As the effect of giant discoveries on sovereign debt ratings is consistently obtained over the long-run, I focus on the effects of giant discoveries on intermediary variables over the 10 years following discoveries.[17] $Z_{i,t}$ is the set of control variables including the history of default and output gap calculated using an HP filter on the log. of real GDP. I also use country-fixed effects α_i to control for time-invariants factors and unobserved heterogeneity, time-fixed effects σ_t to capture common shocks affecting countries, and country-specific time trend $time_i$ to capture the specific trend evolution of each intermediary variable. α_0 is an intercept and $\varepsilon_{i,t}$ is the idiosyncratic error term. By estimating these models on the full, up, and down samples, separately, I can capture the different responses of intermediary variables in each sample. The results are reported in table A.18.

[16] Driscoll and Kraay (1998) robust standard errors are used to correct for the heteroskedasticity, the serial correlation, and the contemporaneous correlation of error terms.

[17] The results for the other horizons can be obtained upon request

2.6.1 Tax resources

According to the Government Financial Statistics Manual (IMF), tax resources is the dominant share of revenue for many governments. It is composed of compulsory transfers including penalties, fines, and excludes social security contributions. This variable is critical since it has been found by Cantor and Packer (2011) and Mellios and Paget-Blanc (2006) that the greater the potential tax base of the borrowing country, the greater the ability of a government to repay debt. In addition, according to Akitoby and Stratmann (2008), tax-financed spending tend to lower spreads of interest rate and then improves sovereign debt ratings. In this study, we find that giant discoveries increase the tax resources in Up sample ten years after the discoveries while the effect is non significant in the Down sample. This result is in line with Abdelwahed (2020) who find, using 46 developed and developing countries, that giant discoveries lead to higher tax collection, which effect is attributed to increased effort on income taxes and international trade especially in developing countries. Then, the positive effect of giant discoveries on sovereign debt rating in Up sample could translate through the increasing level of tax resources in the years following the discoveries.

2.6.2 Public debt

The results in table A.18 show that giant discoveries are associated with a decrease of public debt in the up sample over 10 years while they have no significant effect in the full and down samples. In the down sample, the effect while non-significant, is positive, showing that some countries could have increased public debt the years following discoveries. Recalling that in the benchmark findings I found that an increase of public debt is strongly and negatively associated with sovereign debt ratings in each sample (in line with Cantor and Packer 2011; Mellios and Paget-Blanc 2006; Afonso et al. 2009; Teixeira et al. 2018), this finding suggests that giant discoveries lead to differentiated effects in the up and down samples of countries because of its differentiated effects on public debt. In some countries, debt is reduced following discoveries, and they have a positive effect on sovereign debt ratings (up sample); in others, debt increases even if it is non-significant, and discoveries have a negative effect (down sample). This result shows that the reaction of countries *vis-à-vis* debt and borrowing following the discoveries matter for the effects of discoveries on ratings, the years following this shock.

2.6.3 Development of financial markets

Financial markets is a sub-index of the aggregated financial development index developed by the IMF (Svirydzenka 2016). The financial markets index includes stock and bond markets, and aims at capturing the key features of financial systems, for instance how deep, accessible and efficient are the financial markets.[18] Since it has been found by Andreasen and Valenzuela (2016) that financially integrated countries with the rest of the world are positively evaluated by credit rating agencies, it appears important to analyze whether the development of financial markets could be a channel in this study. Then, we find that giant discoveries increase the development of financial market index in Up sample, but the effect is non significant in Down sample. Therefore, we can confirm that the high level of financial markets in Up sample compared to the Down sample, in the ten years following giant discoveries, is a potential channel transmission of the improvement of rating in these countries as described by Andreasen and Valenzuela (2016).

2.6.4 Total investments

The findings in table A.18 suggest that giant discoveries induce an increase of total investments in the up sample over 10 years while they have a negative and significant effect in the down sample. Recalling that I find that total investments are positively associated with sovereign debt ratings across all samples in the benchmark results (see, Afonso et al. 2011; Arezki et al. 2017; Mellios and Paget-Blanc 2006; Teixeira et al. 2018), these findings show that giant discoveries, when associated with an increase of investments, induce an improvement of financial conditions, however, when associated with a decrease of investments induce a deterioration of financial conditions. Therefore, investments are a possible channel through which giant discoveries affect sovereign debt ratings.

2.6.5 Quality of institutions: high governmental stability and low level of corruption

The quality of institutions is one of the most important determinants of the access to international financial markets, and is critical for sovereign debt ratings (Mellios and Paget-Blanc 2006; Depken et al. 2011; Erdem and Varli 2014; Teixeira et al. 2018). In order to test whether the results could translate through the institutions, I use two institutional variables including the government stability index and the corruption index from ICRG. Government stability index assesses both the government's ability to carry out its declared programs, and its ability to stay in office. Corruption index assesses the corruption level within the political system. The highest level of each of the index reveals lowest risk in the country. In table A.18, I find firstly that giant discoveries increase the government stability in Up sample while the effect is non significant in the Down sample. Secondly, giant discoveries deteriorate significantly the level of corruption

[18] For more details on the components of the financial markets index, see Svirydzenka (2016).

in the aftermath of discoveries in the Down sample while the effect is non significant in Up sample. These results in line with the literature of Tsui (2011) explaining the negative impacts on institutions in poor countries, reveal well how the quality of institutions could be an important transmission channel.

To sum up, this section shows that beyond the differentiated direct effects of giant discoveries found in the benchmark results, giant discoveries also may have differentiated effects through several channels including tax resources, public debt, development of financial markets, total investment, and quality of institutions. Consequently, the differentiated effects of giant discoveries on sovereign debt ratings also depend on the behavior of some macroeconomic and institutional indicators resulting from the actions and policies taken in the discoveries' aftermath. What seems to matter is not only the resources but also how authorities respond to the news of the discovery of those resources.

2.7 Conclusion

In this paper, I shed light on the effects of giant discoveries of natural resources (oil, natural gas, minerals) on sovereign debt ratings in the short- and long-run, which have been overlooked by the literature. Specifically, I show evidence of the differentiated effects of giant discoveries in different countries. To do so, I use a sample of 28 developing and emerging countries, divided into two sets of countries: countries with increasing ratings in the aftermath of giant discoveries (up sample) and decreasing ratings in the aftermath of giant discoveries (down sample), over the period 1990-2014. I further apply a random effect ordered probit models on the full, up, and down samples to check the assumptions that countries may experience a differentiated effect of giant discoveries on their sovereign debt ratings. After controlling for several determinants of sovereign debt ratings, I find that giant discoveries generate differentiated effects, in which some countries experience an improvement of their sovereign ratings while others experience a deterioration of financial conditions. This result shows that the outcome of giant discoveries on ratings is sensitive to the group of countries studied. I also find the evidence of possible learning effects of giant discoveries in countries with increasing sovereign debt ratings, as the history of past discoveries is positively associated with sovereign debt ratings, which is not the case for countries with decreasing ratings. This suggests that while some countries have learned from the past, others have remained at least identical or worse, taking on more often irrelevant actions and policies, the years following discoveries.

More importantly, I show that these differentiated effects depend on the behavior of several macroeconomic and political indicators resulting from the actions and policies taken in the aftermath of the discoveries. I find that giant discoveries also have differentiated effects through some channels, including tax resources, public debt, development of financial markets, total investment, and quality of institutions.

Overall, this paper reveals that giant discoveries are good predictors of sovereign debt ratings and that ratings' agencies and governments should pay attention to them. Also, what seems to matter is not only the resources but also how governments respond to the news of the discovery of those resources. Therefore, taking the right actions and policies, having better management of natural resources, will help countries prevent a deterioration of their financial conditions and increase their access to international capital markets.

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APPENDIX

A

APPENDIX TO CHAPTER 2

A.1 Data and sample

A.1.1 Data description and sources

Table A.1: Variables and their sources

Variables	Nature	Sources
Dependent variable		
Foreign currency long term sovereign debt ratings	Ordinal	Kose et al. (2018)
Giant discoveries data		
Giant discovery of natural resources	Binary	Horn (2011), Minex Consulting Database
History past giant discoveries	Categorical	Author's calculations based on Horn and Minex Consulting Databases
Control variables		
Macroeconomic variables		
Natural resources rents (% of GDP)	Continuous	WDI
Log. of real GDP	Continuous	WDI
Volatility of growth (standard deviation of past-10 years growth)	Continuous	Author's calculations based WDI database
Total investments (% of GDP)	Continuous	IMF Investment and Capital Stock dataset 1960-2015
Public debt (% of GDP)	Continuous	Mbaye et al. (2018) - IMF
History of default crisis	Categorical	Author's calculations based on Reinhart and Rogoff (2014)
External variables		
International reserves (% of GDP)	Continuous	WDI
Current account balance (% of GDP)	Continuous	WDI
Log of exchange rate (LCU/ US$)	Continuous	IFS , 2018 (IMF)
Financial openness index	Continuous	Chinn and Ito (2008)
Institutional variables		
ICRG index score between 0 and 1	Continuous	ICRG
Political rights index	Ordinal	Freedom House dataset
Internal conflicts index	Continuous	ICRG

A.1.2 List of countries

Countries with increasing ratings (Up sample)

Bolivia, Brazil, China, Ecuador, India, Indonesia, Kazakhstan, Mongolia, Pakistan, Peru, Philippines, Romania, Turkey.

Countries with decreasing ratings (Down sample)

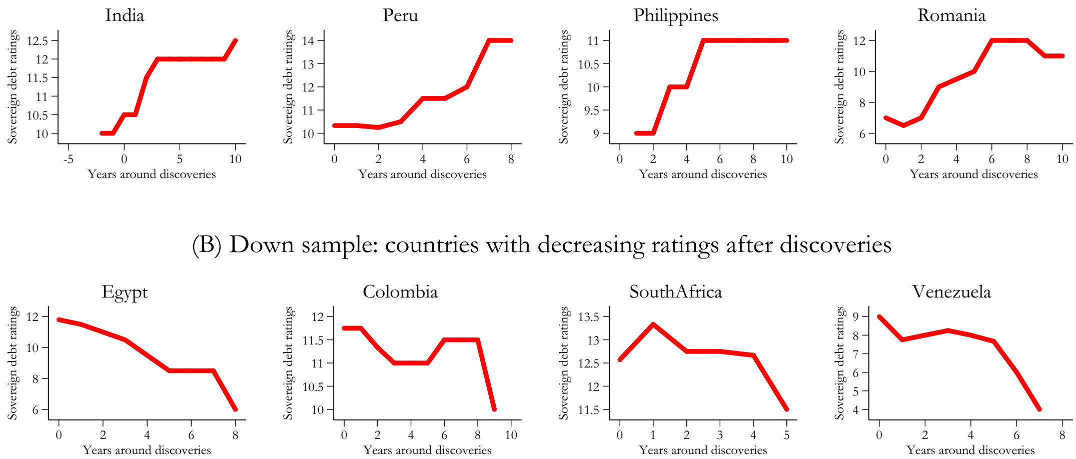
Argentina, Azerbaijan, Colombia, Egypt, Ghana, Guatemala, Mexico, Mozambique, Malaysia, Russia, South Africa, Thailand, Turkmenistan, Venezuela, Vietnam.

A.2 Supplementary tables and graphs

A.2.1 Illustration of the differentiated effects of giant discoveries on sovereign debt ratings

Figure A.1: Trend evolution of rating around the time of giant discoveries

(A) Up sample: countries with increasing ratings after discoveries



A.2.2 Numerical conversion of sovereign debt ratings

A.2.3 Size and value of discoveries of minerals from Minex Consulting Datasets

A.2.4 Summary statistics and differences in means between the up and down samples

Table A.2: Numerical conversion of sovereign debt ratings

Ratings	Moody's	Fitch	Standard & Poor's	Interpretation
21	Aaa	AAA	AAA	Highest credit quality
20	Aa1	AA+	AA+	High credit quality
19	Aa2	AA	AA	
18	Aa3	AA-	AA-	
17	A1	A+	A+	Strong payment capacity
16	A2	A	A	
15	A3	A-	A-	
14	Baa1	BBB+	BBB+	Adequate payment capacity
13	Baa2	BBB	BBB	
12	Baa3	BBB-	BBB-	
11	Ba1	BB+	BB+	Speculative, Credit risk developing due to economic changes
10	Ba2	BB	BB	
9	Ba3	BB-	BB-	
8	B1	B+	B+	High speculative, credit risk present, with limited margin safety
7	B2	B	B	
6	B3	B-	B-	
5	Caa1	CCC	CCC+	High default risk, capacity depending on sustained favourable conditions
4	Caa2	CC	CCC	
3	Caa3	C	CCC-	
2	Ca	RD	CC	Default
1	C	D	C/D	

Sources: Rating agencies Moody's, Fitch, S&P, Elkhoury (2009), Teixeira et al. (2018)

Table A.3: Size and value of mineral's discoveries from Minex Consulting Datasets

	Size Range			
	Moderate	**Major**	**Giant**	**Super Giant**
Gold	> 100 koz Au-eq	> 1 Moz Au-eq	> 6 Moz Au-eq	> 60 Moz Au-eq
Silver	> 5 Moz Ag	> 50 Moz Ag	> 300 Moz Ag	> 3000 Moz Ag
PGE	> 100 koz Au-eq	> 1 Moz Au-eq	> 6 Moz Au-eq	> 60 Moz Au-eq
Copper	> 100 kt Cu-eq	> 1 Mt Cu-eq	> 5 Mt Cu-eq	> 25 Mt Cu-eq
Nickel	> 10 kt Ni	> 100 kt Ni	> 1 mt Ni	> 10 Mt Ni
Zinc	> 250 kt Zn+Pb	> 2.5 Mt Zn+Pb	> 12 Mt Zn+Pb	> 60 Mt Zn+Pb
Lead	> 250 kt Zn+Pb	> 2.5 Mt Zn+Pb	> 12 Mt Zn+Pb	> 60 Mt Zn+Pb
Cobalt	> 100 kt Cu-eq	> 1 Mt Cu-eq	> 5 Mt Cu-eq	> 25 Mt Cu-eq
Molybdenum	> 100 kt Cu-eq	> 1 Mt Cu-eq	> 5 Mt Cu-eq	> 25 Mt Cu-eq
Tungsten	> 100 kt Cu-eq	> 1 Mt Cu-eq	> 5 Mt Cu-eq	> 25 Mt Cu-eq
Uranium Oxide	> 5 kt U3O8	> 25 kt U3O8	> 125 kt U3O8	> 1 Mt U3O8

Table A.4: Summary statistics for the full sample

Variable	Obs	Mean	Sdev	Min	Max
Sovereign debt ratings	567	10.110	3.059	1.000	18.000
Giant discoveries dummy at start	567	0.178	0.383	0.000	1.000
History of past giant discoveries	567	7.051	5.753	0.000	27.000
Natural resources rents (% of GDP)	567	8.225	8.229	0.123	45.570
Log of real GDP	567	12.190	1.494	8.211	15.940
Volatility of growth	567	3.303	2.177	0.454	13.720
Total investments (% of GDP)	567	18.190	7.339	5.634	45.410
Public debt (% of GDP)	567	42.700	22.210	3.673	152.200
History of default	567	0.949	0.832	0.000	3.000
Reserves (% of GDP)	567	15.950	10.690	1.220	53.220
Current account balance (% of GDP)	567	-0.849	7.275	-44.740	33.590
Log of exchange rate (LCU / $US)	567	2.691	3.050	-13.610	9.959
Financial openness index	567	0.428	0.299	0.000	1.000
ICRG index	567	0.615	0.094	0.000	0.801
Political rights index	567	3.550	1.771	1.000	7.000
Internal conflicts index	564	0.729	0.139	0.181	1.000

Table A.5: Summary statistics and differences in means between Up and Down samples

	(1) Up sample					(2) Down sample					Mean difference (1) - (2)	
Variable	Obs	Mean	Sdev	Min	Max	Obs	Mean	Sdev	Min	Max	Diff	SE Diff
Sovereign debt ratings	274	9.661	2.989	2.000	18.000	293	10.530	3.068	1.000	17.000	-0.87***	(0.255)
Giant discoveries dummy at start	274	0.197	0.399	0.000	1.000	293	0.160	0.368	0.000	1.000	0.04	(0.032)
History of past giant discoveries	274	7.164	5.785	0.000	22.000	293	6.945	5.731	0.000	27.000	0.22	(0.484)
Natural resources rents (% of GDP)	274	6.752	7.974	0.123	45.570	293	9.603	8.237	0.562	41.950	-2.85***	(0.682)
Log of real GDP	274	12.320	1.705	8.211	15.940	293	12.070	1.257	8.645	14.350	0.25*	(0.125)
Volatility of growth	274	2.995	1.612	0.526	8.338	293	3.592	2.566	0.454	13.720	-0.60**	(0.181)
Total investments (% of GDP)	274	19.600	7.167	7.212	41.980	293	16.870	7.264	5.634	45.410	2.73***	(0.607)
Public debt (% of GDP)	274	45.710	21.340	5.874	98.450	293	39.890	22.670	3.673	152.200	5.81**	(1.852)
History of default	274	0.985	0.877	0.000	3.000	293	0.915	0.787	0.000	3.000	0.07	(0.070)
Reserves (% of GDP)	274	15.480	10.600	1.558	51.410	293	16.390	10.770	1.220	53.220	-0.91	(0.898)
Current account balance (% of GDP)	274	-1.365	4.820	-27.390	11.860	293	-0.365	8.966	-44.740	33.590	-1.00	(0.611)
Log of exchange rate (LCU / $US)	274	2.847	3.307	-13.610	9.381	293	2.546	2.787	-3.361	9.959	0.30	(0.256)
Financial openness index	274	0.437	0.308	0.000	1.000	293	0.421	0.290	0.000	1.000	0.02	(0.025)
ICRG index	274	0.595	0.105	0.000	0.765	293	0.633	0.078	0.409	0.801	-0.04***	(0.008)
Political rights index	274	3.347	1.752	1.000	7.000	293	3.741	1.769	1.000	7.000	-0.39**	(0.148)
Internal conflicts index	271	0.711	0.145	0.181	1.000	293	0.746	0.132	0.285	1.000	-0.03**	(0.012)

Notes: Differences in means; ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. These summary statistics use the similar samples as in the benchmarl findings.

A.2.5 Benchmark results without control variables

Table A.6: Benchmark results for all the samples, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Panel A: Full sample					
Giant discoveries dummy (1 in the horizon T)	0.135	-0.111	0.022	-0.052	-0.040
	(0.108)	(0.107)	(0.110)	(0.116)	(0.138)
Observations	567	567	567	567	567
AIC	2219.2	2219.7	2220.7	2220.6	2220.7
BIC	2410.2	2410.7	2411.7	2411.5	2411.7
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-1065.6	-1065.8	-1066.4	-1066.3	-1066.3
Panel B: Up sample					
Giant discoveries dummy (1 in the horizon T)	-0.355*	0.265	-0.042	0.577***	0.675***
	(0.183)	(0.170)	(0.178)	(0.175)	(0.196)
Observations	274	274	274	274	274
AIC	1027.4	1028.7	1031.1	1020.2	1019.3
BIC	1182.8	1184.1	1186.5	1175.6	1174.6
Time FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-470.7	-471.4	-472.6	-467.1	-466.6
Panel B: Down sample					
Giant discoveries dummy (1 in the horizon T)	0.425***	-0.250*	0.195	-0.464***	-0.419*
	(0.147)	(0.146)	(0.157)	(0.167)	(0.218)
Observations	293	293	293	293	293
AIC	1159.6	1165.0	1166.4	1160.2	1164.3
BIC	1317.9	1323.3	1324.7	1318.5	1322.5
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-536.8	-539.5	-540.2	-537.1	-539.1

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after for the Full sample (Panel A), the Up sample (Panel B), the Down (Panel C).

A.2.6 Conditional probabilities of marginal effects

Table A.7: Predicted probabilities for each level of sovereign debt ratings

	(1) Full sample				(2) Up sample				(3) Down sample			
	Without discoveries		With discoveries		Without discoveries		With discoveries		Without discoveries		With discoveries	
Ratings	Prob	P-Value	Prob	P-Value	Prob	P-Value	Prob	P-Value	Prob	P-Value	Prob	P-Value
2	0.00	0.77	0.00	0.75	0.00	0.87	0.00	0.88	0.00	0.78	0.01	0.73
3	0.00	0.73	0.00	0.70	0.00	0.86	0.00	0.87	0.00	0.74	0.02	0.67
4	0.00	0.69	0.00	0.65	0.00	0.85	0.00	0.86	0.02	0.68	0.10	0.57
5	0.00	0.62	0.00	0.57	0.00	0.78	0.00	0.80	0.04	0.61	0.23	0.48
6	0.01	0.52	0.04	0.44	0.15	0.65	0.02	0.70	0.14	0.53	0.64	0.36
7	0.10	0.42	0.33	0.34	1.65	0.54	0.32	0.61	0.37	0.44	1.38	0.23
8	3.47	0.21	7.52	0.11	19.14	0.25	7.48	0.40	4.20	0.17	10.91	0.02
9	16.30	0.03	24.49	0.00	40.67	0.00	29.88	0.06	9.40	0.01	16.93	0.00
10	26.67	0.00	29.50	0.00	19.52	0.02	23.10	0.00	18.82	0.00	24.33	0.00
11	32.05	0.00	26.25	0.00	15.41	0.24	27.85	0.03	21.76	0.00	20.45	0.00
12	18.28	0.03	10.66	0.07	3.43	0.51	11.10	0.36	18.50	0.00	12.99	0.00
13	2.80	0.22	1.13	0.26	0.03	0.70	0.25	0.63	12.62	0.00	6.84	0.01
14	0.31	0.38	0.09	0.42	0.00	0.80	0.00	0.77	11.16	0.02	4.42	0.11
15	0.00	0.58	0.00	0.60	0.00	0.90	0.00	0.89	2.41	0.23	0.64	0.41
16	0.00	0.69	0.00	0.70	0.00	1.00	0.00	0.96	0.51	0.46	0.09	0.58
17	0.00	0.76	0.00	0.77	0.00	-	0.00	1.00	0.05	0.65	0.01	0.72
18	0.00	0.82	0.00	0.85	0.00	-	0.00	-	-	-	-	-

Notes: The predicted probabilities are based on column 5 of table 2.1 for the Full sample, table 2.2 for the Up sample, ad table 2.3 for the Down sample. They show the predicted probabilities of marginal effects of giant discoveries over the 10 years following discoveries, for each level of sovereign debt ratings, in countries with discoveries compared to countries without discoveries.

A.2.7 Robustness checks

A.2.7.1 Alternative methodology: Correlated Random Effect

A.2.7.2 Adding history of giant discoveries

Table A.8: Robustness, Correlated Random Effects, full sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries (1 in the horizon T)	-0.036	-0.138	-0.194*	-0.047	-0.381***
	(0.112)	(0.110)	(0.116)	(0.119)	(0.147)
Giant discoveries (1 in the horizon T) avg.	*-1.418*	*10.058****	*-0.143*	*3.768*	*0.594*
	(1.334)	*(3.797)*	*(1.151)*	*(2.813)*	*(1.241)*
Natural ressources rents, one-year lag	-0.046***	-0.044***	-0.046***	-0.046***	-0.044***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Natural ressources rents, one-year lag, avg.	*0.096**	*0.025*	*0.082*	*0.074*	*0.068*
	(0.052)	*(0.047)*	*(0.054)*	*(0.047)*	*(0.054)*
Log of real GDP, one-year lag	0.185	0.084	0.238	0.226	0.258
	(0.439)	(0.432)	(0.441)	(0.441)	(0.440)
Log of real GDP, one-year lag, avg.	*0.821*	*0.907**	*0.641*	*0.698*	*0.564*
	(0.510)	*(0.487)*	*(0.502)*	*(0.490)*	*(0.502)*
Volatility of growth, one-year lag	-0.167***	-0.162***	-0.159***	-0.166***	-0.152***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Volatility of growth, one-year lag, avg.	*-0.076*	*-0.153*	*-0.065*	*-0.120*	*-0.079*
	(0.191)	*(0.179)*	*(0.193)*	*(0.196)*	*(0.191)*
Total investments, one-year lag	0.064***	0.066***	0.066***	0.065***	0.070***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Total investments, one-year lag, avg.	*-0.149****	*-0.147****	*-0.159****	*-0.144****	*-0.164****
	(0.051)	*(0.047)*	*(0.052)*	*(0.051)*	*(0.051)*
Public debt, one-year lag	-0.023***	-0.023***	-0.022***	-0.023***	-0.023***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Public debt, one-year lag, avg.	*-0.033***	*-0.027***	*-0.034***	*-0.034***	*-0.033***
	(0.013)	*(0.013)*	*(0.014)*	*(0.013)*	*(0.014)*
History of default, one-year lag	-0.108	-0.107	-0.103	-0.111	-0.118
	(0.081)	(0.081)	(0.081)	(0.082)	(0.081)
History of default, one-year lag, avg.	*-1.909****	*-1.827****	*-1.931****	*-1.633****	*-1.882****
	(0.436)	*(0.403)*	*(0.442)*	*(0.484)*	*(0.448)*
Reserves, one-year lag	0.064***	0.063***	0.064***	0.063***	0.063***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Reserves, one-year lag, avg.	*0.117****	*0.146****	*0.118****	*0.134****	*0.123****
	(0.041)	*(0.039)*	*(0.042)*	*(0.041)*	*(0.042)*
Current account balance, one-year lag	0.003	0.005	0.003	0.003	0.005
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Current account balance, one-year lag, avg.	*0.030*	*-0.044*	*0.039*	*0.016*	*0.035*
	(0.073)	*(0.073)*	*(0.074)*	*(0.073)*	*(0.074)*
Log of exchange rate (LCU/US), one-year lag	0.199***	0.192***	0.204***	0.194***	0.202***
	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)
Log of exchange rate (LCU/US), one-year lag, avg.	*-0.091*	*-0.080*	*-0.080*	*-0.097*	*-0.077*
	(0.072)	*(0.064)*	*(0.072)*	*(0.072)*	*(0.070)*
Financial openness index, one-year lag	2.248***	2.204***	2.280***	2.218***	2.244***
	(0.267)	(0.268)	(0.268)	(0.268)	(0.267)
Financial openness index, one-year lag, avg.	*-2.060**	*-2.144***	*-2.139**	*-2.590***	*-2.188**
	(1.158)	*(1.067)*	*(1.177)*	*(1.210)*	*(1.186)*
ICRG index, one-year lag	5.024***	5.144***	5.134***	4.981***	5.300***
	(0.720)	(0.718)	(0.725)	(0.719)	(0.730)
ICRG index, one-year lag, avg.	*0.863*	*-3.384*	*1.022*	*0.113*	*0.662*
	(3.059)	*(3.268)*	*(3.130)*	*(3.096)*	*(3.167)*
Constant	0.743***	0.613***	0.770***	0.722***	0.758***
	(0.232)	(0.194)	(0.240)	(0.228)	(0.238)
Observations	567	567	567	567	567
AIC	1895.8	1889.2	1894.2	1895.2	1890.2
BIC	2186.6	2180.0	2185.0	2186.0	2181.0
Time FE	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-880.9	-877.6	-880.1	-880.6	-878.1

Note: Correlated Random Effect model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the availability of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. Time-average variables are reported in italic. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after

Table A.9: Robustness, adding history of giant discoveries, full sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.075	-0.198*	-0.300**	-0.018	-0.508***
	(0.112)	(0.112)	(0.117)	(0.120)	(0.149)
History of past-giant discoveries	0.171***	0.180***	0.185***	0.171***	0.189***
	(0.035)	(0.036)	(0.036)	(0.036)	(0.036)
Natural resources rents, one-year lag	-0.044***	-0.043***	-0.044***	-0.044***	-0.042***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log of real GDP, one-year lag	0.207	0.185	0.204	0.200	0.187
	(0.223)	(0.226)	(0.224)	(0.223)	(0.226)
Volatility of growth, one-year lag	-0.113***	-0.112***	-0.104**	-0.115***	-0.097**
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Total investments, one-year lag	0.063***	0.064***	0.066***	0.063***	0.072***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Public debt, one-year lag	-0.027***	-0.027***	-0.026***	-0.027***	-0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
History of default, one-year lag	-0.927***	-0.897***	-0.945***	-0.913***	-0.968***
	(0.211)	(0.211)	(0.211)	(0.210)	(0.211)
Reserves, one-year lag	0.054***	0.053***	0.054***	0.053***	0.053***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Current account balance, one-year lag	0.009	0.010	0.009	0.009	0.012
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Log of exchange rate (LCU / $US), one-year lag	0.161***	0.163***	0.165***	0.161***	0.164***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Financial openness index, one-year lag	1.850***	1.878***	1.890***	1.847***	1.836***
	(0.273)	(0.273)	(0.274)	(0.273)	(0.273)
ICRG index, one-year lag	4.318***	4.406***	4.545***	4.298***	4.740***
	(0.724)	(0.727)	(0.731)	(0.724)	(0.737)
Constant	3.216***	3.343***	3.323***	3.234***	3.362***
	(0.972)	(1.010)	(1.000)	(0.978)	(1.012)
Observations	567	567	567	567	567
AIC	1878.2	1875.5	1872.1	1878.6	1866.9
BIC	2121.2	2118.5	2115.1	2121.6	2110.0
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-883.1	-881.7	-880.0	-883.3	-877.5

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

Table A.10: Robustness, adding history of giant discoveries, up sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.428**	0.059	-0.347*	0.628***	0.439*
	(0.204)	(0.187)	(0.201)	(0.195)	(0.234)
History of past-giant discoveries	0.335***	0.334***	0.351***	0.346***	0.325***
	(0.051)	(0.051)	(0.052)	(0.051)	(0.051)
Natural resources rents, one-year lag	-0.076***	-0.077***	-0.077***	-0.083***	-0.081***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Log of real GDP, one-year lag	0.841*	0.782*	0.834*	0.890**	0.794*
	(0.435)	(0.434)	(0.448)	(0.449)	(0.433)
Volatility of growth, one-year lag	-0.340***	-0.381***	-0.354***	-0.359***	-0.401***
	(0.077)	(0.074)	(0.076)	(0.074)	(0.075)
Total investments, one-year lag	0.055	0.052	0.058*	0.034	0.033
	(0.033)	(0.033)	(0.034)	(0.034)	(0.035)
Public debt, one-year lag	-0.029***	-0.028***	-0.028***	-0.027***	-0.028***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
History of default, one-year lag	-0.774**	-0.666*	-0.671*	-0.663*	-0.637*
	(0.378)	(0.375)	(0.374)	(0.375)	(0.373)
Reserves, one-year lag	0.033**	0.035**	0.033**	0.034**	0.036**
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)
Current account balance, one-year lag	-0.030	-0.033	-0.029	-0.032	-0.036
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Log of exchange rate (LCU / $US), one-year lag	0.222***	0.215***	0.229***	0.228***	0.209***
	(0.061)	(0.061)	(0.062)	(0.061)	(0.061)
Financial openness index, one-year lag	1.870***	1.758***	1.724***	2.053***	1.975***
	(0.527)	(0.526)	(0.524)	(0.536)	(0.538)
ICRG index, one-year lag	6.308***	6.119***	6.407***	6.289***	5.905***
	(0.950)	(0.946)	(0.959)	(0.950)	(0.952)
Constant	7.537**	7.558**	7.885**	7.970**	7.560**
	(3.319)	(3.320)	(3.499)	(3.519)	(3.296)
Observations	274	274	274	274	274
AIC	830.8	835.1	832.2	824.8	831.7
BIC	1029.5	1033.8	1031.0	1023.5	1030.4
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-360.4	-362.6	-361.1	-357.4	-360.8

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

Table A.11: Robustness, adding history of giant discoveries, down sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	0.228	-0.459***	-0.266	-0.294*	-1.073***
	(0.155)	(0.155)	(0.167)	(0.174)	(0.238)
History of past-giant discoveries	0.020	0.031	0.035	0.028	0.073
	(0.066)	(0.067)	(0.067)	(0.066)	(0.067)
Natural resources rents, one-year lag	-0.004	-0.000	-0.007	-0.007	-0.008
	(0.023)	(0.024)	(0.023)	(0.023)	(0.024)
Log of real GDP, one-year lag	0.277	0.263	0.266	0.248	0.136
	(0.337)	(0.343)	(0.333)	(0.334)	(0.346)
Volatility of growth, one-year lag	0.054	0.067	0.049	0.053	0.080
	(0.059)	(0.059)	(0.058)	(0.058)	(0.059)
Total investments, one-year lag	0.120***	0.125***	0.125***	0.120***	0.130***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Public debt, one-year lag	-0.025***	-0.024***	-0.025***	-0.025***	-0.026***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
History of default, one-year lag	-1.093***	-1.098***	-1.135***	-1.132***	-1.237***
	(0.315)	(0.317)	(0.314)	(0.313)	(0.317)
Reserves, one-year lag	0.092***	0.096***	0.096***	0.090***	0.095***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)
Current account balance, one-year lag	0.026*	0.026*	0.025*	0.027**	0.031**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log of exchange rate (LCU / $US), one-year lag	0.125	0.127	0.108	0.122	0.125
	(0.120)	(0.122)	(0.119)	(0.118)	(0.122)
Financial openness index, one-year lag	1.950***	2.102***	2.024***	1.935***	2.253***
	(0.367)	(0.373)	(0.371)	(0.366)	(0.376)
ICRG index, one-year lag	2.803*	3.005*	2.573	2.689	2.913*
	(1.653)	(1.658)	(1.641)	(1.646)	(1.659)
Constant	2.028**	2.154**	2.007**	1.961**	2.140**
	(0.980)	(1.030)	(0.964)	(0.950)	(1.021)
Observations	293	293	293	293	293
AIC	984.5	977.9	984.2	983.9	966.2
BIC	1187.0	1180.4	1186.6	1186.3	1168.6
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-437.3	-434.0	-437.1	-436.9	-428.1

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

A.2.7.3 Including political rights and internal conflicts

Table A.12: Robustness, adding political rights and internal conflicts, full sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.028	-0.155	-0.196*	-0.046	-0.385***
	(0.113)	(0.112)	(0.116)	(0.119)	(0.147)
Natural resources rents, one-year lag	-0.039***	-0.038***	-0.039***	-0.038***	-0.037***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log of real GDP, one-year lag	0.658***	0.663***	0.678***	0.653***	0.678***
	(0.199)	(0.200)	(0.200)	(0.199)	(0.201)
Volatility of growth, one-year lag	-0.125***	-0.123***	-0.118***	-0.125***	-0.113***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Total investments, one-year lag	0.066***	0.067***	0.068***	0.066***	0.073***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Public debt, one-year lag	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
History of default, one-year lag	-0.919***	-0.895***	-0.932***	-0.913***	-0.952***
	(0.203)	(0.202)	(0.202)	(0.201)	(0.203)
Reserves, one-year lag	0.056***	0.056***	0.056***	0.055***	0.055***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Current account balance, one-year lag	0.002	0.002	0.002	0.002	0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Log of exchange rate (LCU / $US), one-year lag	0.196***	0.200***	0.201***	0.195***	0.201***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Financial openness index, one-year lag	2.009***	2.037***	2.045***	2.002***	2.015***
	(0.270)	(0.271)	(0.271)	(0.271)	(0.270)
Political rights index	-0.061	-0.064	-0.060	-0.063	-0.067
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Internal conflicts index	2.101***	2.232***	2.197***	2.108***	2.262***
	(0.590)	(0.596)	(0.592)	(0.589)	(0.593)
Constant	2.839***	2.895***	2.896***	2.839***	2.936***
	(0.869)	(0.885)	(0.884)	(0.869)	(0.896)
Observations	564	564	564	564	564
AIC	1901.6	1899.7	1898.8	1901.5	1894.8
BIC	2144.4	2142.5	2141.5	2144.3	2137.6
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-894.8	-893.9	-893.4	-894.8	-891.4

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

Table A.13: Robustness, adding political rights and internal conflicts, up sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.367*	0.194	-0.121	0.482**	0.534**
	(0.202)	(0.183)	(0.196)	(0.191)	(0.230)
Natural resources rents, one-year lag	-0.062***	-0.063***	-0.062***	-0.066***	-0.067***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Log of real GDP, one-year lag	1.293***	1.243***	1.273***	1.338***	1.259***
	(0.382)	(0.378)	(0.386)	(0.392)	(0.382)
Volatility of growth, one-year lag	-0.333***	-0.366***	-0.358***	-0.350***	-0.392***
	(0.076)	(0.074)	(0.076)	(0.074)	(0.075)
Total investments, one-year lag	0.072**	0.067**	0.073**	0.058*	0.047
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
Public debt, one-year lag	-0.025***	-0.025***	-0.025***	-0.024***	-0.025***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
History of default, one-year lag	-0.777**	-0.719**	-0.681*	-0.687*	-0.662*
	(0.366)	(0.364)	(0.363)	(0.365)	(0.364)
Reserves, one-year lag	0.015	0.017	0.016	0.016	0.020
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Current account balance, one-year lag	-0.007	-0.010	-0.007	-0.007	-0.014
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Log of exchange rate (LCU / $US), one-year lag	0.313***	0.304***	0.318***	0.321***	0.298***
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Financial openness index, one-year lag	2.107***	2.072***	2.014***	2.243***	2.287***
	(0.518)	(0.516)	(0.515)	(0.525)	(0.529)
Political rights index	-0.112	-0.116	-0.123	-0.126	-0.125
	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)
Internal conflicts index	3.782***	3.725***	3.865***	3.733***	3.520***
	(0.852)	(0.856)	(0.854)	(0.853)	(0.862)
Constant	5.643**	5.546**	5.730**	5.933**	5.708**
	(2.470)	(2.427)	(2.510)	(2.601)	(2.495)
Observations	271	271	271	271	271
AIC	867.1	869.3	870.1	864.1	865.0
BIC	1065.3	1067.4	1068.2	1062.2	1063.2
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-378.6	-379.7	-380.0	-377.0	-377.5

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

Table A.14: Robustness, adding political rights and internal conflicts, up sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	0.235	-0.485***	-0.272	-0.257	-1.012***
	(0.155)	(0.158)	(0.167)	(0.176)	(0.239)
Natural resources rents, one-year lag	-0.008	-0.004	-0.010	-0.010	-0.007
	(0.023)	(0.024)	(0.023)	(0.023)	(0.024)
Log of real GDP, one-year lag	0.387	0.398	0.399	0.376	0.356
	(0.299)	(0.314)	(0.303)	(0.295)	(0.321)
Volatility of growth, one-year lag	0.046	0.058	0.043	0.046	0.077
	(0.059)	(0.060)	(0.059)	(0.059)	(0.060)
Total investments, one-year lag	0.123***	0.128***	0.129***	0.124***	0.134***
	(0.023)	(0.024)	(0.024)	(0.023)	(0.024)
Public debt, one-year lag	-0.026***	-0.026***	-0.026***	-0.027***	-0.027***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
History of default, one-year lag	-1.193***	-1.182***	-1.211***	-1.213***	-1.241***
	(0.296)	(0.302)	(0.298)	(0.294)	(0.304)
Reserves, one-year lag	0.094***	0.099***	0.098***	0.092***	0.099***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)
Current account balance, one-year lag	0.025*	0.024*	0.024*	0.026*	0.027**
	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)
Log of exchange rate (LCU / $US), one-year lag	0.069	0.072	0.053	0.068	0.081
	(0.120)	(0.125)	(0.122)	(0.119)	(0.127)
Financial openness index, one-year lag	2.018***	2.189***	2.105***	2.012***	2.357***
	(0.361)	(0.368)	(0.366)	(0.360)	(0.373)
Political rights index	0.077	0.080	0.080	0.061	0.022
	(0.088)	(0.089)	(0.088)	(0.088)	(0.090)
Internal conflicts index	1.410	1.808*	1.300	1.074	1.049
	(0.993)	(1.011)	(0.986)	(0.984)	(0.990)
Constant	2.038**	2.304**	2.131**	1.968**	2.371**
	(0.942)	(1.065)	(0.987)	(0.911)	(1.100)
Observations	293	293	293	293	293
AIC	985.3	978.1	984.9	985.4	969.3
BIC	1187.7	1180.5	1187.3	1187.8	1171.7
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-437.6	-434.0	-437.4	-437.7	-429.6

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

A.2.7.4 Drop top 5% and bottom 5% of sovereign debt ratings

Table A.15: Robustness, drop top 5% and bottom 5% of sovereign debt ratings, full sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.095	-0.118	-0.220*	-0.064	-0.421***
	(0.124)	(0.123)	(0.126)	(0.131)	(0.155)
Natural ressources rents, one-year lag	-0.043***	-0.041***	-0.043***	-0.041***	-0.040***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Log of real GDP, one-year lag	0.665***	0.655***	0.672***	0.656***	0.675***
	(0.171)	(0.173)	(0.173)	(0.172)	(0.173)
Volatility of growth, one-year lag	-0.127***	-0.128***	-0.123***	-0.129***	-0.116**
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Total investments, one-year lag	0.006	0.008	0.009	0.007	0.014
	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)
Public debt, one-year lag	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
History of default, one-year lag	-0.796***	-0.766***	-0.796***	-0.777***	-0.802***
	(0.234)	(0.235)	(0.234)	(0.234)	(0.233)
Reserves, one-year lag	0.055***	0.054***	0.055***	0.055***	0.055***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Current account balance, one-year lag	-0.005	-0.005	-0.005	-0.005	-0.003
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Log of exchange rate (LCU / $US), one-year lag	0.121**	0.123**	0.126**	0.119**	0.127**
	(0.050)	(0.050)	(0.050)	(0.050)	(0.051)
Financial openness index, one-year lag	1.588***	1.612***	1.595***	1.599***	1.588***
	(0.310)	(0.310)	(0.309)	(0.309)	(0.310)
ICRG index, one-year lag	4.191***	4.181***	4.320***	4.149***	4.506***
	(0.770)	(0.769)	(0.775)	(0.768)	(0.780)
Constant	1.716***	1.759***	1.762***	1.723***	1.767***
	(0.619)	(0.636)	(0.634)	(0.622)	(0.632)
Observations	494	494	494	494	494
AIC	1561.2	1560.9	1558.8	1561.6	1554.4
BIC	1754.6	1754.2	1752.1	1754.9	1747.7
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-734.6	-734.5	-733.4	-734.8	-731.2

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

Table A.16: Robustness, drop top 5% and bottom 5% of sovereign debt ratings, up sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	-0.374*	0.433**	0.169	0.409**	0.721***
	(0.220)	(0.197)	(0.222)	(0.207)	(0.237)
Natural ressources rents, one-year lag	-0.064***	-0.066***	-0.066***	-0.067***	-0.072***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Log of real GDP, one-year lag	1.108***	1.093***	1.047***	1.091***	1.076***
	(0.341)	(0.351)	(0.353)	(0.344)	(0.366)
Volatility of growth, one-year lag	-0.245***	-0.275***	-0.296***	-0.264***	-0.314***
	(0.078)	(0.076)	(0.078)	(0.076)	(0.077)
Total investments, one-year lag	0.035	0.033	0.035	0.019	0.004
	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)
Public debt, one-year lag	-0.036***	-0.039***	-0.037***	-0.034***	-0.037***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
History of default, one-year lag	-0.409	-0.290	-0.224	-0.373	-0.185
	(0.461)	(0.465)	(0.474)	(0.467)	(0.488)
Reserves, one-year lag	0.020	0.022	0.021	0.020	0.022
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Current account balance, one-year lag	-0.014	-0.015	-0.016	-0.018	-0.021
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Log of exchange rate (LCU / $US), one-year lag	0.333***	0.329***	0.334***	0.331***	0.323***
	(0.073)	(0.072)	(0.072)	(0.072)	(0.072)
Financial openness index, one-year lag	2.900***	3.091***	2.902***	2.924***	3.306***
	(0.566)	(0.581)	(0.575)	(0.567)	(0.594)
ICRG index, one-year lag	5.675***	5.511***	5.552***	5.611***	5.332***
	(0.977)	(0.981)	(0.982)	(0.978)	(0.989)
Constant	4.169**	4.499**	4.559**	4.281**	4.990**
	(2.100)	(2.251)	(2.296)	(2.172)	(2.539)
Observations	244	244	244	244	244
AIC	757.1	755.1	759.4	756.0	750.6
BIC	917.9	916.0	920.2	916.9	911.5
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-332.5	-331.6	-333.7	-332.0	-329.3

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

Table A.17: Robustness, drop top 5% and bottom 5% of sovereign debt ratings, down sample, coefficients

	(1)	(2)	(3)	(4)	(5)
Horizon T	**[0,2]**	**[3,5]**	**[0,5]**	**[6,10]**	**[0,10]**
Giant discoveries dummy (1 in the horizon T)	0.268	-0.343*	-0.100	-0.567***	-1.244***
	(0.186)	(0.183)	(0.199)	(0.212)	(0.294)
Natural ressources rents, one-year lag	-0.060**	-0.060**	-0.066**	-0.062**	-0.063**
	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)
Log of real GDP, one-year lag	0.806**	0.797**	0.806**	0.818**	0.812**
	(0.331)	(0.339)	(0.334)	(0.323)	(0.343)
Volatility of growth, one-year lag	-0.038	-0.039	-0.045	-0.029	-0.023
	(0.067)	(0.068)	(0.067)	(0.067)	(0.068)
Total investments, one-year lag	0.033	0.039	0.035	0.022	0.031
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Public debt, one-year lag	-0.017**	-0.018**	-0.020**	-0.019**	-0.022***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
History of default, one-year lag	-0.771*	-0.746*	-0.792**	-0.824**	-0.790**
	(0.398)	(0.401)	(0.395)	(0.395)	(0.403)
Reserves, one-year lag	0.156***	0.159***	0.159***	0.155***	0.167***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Current account balance, one-year lag	0.023	0.023	0.022	0.022	0.021
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)
Log of exchange rate (LCU / $US), one-year lag	-0.166	-0.179	-0.187	-0.160	-0.203
	(0.154)	(0.158)	(0.156)	(0.150)	(0.161)
Financial openness index, one-year lag	-0.414	-0.295	-0.438	-0.472	-0.115
	(0.491)	(0.499)	(0.493)	(0.490)	(0.500)
ICRG index, one-year lag	9.744***	9.507***	9.541***	10.049***	9.445***
	(2.136)	(2.140)	(2.138)	(2.156)	(2.198)
Constant	2.791**	2.941**	2.845**	2.607**	2.963**
	(1.350)	(1.428)	(1.384)	(1.266)	(1.452)
Observations	250	250	250	250	250
AIC	723.2	721.8	725.1	718.1	706.7
BIC	885.2	883.8	887.0	880.1	868.7
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-315.6	-314.9	-316.5	-313.1	-307.4

Notes: Random effect ordered probit model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variable is sovereign debt ratings ranging from 2 to 18 (given the avaibility of data). The table reports the coefficient associated with each variable included as determinants of sovereign debt ratings. For simplicity of presentation, I do not report the estimated cut-off points. The control variables are included with one-year lag to limit reverse causality bias. I capture the effect of giant discoveries on sovereign debt ratings over several horizons following discoveries: (column 1) from the year of discovery to up to 2 years after, (column 2) between 3 and 5 years after the discovery, (column 3) from the year of discovery to up to 5 years after, (column 4) between 6 and 10 years after the discovery, and (column 5) from the year of discovery to up to 10 years after.

A.2.8 Channels

Table A.18: Channels

	(1)	(2)	(3)
	Full	Up	Down
Panel A: Tax revenue as a % of GDP, IMF			
Giant discoveries dummy (1 in the horizon T)	1.241***	2.001***	-0.146
	(0.413)	(0.245)	(0.568)
History of default, one-year lag	0.069	-0.121	0.308**
	(0.054)	(0.073)	(0.111)
Output gap (hp filter on log. of real GDP	6.673***	8.166*	6.513***
	(2.015)	(4.114)	(2.084)
Observations	750	354	396
R-squared	0.688	0.728	0.688
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Specific-trend	Yes	Yes	Yes
Panel B: Public debt			
Giant discoveries dummy (1 in the horizon T)	-0.872	-7.352**	1.990
	(2.813)	(3.549)	(2.622)
History of default, one-year lag	0.411	0.466	0.624
	(0.783)	(0.578)	(0.915)
Output gap (hp filter on log. of real GDP	-100.003***	-109.554***	-84.674**
	(23.752)	(20.602)	(34.667)
Observations	1071	478	593
R-squared	0.504	0.640	0.493
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Specific-trend	Yes	Yes	Yes
Panel C: Financial Markets Index			
Giant discoveries dummy (1 in the horizon T)	0.020**	0.044***	0.005
	(0.009)	(0.012)	(0.008)
History of default, one-year lag	-0.007	-0.000	-0.009
	(0.006)	(0.004)	(0.008)
Output gap (hp filter on log. of real GDP	0.020	-0.021	0.002
	(0.054)	(0.145)	(0.026)
Observations	1010	473	537
R-squared	0.650	0.724	0.598
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Specific-trend	Yes	Yes	Yes
Panel D: Total Investments			
Giant discoveries dummy (1 in the horizon T)	0.496	1.892***	-1.210**
	(0.329)	(0.325)	(0.507)
History of default, one-year lag	0.225***	0.015	0.444**
	(0.060)	(0.072)	(0.188)
Output gap (hp filter on log. of real GDP	27.659***	31.175***	26.672***
	(1.632)	(6.020)	(3.512)
Observations	1126	547	579
R-squared	0.601	0.750	0.469
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Specific-trend	Yes	Yes	Yes
Panel E: Government stabilty index, ICRG			
Giant discoveries dummy (1 in the horizon T)	0.010	0.037*	0.012
	(0.017)	(0.018)	(0.029)
History of default, one-year lag	0.013**	0.018***	0.006
	(0.005)	(0.005)	(0.007)
Output gap (hp filter on log. of real GDP	0.449***	0.333***	0.477***
	(0.082)	(0.081)	(0.105)
Observations	789	380	409
R-squared	0.642	0.699	0.667
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Specific-trend	Yes	Yes	Yes
Panel F: Corruption index, ICRG			
Giant discoveries dummy (1 in the horizon T)	-0.004	0.004	-0.027**
	(0.007)	(0.005)	(0.013)
History of default, one-year lag	-0.012**	-0.012**	-0.014*
	(0.005)	(0.005)	(0.007)
Output gap (hp filter on log. of real GDP	0.111**	0.335***	0.026
	(0.045)	(0.046)	(0.055)
Observations	789	380	409
R-squared	0.626	0.595	0.674
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Specific-trend	Yes	Yes	Yes

Notes: Panel-fixed effects model. ***, **, and * denote statistical significance at the 1%, the 5%, and the 10% level, respectively. Dependent variables are intermediary variables used as control variables in the benchmark model, also known as being critical for sovereign debt ratings (see text). Country-fixed effects included to control for time-invariants factors and unobserved heterogeneity, time-fixed effects included to capture common shocks affecting countries, and country-specific time trend included to capture the specific trend evolution of each intermediary variable. R-squared is relatively high for all specifications. The giant discoveries dummy takes the values of 1 in the 10 years following the discoveries, and 0 otherwise, capturing the long-term effect on intermediary variables. Control variables include history of default and output gap.

Chapter 3

The heterogeneous effects of the peak of giant discoveries on country credit ratings using Synthetic Control Method

Abstract

We examine the causal effects of the peak of oil and mineral giant discoveries on investor country credit ratings by applying the synthetic control method on five developing countries, including Angola, Cameroon, Gabon, Kazakhstan, and Romania, over the period 1985–2014. We confirm the differentiated effects of giant natural resources discoveries on the access to financial markets proxied by the investor country credit rating, as evidenced by Seri (2020). Specifically, we find that country credit ratings improve following the peak of giant discoveries for Angola, Kazakhstan, and Romania. In contrast, country credit ratings deteriorate following the peak of giant discoveries in Cameroon and Gabon. These findings show that the "resource curse" in terms of access to markets does not apply to all countries and calls for considering country specificity in analyzing the effects of giant discoveries. Moreover, what seems to matter is not the news of the discoveries but how countries react to them, especially regarding borrowing policy.

Giant discoveries; Natural resources; Country ratings; Developing countries; Synthetic Control Method
JEL Codes: C32; G15; Q32; Q33

3.1 Introduction

Over the last decades, several natural resource sites have been discovered in developing countries. These discoveries have been a blessing for some countries like Botswana as materialized by, e.g., growing GDP per capita, development of local infrastructures, domestic capital markets, and prolonged macroeconomic stability. For other countries like Ghana, they have been a curse so far, resulting in lower GDP per capita growth, deterioration of financial conditions (lower ratings), higher level of debt, and debt sustainability issues. As shown by Seri (2020), giant discoveries of natural resources (oil, gas, minerals) have differentiated effects, i.e., both positive and negative effects, on sovereign debt ratings. These differentiated effects are linked to the behavior of macroeconomic and political indicators resulting from the actions and policies taken in the aftermath of the discoveries. One criticism was that this paper divides the sample into two groups based on an ad-hoc graphical analysis.

This paper aims to confirm these findings using the synthetic control method (SCM). This method has several advantages. First, it allows us to analyze the effects of giant discoveries on ratings in comparative case studies while considering the specificity of each country, therefore preventing us from capturing an average effect, as in previous analyses, which is a mix of "resource curse" and "resource blessing". Second, it does not rely on parallel trends like the difference-in-differences method and consequently can account for the effects of confounders changing over time by weighting the control group to better match the treatment group before the peak of the discoveries. Third, it allows us to differentiate the short- and long-term effects of the peak of giant discoveries by providing an estimate of the effects over a long post-peak discoveries period. Moreover, in this paper, we focus on the peak of giant discoveries rather than giant discovery, identified as the year where the cumulated volume of discoveries reaches its peak, i.e., is maximum (Tsui, 2011), because of its plausible exogeneity. Indeed, the peak of giant natural resources discoveries is likely to be more exogenous because it depends more on geological factors than exploration (Masi and Ricciuti 2019). Also, the peak of giant discoveries is more likely to be associated with amplified economic, financial, and social effects, given its volume and size. This makes the peak of discoveries particularly interesting to analyze. Specifically, we identify the year of the peak as the first year, where the cumulated volume over the next five years of giant discoveries is at its highest level (Tsui 2011). In other words, it is the point in time when the volume of discoveries begins to decline. Unfortunately, only a few papers have analyzed the effects of the peak of giant discoveries, with the notable exception of Tsui (2011) and Masi and Ricciuti (2019).

Our paper is related to two strands of the literature: the literature on the general effects of natural resource discoveries and the literature on the determinants of sovereign ratings. Regarding the former, the results are generally mixed and inconclusive and can be divided into three categories: the papers finding negative, positive, and ambiguous effects of natural resources. First, the papers finding negative effects of natural resources are related to resource curse literature. They show that natural resources lead to a deterioration of economic activity and institutions, an appreciation of the exchange rate, a de-industrialization of the economy, an increase in conflicts, and an increase in poverty.[1] For instance, Lei and Michaels (2014) use a panel estimation on 193 countries between 1946 and 2008 and show that oilfield discoveries increase the incidence of armed conflicts by 5-8 pp. Harding et al. (2020) use a difference-in-differences specification on 172 countries over 1970-2013 and find that giant discoveries of oil and gas lead to an appreciation of exchange rate of 14% the ten years following the discovery, in line with the Dutch disease theory. Smith and Wills (2018) use a difference-in-differences estimation on 36 countries from 2000 to 2013 and reveal that oil discoveries increase poverty and inequality. Tsui (2011) and Masi and Ricciuti (2019) find that the peak of oil discoveries induces a change of the institutional framework towards autocracy and deteriorates the level of democracy, which is more critical in countries with a low quality of institutions, respectively.

Second, the papers showing the positive effects of natural resources reveal that they are

[1] Please refer to Corden and Neary (1982); Sachs and Warner (1995, 2001); Van Der Ploeg and Poelhekke (2017) for the literature on the resource curse.

associated with higher employment, foreign direct investment (FDI), lower inequality, lower outward migration, and lower incidence of conflicts. For instance, Toews and Vezina (2017) focus exclusively on Mozambique and use the SCM and difference-in-differences method. They find that giant discoveries favor an increase in FDI by 58% in non-resource extraction sectors the two years after the discoveries. The increase in FDI favors an employment effect as for each new FDI job, an additional 4.4 jobs are created locally, with 2.1 of them being formal jobs. Hartwell et al. (2019) use the SCM and focus exclusively on three developed countries (Denmark, Netherlands, and Norway) between 1947 and 2009. They show that giant discoveries decrease or have no effect on income inequality because of their sample's high institutional quality. Cust and Mensah (2020) reveal that oil, gas, and mineral discoveries positively impact the citizen's expectations, which is materialized by a decrease in outward migration and an increase in fertility in the short term. Bhattacharyya and Mamo (2021) show that oil and mineral discoveries reduce the likelihood of conflict in 48 African countries, which is mainly driven by an improvement of economic development and efficient political distribution patronage in districts with discoveries.

Third, the papers highlighting ambiguous effects of natural resources show that their effects vary over time and depend on the country's characteristics and actions taken by governments following the discoveries. Specifically, Arezki et al. (2017) highlight that the current account and saving rate decline for the first five years and rise sharply during the subsequent years, investment rises robustly soon after the news arrives, while GDP does not increase until the fifth year, and employment rates fall slightly for a sustained period. Altogether, this paper shows that the effects of giant discoveries may differ in the short, medium, and long run; therefore, the papers focusing only on one of these periods may not capture the overall effects of giant discoveries. Seri (2020) employs 28 developing and emerging countries over the period 1990-2014 and applies a random-effects ordered probit model on different sets of samples. She shows evidence of the differentiated effects (positive and negative) of giant discoveries on sovereign ratings. Specifically, for 13 countries, the study finds that giant discoveries are associated with a deterioration of sovereign debt ratings in the short term but an increase in the medium- and long-term. For the other 15 countries, giant discoveries have no effect in the short term but reduce ratings in the medium- to long term. These differentiated effects depend on the behavior of macroeconomic and political indicators resulting from the actions and policies taken in the aftermath of the discoveries. It concludes that "what seems to matter is not only the resources but also how governments respond to the news of the discovery". Indeed, in countries with increasing ratings, on average, giant discoveries are associated with increased tax revenues to GDP, investments, decreased public debt to GDP, and improved government stability. Contrarily, in countries with decreasing ratings, giant discoveries are associated with a reduction in investments and an increase in corruption.

In the second strand of the literature, three categories of determinants of sovereign debt ratings have been identified. The first category includes the macroeconomic factors: higher income per capita, lower inflation, higher GDP growth, higher tax base, lower external debt, and higher investment are positively associated with financial conditions (see, e.g. Cantor and Packer 2011; Larraín et al. 1997; Bissoondoyal-Bheenick 2005; Mellios and Paget-Blanc 2006; Depken et al. 2011a; Afonso et al. 2011; Jaramillo and Tejada 2011; Erdem and Varli 2014). The second category includes institutional factors: greater political stability, lower corruption, absence of violence and terrorism, and no default history are positively associated with financial conditions (see, e.g. Cantor and Packer 2011; Afonso et al. 2011; Mellios and Paget-Blanc 2006; Teixeira et al. 2018; Depken et al. 2011b; Erdem and Varli 2014; Andreasen and Valenzuela 2016). Finally, the third category includes external factors: good terms of trade and sustained exports are positively associated with financial conditions (see, e.g. Mellios and Paget-Blanc 2006; Hilscher and Nosbusch 2010; Erdem and Varli 2014). Also, giant discoveries have been found to affect sovereign debt ratings significantly (Seri 2020).

Taking stock of these existing pieces of literature, we contribute to the literature on giant discoveries in three ways. First, we focus on the effects of the peak of giant oil and mineral discoveries on financial conditions instead of giant discoveries of reserves used in previous analyses (Hooper 2015; Melina et al. 2016; Seri 2020). As previously highlighted, the peak of giant discoveries is more exogenous and could induce amplified effects on financial conditions. Second, we measure financial conditions by the Institutional Investor's Country Credit Ratings (ICR), which encompass sovereign credit risk, political risk, exchange rate risk, economic risk, and transfer risk, and help investors navigate the associated risks with investing abroad. Third, we use the SCM because it captures the country-specific causal effect of the peak of giant discoveries (Abadie 2019; Masi and Ricciuti 2019; Hartwell et al. 2019). It compares the observed trajectory of financial conditions of the treated country in the years after the event with the trajectory of a counterfactual obtained as a weighted combination of countries that are the best pre-treatment match of the treated country.

The rest of the paper is organized as follows. Section 3.2 discusses data. Section 3.3 and Section 3.4 present the methodology and the baseline results, respectively. Section 3.5 concludes.

3.2 Data and their sources

We use several data sources. First, our data on giant discoveries come from Horn (2011) and MinExConsultingDatasets (2014). Second, our data on country credit ratings are obtained from the Institutional Investor Index dataset. Third, our data on the macroeconomic and institutional variables used in our specification come from the World Development Indicators of the World Bank, World Economic Outlook (WEO), the Global Economic Environment (GEE) of the IMF, and Varieties of Democracy (VDEM).

Our outcome variable is the Institutional Investor's Country Credit Ratings (ICR). It is a measure of financial conditions and a proxy of the access to international markets that is relevant for developing countries. It encompasses sovereign credit risk, political risk, exchange rate risk, economic risk, and transfer risk and helps investors navigate the complex risks of investing abroad. Ranked from 0 to 100, with lower values representing the higher likelihood of default and higher values the lower probability of default, this variable has broader coverage than other measures of country risks. For instance, it covers 186 countries, including 49 in Africa, from 1980 to 2014, which helps us analyze the impact of the peak of giant discoveries in developing countries over a long period.

Our variable of interest is the peak of giant discoveries of oil and minerals.[2] These discoveries may serve as quasi-natural experiments as they are likely to be exogenous as described by Arezki et al. (2017); Khan et al. (2016). They have three features that make them interesting to study, including the relatively significant size, the production lag, and the plausible exogenous timing of discoveries (see, e.g. Arezki et al. 2017; Seri 2020, for more details). We use the peak of discoveries rather than giant discoveries since it is more likely to be exogenous and associated with amplified economic, financial, and social effects. For each country in our sample, we identify the peak of the giant discoveries as the first year where the cumulated volume over the next five years of giant discoveries is at its highest level since the first year in our data (i.e., 1868 for oil discoveries, and 1950 for mineral discoveries). After identifying the peak of giant discoveries, we keep in our sample the countries for which the peak occurs during the years 1985-2004 to have a pre-peak of discoveries period of at least five years and a post-peak of discoveries period of at least ten years. Our final sample includes five developing countries over the period 1980-2014, including Angola, Cameroon, Gabon, Kazakhstan, and Romania. This sample is determined by data availability over a relatively long period. The donor pool or set of countries used as control/counterfactuals includes the countries that have never experienced a discovery of either oil or minerals over the period of study.[3]

Our set of confounding factors is derived from the existing literature on the determinants of

[2]According to Horn (2011), giant discoveries of oil are discoveries with a recoverable volume of at least 500 million barrels of ultimately recoverable oil equivalent (boe). Also, for Bhattacharyya and Mamo (2021), mineral discoveries are defined as giant if they generate an amount of at least USD 0.5 billion of annual revenue for 20 years or more

[3]The list of countries in the donor pool includes: Algeria, Belarus, Croatia, Dominican Republic, Georgia, Haiti, Jordan, Kenya, Malaysia, Philippines, Poland, Senegal, South Africa, Sri Lanka, Eswatini, Togo, Turkey, Uganda

Table 3.1: Peak of discoveries by country, and by category of natural resources

Giant oil discoveries		Giant minerals discoveries	
Treated Countries	***Year of Peak***	***Treated Countries***	***Year of Peak***
Angola	2003	Cameroon	1995
Gabon	1987	Romania	1998
Kazakhstan	2000		

Note: This table presents the different treated countries with their peak year of oil or mineral discoveries. The peak of giant discoveries are defines from 1995 to 2004 in order to obtain at least 5 years pre-period and 10 years post-period.

credit ratings. It includes as macroeconomic factors: log of real GDP per capita, real growth (in PPP terms), international reserves (% of GDP), public debt (% of GDP), trading partners' growth, and occurrence of the financial crisis. In addition, it includes as institutional factors: the corruption index and the physical violence index. The variables used in this analysis, their sources, and their summary statistics are reported in Table B.1 and Table B.2, respectively.

3.3 Empirical strategy

We follow closely Smits et al. (2016); Abadie (2019); Hartwell et al. (2019); Masi and Ricciuti (2019) and employ the SCM to estimate the effect of the peak of oil and mineral discoveries on country credit ratings. This model is appropriate for comparative case studies aiming to isolate the effect of an intervention on the outcome variable of interest in a specific treated unit or country. The treated unit is the unit exposed to the intervention, while the untreated units or donor pool are those that are unexposed to the intervention. Moreover, this methodology allows to identify a counterfactual that is given by the weighted outcome of all comparison units that best reproduce the characteristics of the treated unit or country under examination.

In order to design the SCM model, let us assume that we have a panel of I+1 countries indexed by i and observed over T years. Country i=1 is the treated country and has reached the peak of giant discoveries of natural resources at the time To < T; the remaining countries representing the donor pool are not affected by the peak of giant discoveries and therefore have never experienced a discovery.

Let us assume that Y_{1t} is the observed outcome of the treated country $i = 1$ for the post-intervention period where $T > T_o$. Y_{1t}^N is the corresponding outcome that is observed in country i in the absence of the intervention. Then, the effect of the peak of giant discoveries is given by:

$$\alpha_{1t} = Y_{1t} - Y_{1t}^N \tag{3.1}$$

According to Abadie et al. (2010), the SCM estimates Y_{1t}^N by finding a weighted average of the untreated unit that represents the synthetic control. The difference between the outcome of the treated unit and the outcome of the untreated unit at period t is given by $\widehat{\alpha}_{1t}$ where :

$$\widehat{\alpha}_{1t} = Y_{1t} - \sum_{i=2}^{I+1} w_i^* Y_{it} \tag{3.2}$$

The weights w_i^* are chosen so that the predictors of the treated country best match those of the synthetic control in the pre-treatment period. The predictor can be a pre-intervention value of any variable, including the outcome variable. For example, they could be lagged values of the outcome variable. We use as predictors: one-, two-, and three-year lagged value for the outcome variable, and also one-year lagged values for other confounding variables to limit endogeneity issues.

Let us assume K is the number of predictors for the outcome variable. X_{1k} is the pre-event value of the k-th rating predictor for the treated unit. X_{0k} is a $(1XI)$ vector of the pre-event values of the same variable $k^t h$ for the units in the donor pool. Therefore, the vector W^* that contains the weights related to each control unit is chosen to minimize the following sum:

$$V^* = \sum_{k=1}^{K} v_k (X_{1k} - X_{0k} W)^2 \qquad where w_i \geq ; and \sum_{i=2}^{I} w_i = 1 \tag{3.3}$$

Following Abadie and Gardeazabal (2003), we compute for each treated country the Mean Square Predictor Error (MSPE) of the outcome variable in the pre-event period, which measures the expected square distance between the outcome of the treated unit and the outcome of the synthetic control in the pre-event time.[4] Lower is the MSPE, the higher is the resemblance between the synthetic control and the treated unit in the pre-peak of discoveries. In other words, the synthetic control is a good counterfactual. We use the nested optimization procedure in Stata to obtain the lowest MSPE. As shown by Masi and Ricciuti (2019); Hartwell et al. (2019); Abadie (2019), the combination of unaffected units provides a more appropriate comparison than any single unaffected unit.

To summarize, the SCM has some advantages: i) it allows to focus on a specific country and provides the cross-country heterogeneous effects; ii) it shows the dynamic causal effects of the outcome variable in the years following the event; iii) it controls for both observed and time-varying unobserved effects; and iv) it provides a suitable identification of counterfactuals (the "donor pool") based on similar characteristics.

[4] See Abadie and Gardeazabal (2003); Abadie et al. (2010); Abadie (2019); Hartwell et al. (2019); Masi and Ricciuti (2019) for more details.

3.4 Baseline results

This section presents the baseline results of the heterogeneous effects of the peak of giant natural resources discoveries (oil for Angola, Gabon, and Kazakhstan, and minerals for Cameroon and Romania) on ICR. Our final sample of treated countries is driven by data availability over a long period of study and the quality of matching between the pre-event outcomes for the treated groups and those of the synthetic control groups. The quality of matching is measured by the Root Mean Squared Prediction (RMSPE) and is presented in Table 3.2. This table shows that each treated unit's characteristics are almost similar to their weighted averaged synthetic control. Finally, we present in Table 3.4 the countries and their respective weights used to obtain the synthetic control out of the large set of donor pool countries.

Our main findings are depicted in Figure D.1 to Figure D.2, where we present the dynamic of institutional country ratings (ICR) following the peak of oil or mineral giant discoveries for the treated units against the dynamic of their synthetic control. The gap obtained in the aftermath of the peak of the discoveries can be interpreted as their causal effect on ICR, especially given their exogeneity. In these charts, we also test the significance of the gap by calculating p-values defined as the percent of placebo tests with a higher gap after the simulated peak of discoveries (the same year as for the treated unit) than the gap observed for the treated unit. Indeed, if the gap observed for the treated unit can be attributed to the peak of discoveries only, we should not have a similar or higher gap for countries in the donor pool without any discovery for which we simulate a peak of discoveries. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019), and Masi and Ricciuti (2019). For each treated country, the left-hand side chart (A) displays the effect of the peak of giant discoveries on ICR for the country (solid red line) compared to its synthetic (black dashed line); and the right-hand side chart (B) displays the p-value (solid red line) at each horizon in the post-event period.

Table 3.2: Predictor balance and root mean squared prediction error (RMSPE) - Oil discoveries

	Giant discoveries of oil					
	Angola		Gabon		Kazhastan	
Predictors balance	Treated	Syntetic control	Treated	Syntetic control	Treated	Syntetic control
Log of real GDP per capita, one-year lag	8,1966	7,7584	9,9346	9,0377	9,0880	8,1503
Log of Real growth (in PPP terms), one-year lag	4,0155	2,9985	0,2282	0,1359	-2,8861	3,8440
Log of financial crises, one-year lag	1,0000	0,5271	0,0000	0,4174	0,0000	0,4658
Log of international reserves (% of GDP), one-year lag	1,6793	1,6175	1,2091	-0,0934	1,7548	1,7497
Log of central government public debt (% of GDP), one-year lag	4,9832	3,7925	3,4300	3,3956	3,0746	3,5919
Corruption index, one-year lag	-0,8310	-0,8026	-0,8710	-0,5036	-0,7952	-0,7226
Physical violence index	0,1936	0,5926	0,5120	0,0852	0,5693	0,5724
Trading partners' growth	6,3586	3,7381	4,8191	3,1760	2,6479	3,6588
ICR, one year before the peak	13,3500	14,5730	40,3000	37,1473	28,8000	28,0595
ICR, two years before the peak	12,3500	14,0323	38,1500	41,2354	27,0500	26,3522
ICR, three years before the peak	12,2500	13,5646	35,5000	40,7116	22,4500	23,4608
RMSPE	1,0550		4,2835		1,6756	

Note: This table reports for each case study and for each type of giant discovery, the predictors balance between the treated unit and its synthetic control and the Root Mean Squared Prediction Error (RMSPE).

Table 3.3: Predictor balance and root mean squared prediction error (RMSPE) - Mineral discoveries

	Giant discoveries of minerals			
	Cameroon		Romania	
Predictors balance	Treated	Syntetic control	Treated	Syntetic control
Log of real GDP per capita, one-year lag	8,0923	8,4197	9,2058	8,8612
Log of Real growth (in PPP terms), one-year lag	-3,3678	-1,4083	-1,1388	0,9299
Log of financial crises, one-year lag	0,9000	0,6722	0,5714	0,5319
Log of international reserves (% of GDP), one-year lag	-1,1927	0,5297	1,2713	2,1803
Log of central government public debt (% of GDP), one-year lag	3,6345	4,4392	1,8385	3,3301
Corruption index, one-year lag	-0,8170	-0,7451	-0,7461	-0,4524
Physical violence index	0,3910	0,4530	0,9016	0,5215
Trading partners' growth	4,1857	3,4468	1,4524	2,0822
ICR, one year before the peak	19,4500	20,2836	33,4000	33,5900
ICR, two years before the peak	21,5500	20,7966	30,9500	30,5950
ICR, three years before the peak	21,7500	21,5019	28,9000	28,9776
RMSPE	5,6632		2,0876	

Note: This table reports for each case study and for each type of giant discovery, the predictors balance between the treated unit and its synthetic control and the Root Mean Squared Prediction Error (RMSPE).

Table 3.4: Country weights

Treated (oil)	Control group	Weight
Angola	Belarus	0,1470
	Georgia	0,2220
	Haiti	0,4920
	Togo	0,1400
Gabon	Philippines	0,1470
	Turkey	0,4070
	South Africa	0,4460
Kaazhastan	Dominican Republic	0,2600
	Croatia	0,2650
	Uganda	0,4750
Treated (minerals)	Control group	Weight
Cameroon	Algeria	0,3920
	Haiti	0,4730
	Malaysia	0,0820
	Senegal	0,0530
Romania	Algeria	0,1970
	Poland	0,1910
	Senegal	0,0330
	Swaziland	0,5790

This table presents for each type of giant discovery and for each treated country and fo, the combination of the average countries with similar characteristics (on the ICR) notably during the pre-event period.

3.4.1 The case of Angola

Figure D.1 displays the ICR trajectory of Angola and its synthetic control over the period 1996–2014. Our estimate of the effects of the peak of giant discoveries is given by the gap between Angola and its synthetic control in the post-peak discoveries period. It shows that following the peak of oil discovery in 2003, ICR significantly increased between 2007 and 2014 compared to the synthetic control. The peak of oil discoveries did not significantly impact the first four years immediately following its occurrence. Starting in 2007, Angola's ICR significantly diverged to its synthetic over the entire study period. The gap increased until 2010, peaking at around 20, but remained significant afterward (despite the global financial crisis—GFC). The synthetic control is obtained as a weighted average of the ICR for Haiti (49.2%), Georgia (22.2%), Belarus (14.7%), and Togo (14%) as presented in Table 3.4.[5] It almost exactly reproduces Angola's ICR during the pre-peak of discovery period (i.e., from 1996 to 2002), also confirmed by the close fit we obtained for the ICR predictors before the peak of the discoveries between Angola and its synthetic control and a lower pre-RMSPE of 1.05 (see Table 3.2).

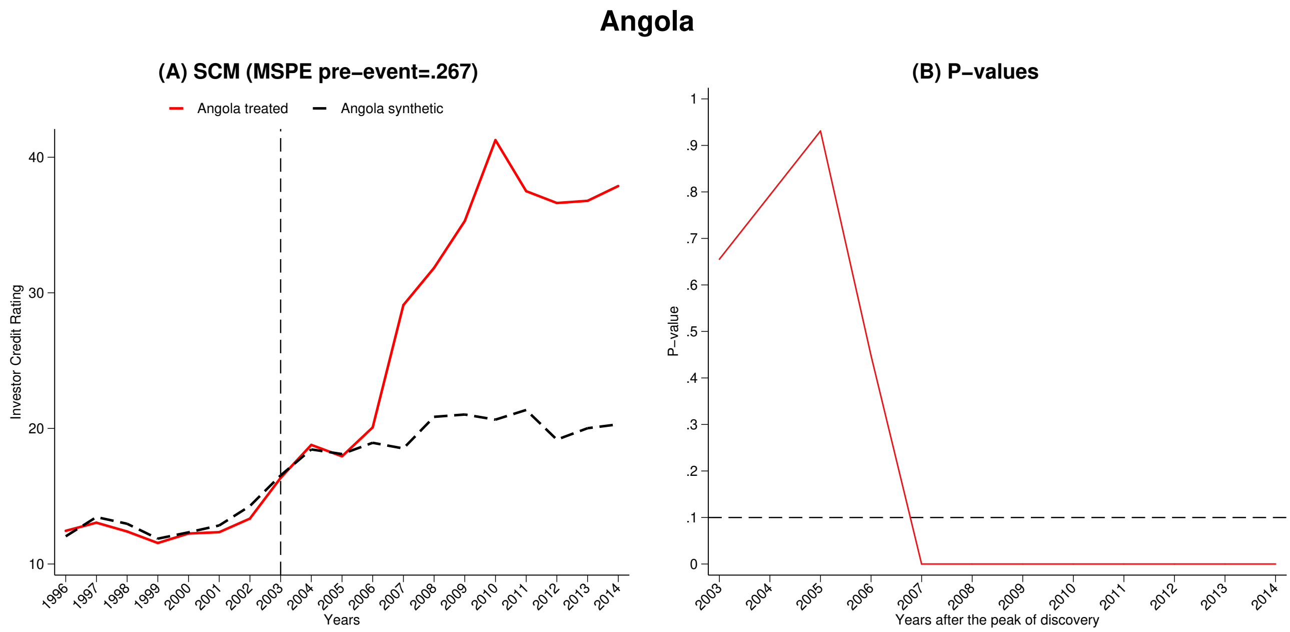
The country had a long history of instability and civil war from 1975 to 2002. However, since 2002, Angola has embarked on a different train to ensure its stability and development, supported by an offshore oil production boom between 2002 and 2008 with annual production growth of around 15 percent per year. Angola is now the second-largest oil-producing country in Sub-Saharan Africa and has continued its socio-economic development by preserving political stability and conducting structural transformation and diversification. The windfalls from the deep-water oilfields, coupled with favorable economic conditions and relative political stability, supported economic activity, the rehabilitation of infrastructures, and non-oil private sector growth. As a result, exports to GDP rose after 2013 before declining in the post-GFC period, and so did international reserves to GDP. Moreover, higher oil revenues lead to a high primary fiscal surplus despite a significant increase in non-interest expenditures. Thus, both debt to GDP and debt services to exports significantly decreased (see Figure B.1). These stylized facts point to improved economic activity and financial conditions that resulted in an improvement in credit ratings. However, this highly oil-dependent country should continue its transformation and diversification, enhance political stability, and improve the financial ecosystem to improve the living standards of its population and accelerate its economic and social development.

3.4.2 The case of Kazakhstan

The case of Kazakhstan is like the one presented for Angola. Figure D.2 shows the ICR trajectory of Kazakhstan and its synthetic control over the period 1994–2014. Our estimate of the effects of the peak of giant oil discoveries is given by the gap between Kazakhstan and its synthetic control in the post-peak discoveries period. It shows that following the peak of oil discovery in 2000, ICR significantly increased between 2003 and 2014 compared to the synthetic control. The peak of oil discoveries did not significantly impact the first three years immediately following its occurrence. Starting in 2003, Kazakhstan's ICR significantly diverged

[5] The weights are presented in parentheses

Figure 3.1: Path of ICR for Angola: Treated country vs Synthetic control



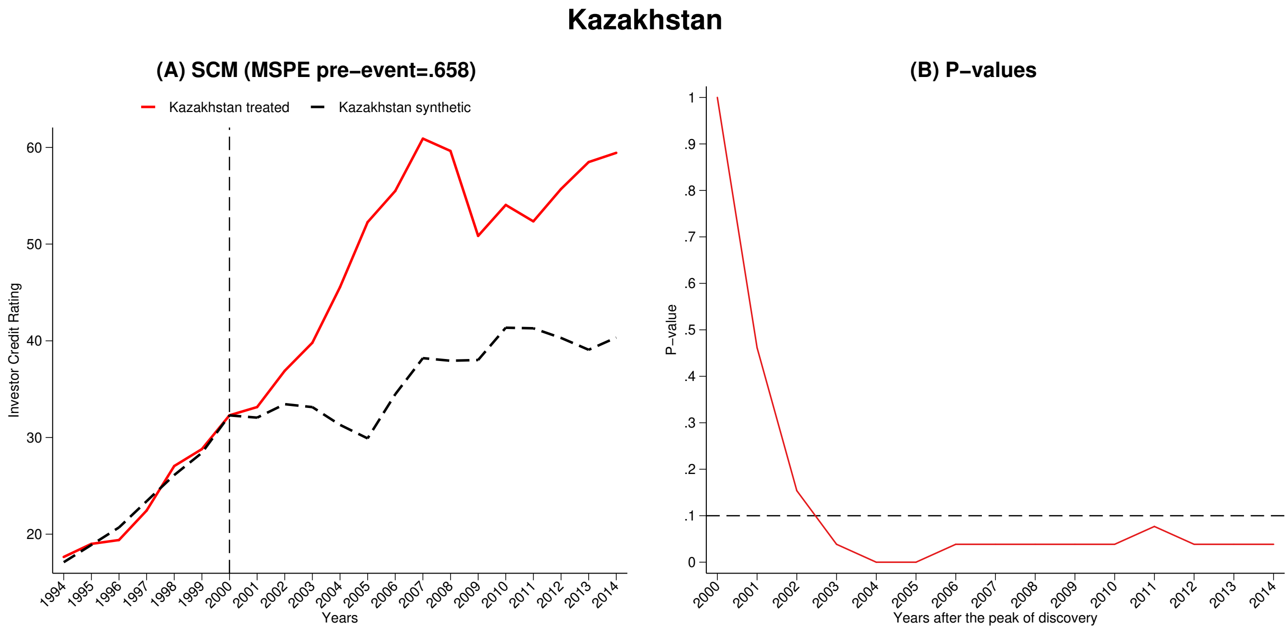
Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Angola, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

to its synthetic over the entire study period. The gap increased until 2008, peaking at around 22, but remained significant afterward (despite the global financial crisis—GFC). The synthetic control is obtained as a weighted average of the ICR for Uganda (47.5%), Croatia (26.5%), and the Dominican Republic (26%) as presented in Table 3.4. It almost exactly reproduces Kazakhstan's ICR during the pre-peak of the discovery period (i.e., from 1994 to 1999), also confirmed by the close fit we obtained for the ICR predictors before the peak of the discoveries between Kazakhstan and its synthetic control and a lower pre-RMSPE of 1.67 (see Table 3.2).

Kazakhstan is the largest oil producer in Central Asia and one of the world's top ten fastest-growing economies until 2015. Following the peak of oil discoveries in 2000, real GDP per capita increased from USD 1230 to USD 13709 in 2014, driven by an expansion in oil production. Employment significantly increased, also in non-oil sectors. Rapid growth translated into lower poverty. Despite easing oil prices, the rising volume of oil production resulted in large receipts from exports as well as total revenues and international reserves. These higher revenues helped finance spending, especially social spending, with the objectives of improving the population's living standards and reducing inequality (see Figure B.2). The

National Fund of the Republic of Kazakhstan was established in 2001 to smooth economic activities through the oil price cycles and save part of oil income for the future generation. In addition, efforts were devoted to enhancing the attractiveness of the investment climate, making Kazakhstan an attractive destination.

Figure 3.2: Path of ICR for Kazakhstan: Treated country vs Synthetic control



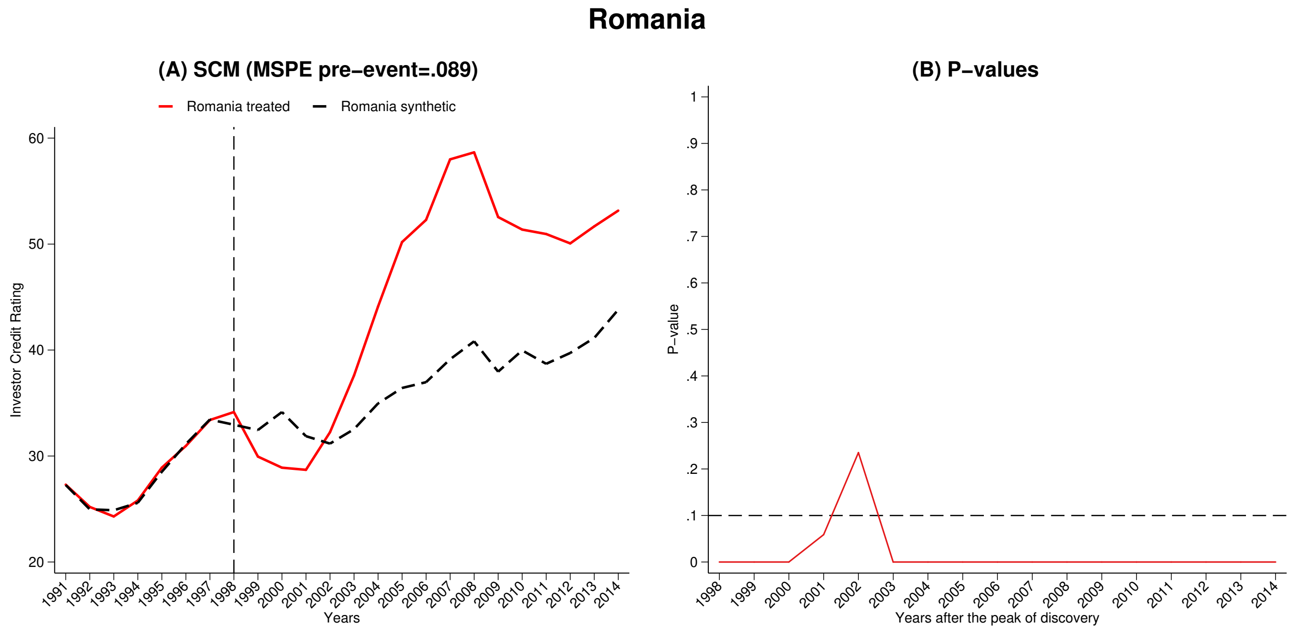
Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Kazakhstan, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

3.4.3 The case of Romania

Figure D.3 displays the ICR trajectory of Romania and its synthetic control over the period 1991–2014. Our estimate of the effects of the peak of giant discoveries is given by the gap between Romania and its synthetic control in the post-peak discoveries period. It shows that following the peak of oil discovery in 1998, ICR significantly decreased over the fourth first years compared to the synthetic control before significantly increasing in the subsequent years until the end of the study period. The positive gap peaked in 2008 at close to 18 before declining in the post-GFC period. The synthetic control is obtained as a weighted average of the ICR for Eswatini (57.9%), Algeria (19.7%), Poland (19.1%), and Senegal (3.3%) as presented in Table 3.4. It almost exactly reproduces Romania's ICR during the pre-peak of the discovery period (i.e., from 1991 to 1997), also confirmed by the close fit we obtained for the ICR predictors before the peak of the discoveries between Romania and its synthetic control and a lower pre-RMSPE of 2.09 (see Table 3.3).

Romania is one of the largest rich countries in mineral resources in Europe, with around 60 different minerals, including metallic ores, iron, manganese, chrome, nickel, molybdenum, aluminum, zinc, copper, tin, titanium, vanadium, lead, gold, and silver. The country has the largest deposit of gold deposit in Europe. Its mineral productions have served as an input for its manufacturing sector. Its adhesion to the EU in 2007 has improved its mining activities, particularly for gold, iron ore, lead, copper, and zinc. The revenues from gold exploitation contributed to the development of the industry, especially of the country's large and ever-expanding metallurgical and machine-building industries. Following the peak in mineral discoveries, GDP per capita jumped, and growth surged. Exports also significantly increased, and so did international reserves. Gross debt to GDP declined from a very high level before jumping again in the post-GFC period (see Figure B.3).

Figure 3.3: Path of ICR for Romania: Treated country vs Synthetic control



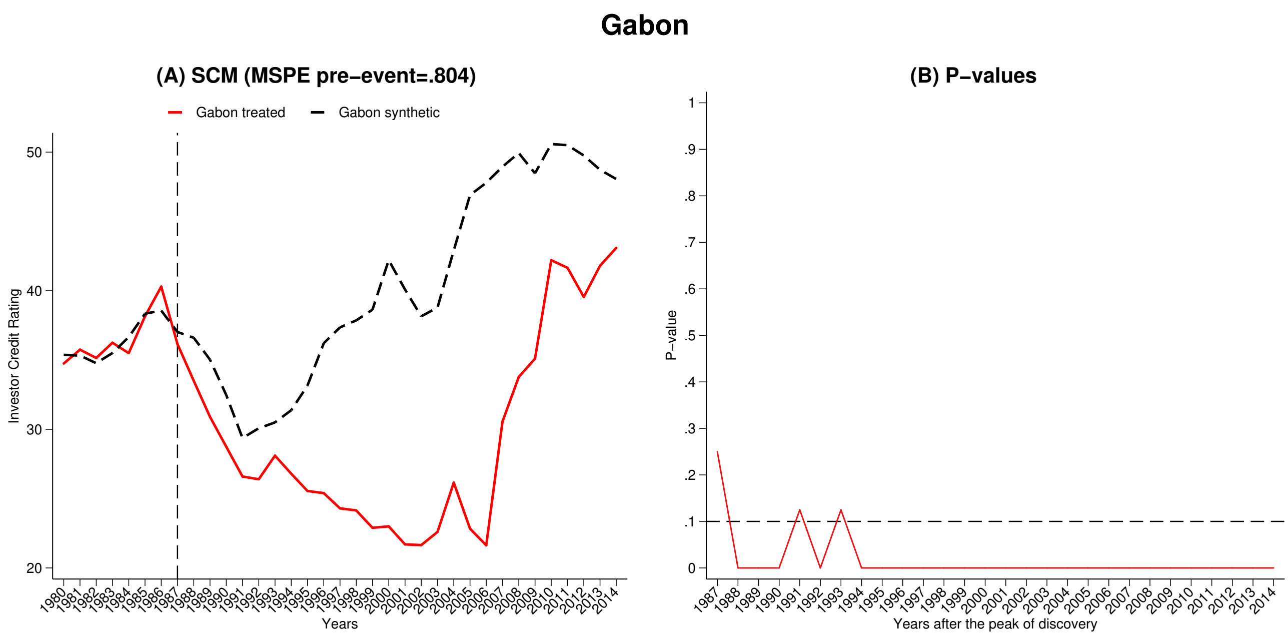
Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Romania, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

3.4.4 The case of Gabon

Contrary to the cases presented above, the cases of Gabon and Cameroon (below) reveal a different story. Figure 4.5 displays the ICR trajectory of Gabon and its synthetic control over the period 1980–2014. Our estimate of the effects of the peak of giant discoveries is given by the gap between Gabon and its synthetic control in the post-peak discoveries period. It shows that following the peak of oil discovery in 1987, ICR significantly decreased compared to the synthetic control over the entire study period. The negative gap peaked in 2006 at close to 26, before declining in the subsequent years. The synthetic control is obtained as a weighted average of the ICR for South Africa (44.6%), Turkey (40.7%), and Philippines (14.7%) as presented in Table 3.4. It almost exactly reproduces Gabon's ICR during the pre-peak of the discovery period (i.e., from 1980 to 1986), also confirmed by the close fit we obtained for the ICR predictors before the peak of the discoveries between Gabon and its synthetic control and a lower pre-RMSPE of 4.28 (see Table 3.2).

Gabon is the fifth-largest oil producer in Africa and, unfortunately, a good example of the "resource curse". The country is less diversified with a weak industrial system, whereas oil remains the main driver of economic activity. Furthermore, the agriculture sector has been neglected. For example, it is hard to find domestically grown bananas despite a significant endowment in arable land. The decline in agriculture was so steep that it went from being a net exporter of agricultural products before independence to importing nearly 90 percent of its food by 2004 (King 2009). Oil has contributed to delinking the state-society linkages, as the authorities are not dependent on income and taxes and do not have to fulfill the social contract. Indeed, the same party has dominated the political landscape and ruled out the country since 1968. Corruption is a serious issue, with few people becoming rich with the money from oil while most citizens see little benefit from it. Following the peak of discoveries in 1987, GDP per capita increased for a few years and then decreased until 2002 before increasing considerably. Real GDP has been very volatile in line with the volatility of oil prices (see Figure B.4).

Figure 3.4: Path of ICR for Gabon: Treated country vs Synthetic control



Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Gabon, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

3.4.5 The case of Cameroon

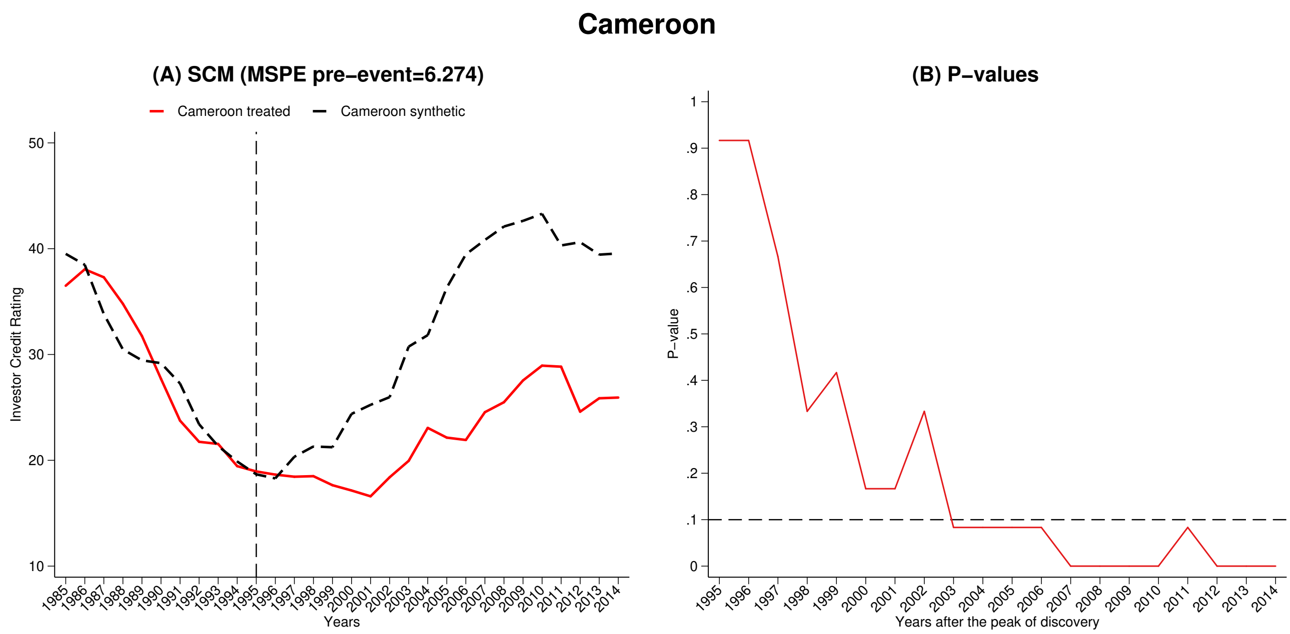
Figure D.2 displays the ICR trajectory of Cameroon and its synthetic control over the period 1985–2014. Our estimate of the effects of the peak of giant discoveries is given by the gap between Cameroon and its synthetic control in the post-peak discoveries period. It shows that following the peak of oil discovery in 1995, ICR significantly decreased compared to the synthetic control over the entire study period. The negative gap peaked in 2006 at close to 18, before declining in the subsequent years. The synthetic control is obtained as a weighted average of the ICR for Haiti (47.3%), Algeria (39.2%), Malaysia (8.2%), and Senegal (5.3%) as presented in Table 3.4. It almost exactly reproduces Cameroon's ICR during the pre-peak of the discovery period (i.e., from 1985 to 1994), also confirmed by the close fit we obtained for the ICR predictors before the peak of the discoveries between Cameroon and its synthetic control and a lower pre-RMSPE of 5.66 (see Table 3.3).

Cameroon's mineral sector is underdeveloped despite significant reserves of bauxite, cobalt, cassiterite, gold, granite, iron ore, lignite, nepheline, syenite, nickel, rutile, and uranium. Most resources have not yet been exploited due to lagging transportation infrastructures. The only significant mining commodity produced in Cameroon has been pozzolana (siliceous volcanic ash used to produce hydraulic cement), and the other mining sites have been mostly artisanal. Following the peak of mineral discoveries in 1995, GDP per capita declined until 2000 before an increase afterward and despite real GDP growth of around 5 percent. In addition, debt services in percentage of exports was high around and after the peak before declining after 2000 (see Figure B.5). Based on our findings, Cameroon could have enjoyed more favorable access to capital markets if the country had properly exploited its mineral resources. Nevertheless, for this to happen, Cameroon has yet to improve and diversify its economic activity, invest in providing public goods and investing in transportation infrastructures, improve governance and reduce corruption.

To summarize, our findings show evidence of the heterogeneous effects of both the peak of oil and mineral giant discoveries on ICR, similarly to the findings in Seri (2020), which focuses on a large set of countries and panel analysis. More specifically, we find that country credit ratings improve following the peak of giant discoveries for Angola, Kazakhstan, and Romania. In contrast, country credit ratings deteriorate following the peak of giant discoveries in Cameroon and Gabon. These findings show that the "resource curse" in terms of access to markets does not apply to all countries and calls for considering country specificity in analyzing the effects of giant discoveries. These findings reinforce the conclusion in Seri (2020) that what seems to matter is not the resource per se but how the authorities react to the news of the discoveries.

We further consider additional predictors of credit ratings following Afonso et al. (2011) and Teixeira et al. (2018), including the volatility of growth (in PPP terms), domestic credit to the private sector in percent of GDP, total investments in percent of GDP, current account in percent of GDP, natural resources rents in percent of GDP, and the intensity of conflicts. The results of

Figure 3.5: Path of ICR for Gabon: Treated country vs Synthetic control



Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Cameroon, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

this robustness are displayed in Figure B.6 to Figure B.9.[6] They show that our baseline findings are qualitatively and almost quantitatively unchanged to additional predictors.

3.5 Conclusion

This paper studies the effects of the peak of oil and mineral discoveries on country ratings in five developing countries, including Angola, Kazakhstan, Romania, Gabon, and Cameroon, over the period 1985-2014, using the SCM. We take a different route from the previous papers by investigating the impact of the peak of giant discoveries rather than any giant discoveries or natural resources endowments because the peak of discoveries appears to be more exogenous and could also be associated with more significant and amplified effects on sovereign debt ratings (Masi and Ricciuti 2019). Moreover, the SCM employed is appropriate for comparative case studies. It helps us to capture the country-specific causal effects of the peak of giant discoveries on credit ratings.

[6] We are unable to present the results of this robustness for Romania due to missing data for some of the newly added predictors.

We find evidence of the heterogeneous effects of both the peak of oil and mineral giant discoveries on ICR, similarly to the findings in Seri (2020), which focuses on a large set of countries and panel analysis. More specifically, we find that country credit ratings improve following the peak of giant discoveries for Angola, Kazakhstan, and Romania. In contrast, country credit ratings deteriorate following the peak of giant discoveries in Cameroon and Gabon. These findings show that the "resource curse" in terms of access to markets does not apply to all countries and calls for considering country specificity in analyzing the effects of giant discoveries. In addition, these findings reinforce the conclusion in Seri (2020) that what seems to matter is not the resource per se but how the authorities react to the news of the discoveries.

The description of our case studies offers some explanations of why sometimes natural resources can be a curse or sometimes a blessing. It shows that, among others, diversification policies, sound macroeconomic and borrowing policies, strong governance and resource management, transparency, appropriate investments in public goods and infrastructures, and saving policies to smooth the commodity price cycles and preserve part of the resources' windfall for future generations, and improvements of the business climate matter to make the country and its population benefit from the resources equitably.

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APPENDIX

B

Appendix to Chapter 3

B.1 Tables

Table B.1: Data Sources

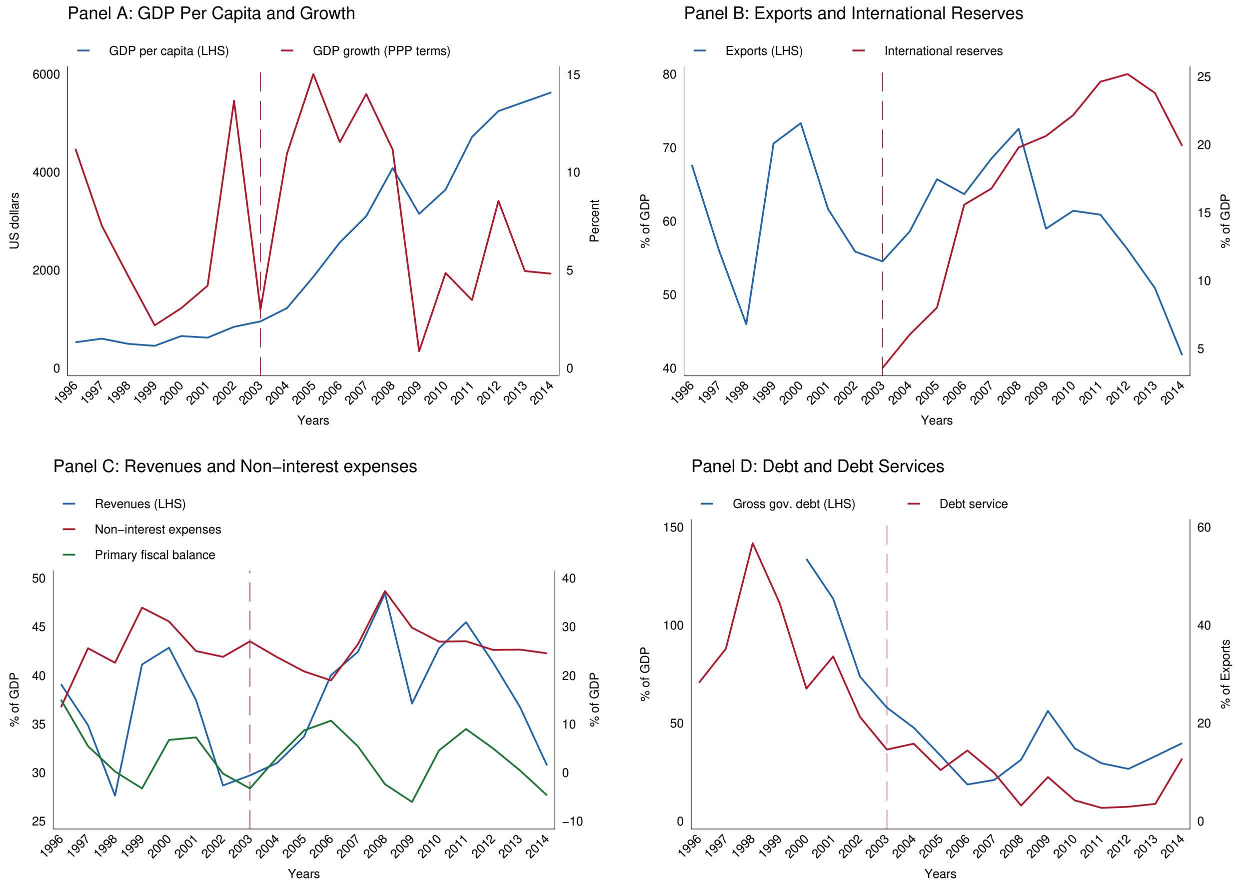
Variables	**Nature**	**Sources**
Dependent variable		
Investor Country Credit Rating	Ordinal	International Monetary Fund (IMF)
Variable of interest		
Peak of giant discoveries of natural resources	Binary	Horn (2011), MinexConsultingDataset (2019)
Control variables		
Log of real GDP per capita	Continuous	World Development Indicators (WDI)
Real growth (in PPP terms)	Continuous	World Development Indicators (WDI)
Financial crises	Binary	Das et al. (2012), Reinhart and Rogoff (2009), Laeven and Valencia (2018), Medas et al. (2018)
International reserves (% of GDP)	Continuous	World Development Indicators (WDI)
General or central government public debt (% of GDP)	Continuous	Mbaye et al. (2018)
Corruption index	Ordinal	Varieties of Democracy (VDEM)
Physical violence index	Ordinal	Varieties of Democracy (VDEM)
Trading partners' growth	Continuous	IMF-GEE (Global Economic Environment)
Additional control variables for Robustness		
Volatility of growth (in PPP terms)	Continuous	International Monetary Fund (IMF)
Domestic credit to the private sector (% of GDP)	Continuous	IMF-GEE (Global Economic Environment)
Total investments (% of GDP)	Continuous	World Economic Outlook (WEO)
Natural resources rents (% of GDP)	Continuous	World Bank (WB)
Intensity of conflicts	Ordinal	Major Episode of Political Violence (MEPV)

Table B.2: Summary Statistics

	Obs.	Mean	St. Dev	Min	Max
Institutional Investor Country Rating	1577	34,38	16,98	4,05	80,20
Log of real GDP per capita	2598	8,71	1,03	5,72	11,41
Real growth (in PPP terms)	2554	2,00	5,83	-56,99	68,31
Financial crises	2940	0,18	0,39	0,00	1,00
International reserves (% of GDP)	2362	1,69	1,62	-5,84	4,68
General or central government public debt (% of GDP)	2253	3,54	0,91	-3,74	7,65
Corruption index	2713	-0,61	0,22	-0,96	-0,07
Physical violence index	2758	0,49	0,28	0,02	0,97
Trading partners' growth	1960	3,68	2,13	-12,68	18,08

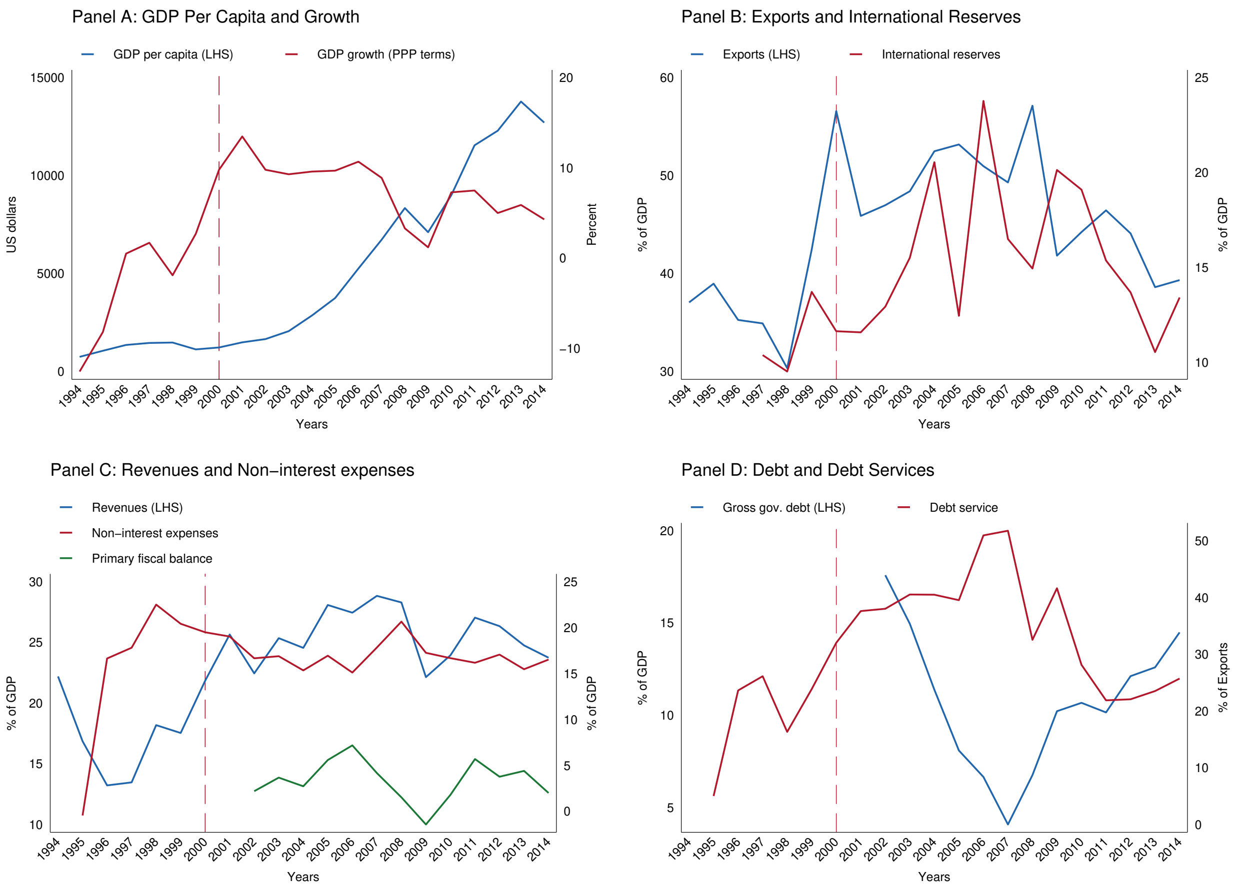
B.2 Additional figures for baseline results

Figure B.1: Trends of some macroeconomic variables for Angola



Source: WEO, April 2022
Notes: Panel A reports the trends of the GDP per capita and the GDP growth in PPP terms. Panel B displays the trajectory of Exports in percent of GDP and International reserves assets in percent of GDP. Panel C shows the trends of the General government revenues, the Non-interest expenses and the Primary fiscal balance in percent of GDP. Panel D exhibits the evolution of Gross government debt in percent of GDP and the total debt service in percent of total exports of goods and services in USD.
The horizontal dashed line corresponds to the year of the peak of discovery for each country (Angola: peak of year=2003)

Figure B.2: Trends of some macroeconomic variables for Kazakhstan

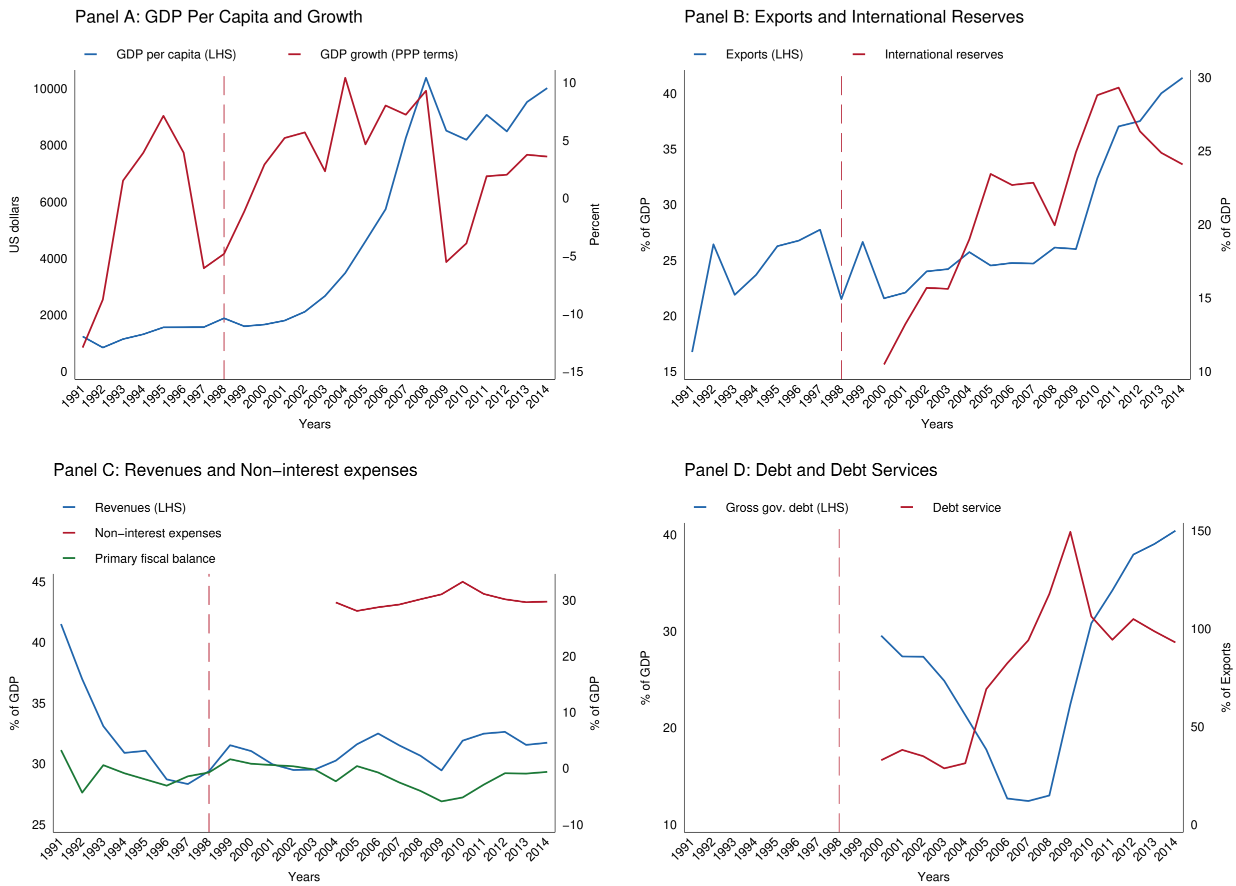


Source: WEO, April 2022

Notes: Panel A reports the trends of the GDP per capita and the GDP growth in PPP terms. Panel B displays the trajectory of Exports in percent of GDP and International reserves assets in percent of GDP. Panel C shows the trends of the General government revenues, the Non-interest expenses and the Primary fiscal balance in percent of GDP. Panel D exhibits the evolution of Gross government debt in percent of GDP and the total debt service in percent of total exports of goods and services in USD.

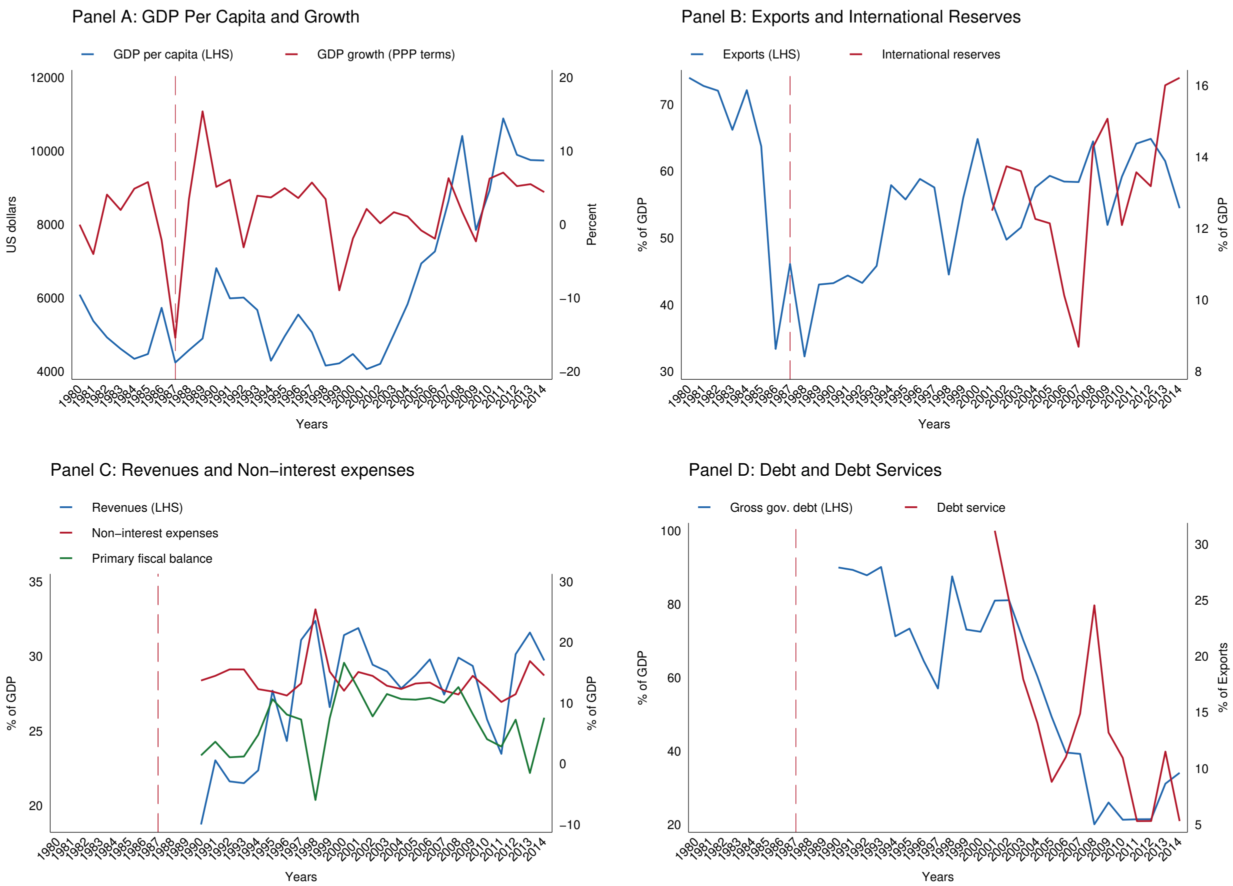
The horizontal dashed line corresponds to the year of the peak of discovery for each country (Kazakhstan: peak of year=2000)

Figure B.3: Trends of some macroeconomic variables for Romania



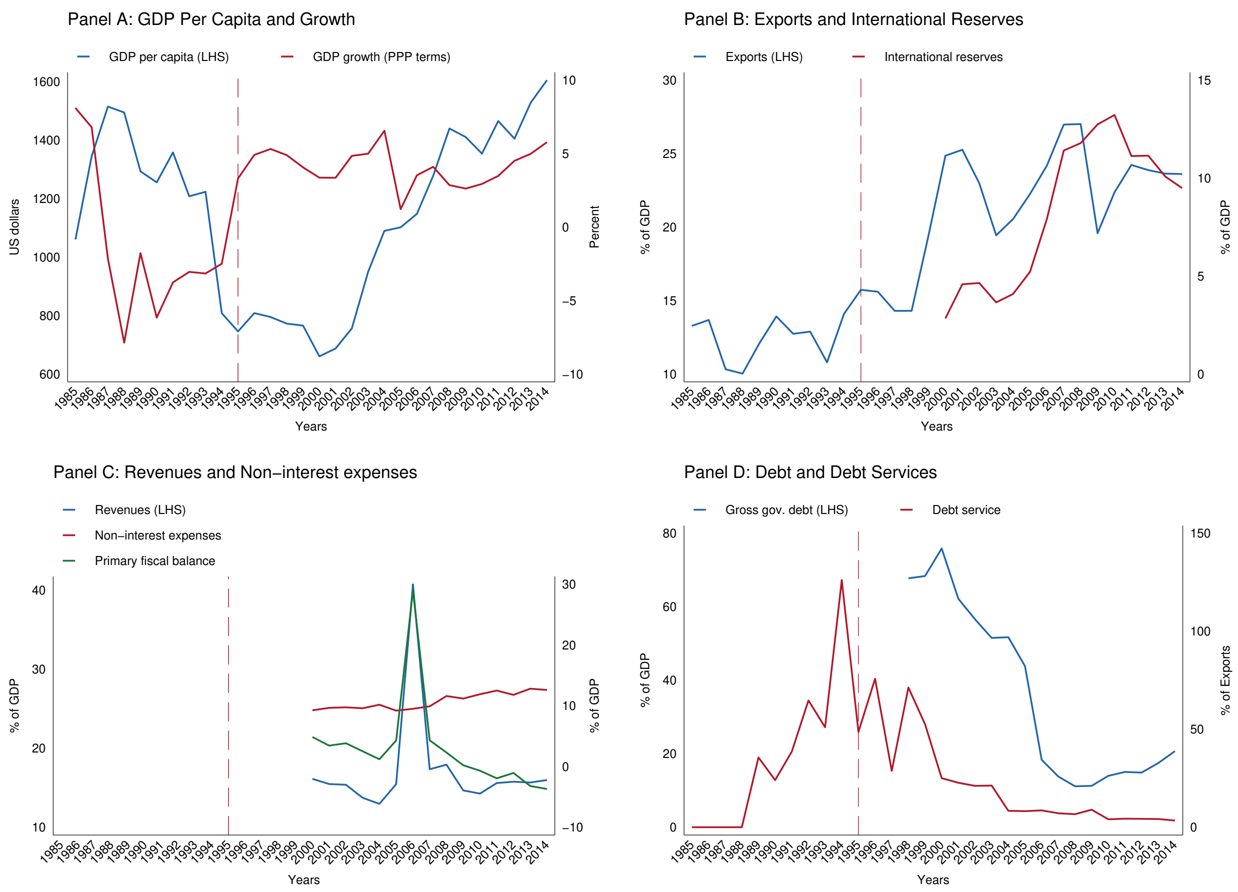
Source: WEO, April 2022
Notes: Panel A reports the trends of the GDP per capita and the GDP growth in PPP terms. Panel B displays the trajectory of Exports in percent of GDP and International reserves assets in percent of GDP. Panel C shows the trends of the General government revenues, the Non-interest expenses and the Primary fiscal balance in percent of GDP. Panel D exhibits the evolution of Gross government debt in percent of GDP and the total debt service in percent of total exports of goods and services in USD. The horizontal dashed line corresponds to the year of the peak of discovery for each country (Romania: peak of year=1998.)

Figure B.4: Trends of some macroeconomic variables for Gabon



Source: WEO, April 2022
Notes: Panel A reports the trends of the GDP per capita and the GDP growth in PPP terms. Panel B displays the trajectory of Exports in percent of GDP and International reserves assets in percent of GDP. Panel C shows the trends of the General government revenues, the Non-interest expenses and the Primary fiscal balance in percent of GDP. Panel D exhibits the evolution of Gross government debt in percent of GDP and the total debt service in percent of total exports of goods and services in USD.
The horizontal dashed line corresponds to the year of the peak of discovery for each country (Gabon: peak of year=1997)

Figure B.5: Trends of some macroeconomic variables for Cameroon

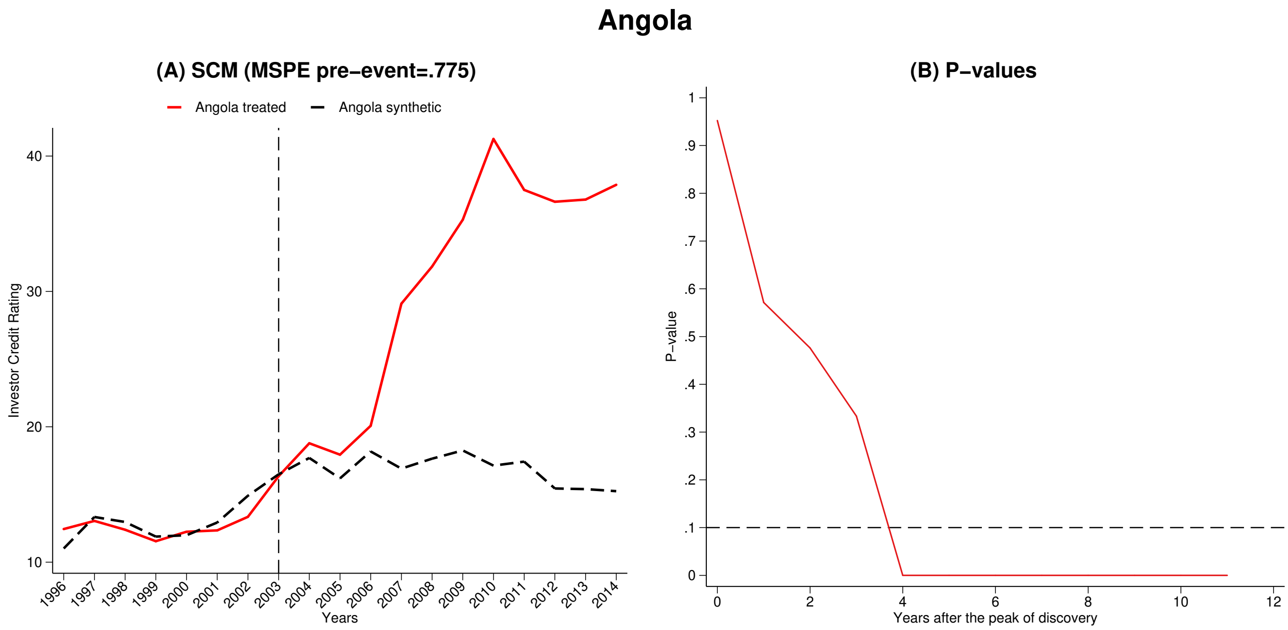


Source: WEO, April 2022
Notes: Panel A reports the trends of the GDP per capita and the GDP growth in PPP terms. Panel B displays the trajectory of Exports in percent of GDP and International reserves assets in percent of GDP. Panel C shows the trends of the General government revenues, the Non-interest expenses and the Primary fiscal balance in percent of GDP. Panel D exhibits the evolution of Gross government debt in percent of GDP and the total debt service in percent of total exports of goods and services in USD.
The horizontal dashed line corresponds to the year of the peak of discovery for each country (Cameroon: peak of year=1995)

B.3 Robustness checks: Figures

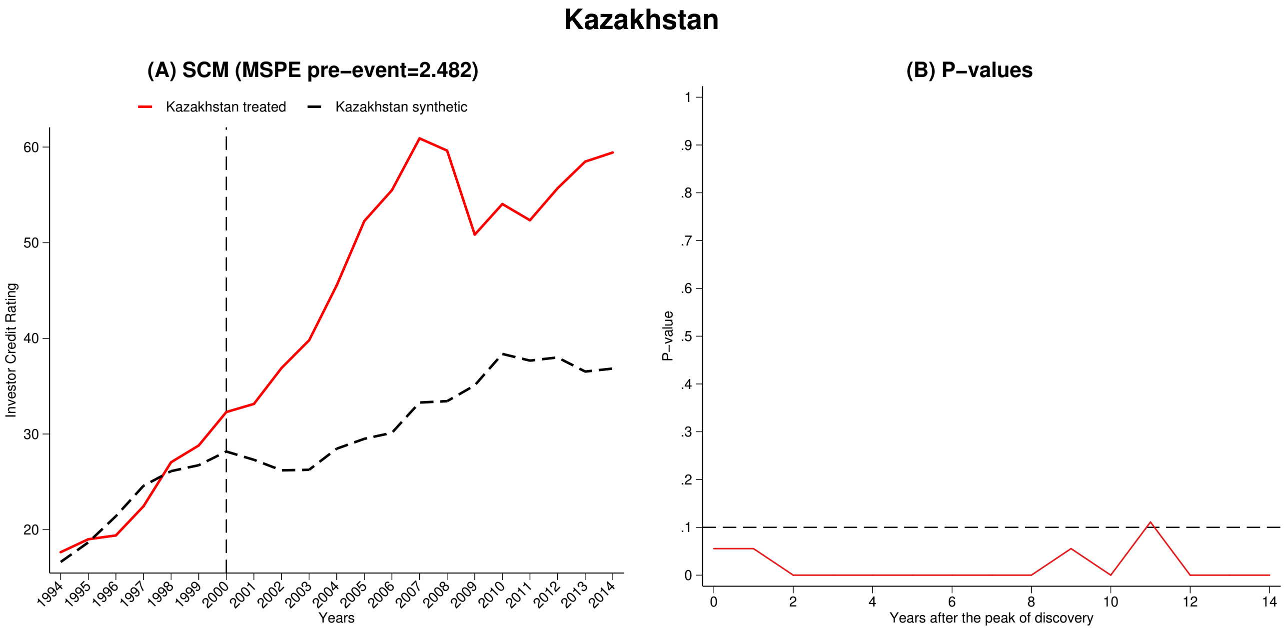
B.3.1 Additional control variables

Figure B.6: Path of ICR for Angola: Treated country vs Synthetic control



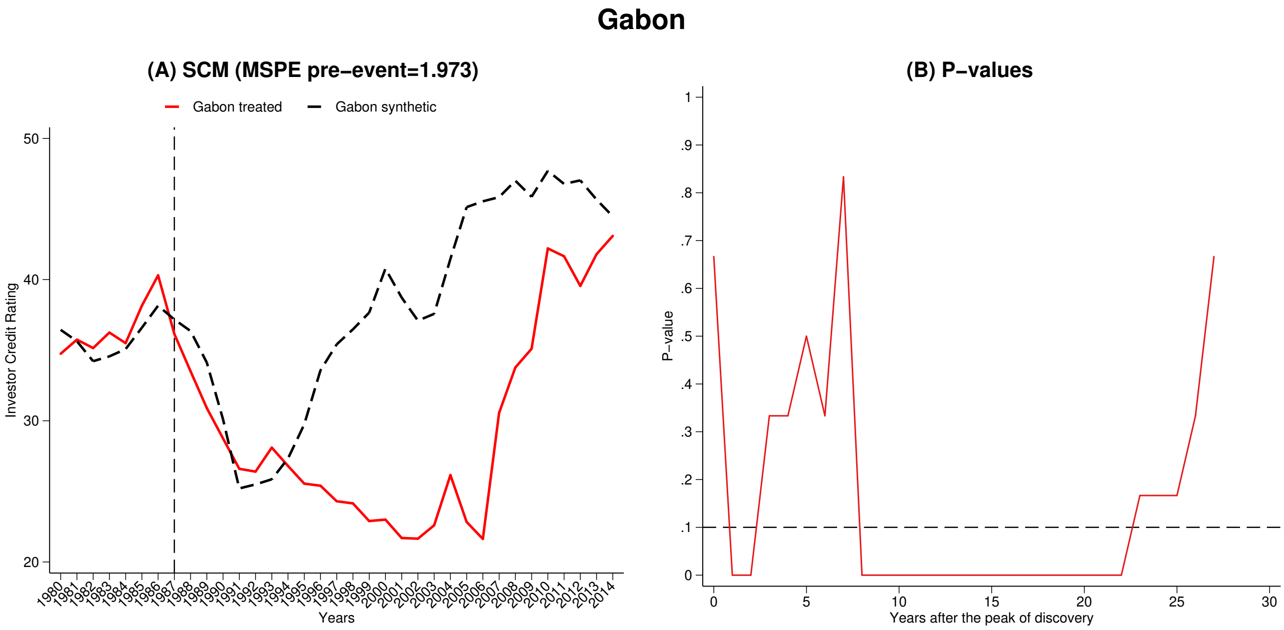
Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Cameroon, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

Figure B.7: Path of ICR for Kazakhstan: Treated country vs Synthetic control



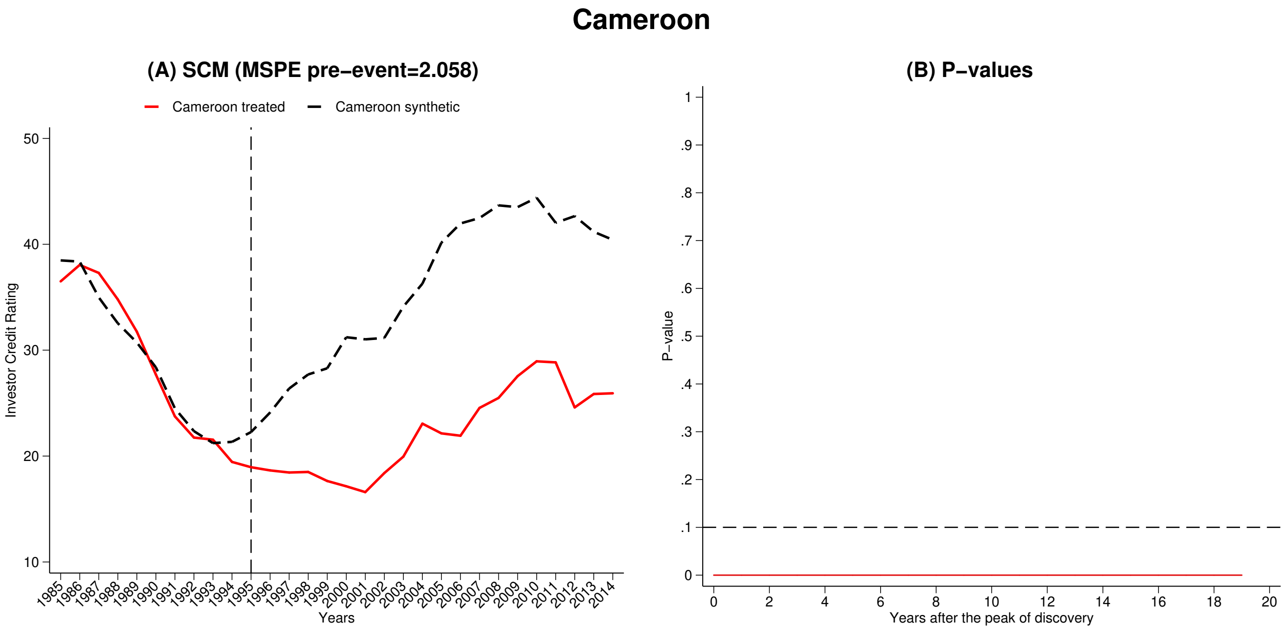
Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Cameroon, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

Figure B.8: Path of ICR for Gabon: Treated country vs Synthetic control



Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Gabon, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

Figure B.9: Path of ICR for Cameroon: Treated country vs Synthetic control



Notes: Panel (A) plots the effect of the peak of oil discoveries (vertical dashed line) on the trajectory of Investor Country Credit Rating (ICR) for Cameroon, the treated country (solid red line) relative to its synthetic (dashed black line). Panel (B) displays the p-value at each horizon in the post-event period. We use the threshold of 10 percent for the significance following Abadie (2019), Hartwell et al. (2019) and Masi and Ricciuti (2019).

Part II:

The Microeconomic Impacts of Mineral Discoveries on Intergenerational Mobility in Africa

CHAPTER 4

IS EDUCATION NEGLECTED IN NATURAL RESOURCE-RICH COUNTRIES? AN INTERGENERATIONAL APPROACH IN AFRICA

This chapter is joint work with Jean-Marc B. Atsebi (IMF) and Rasmane Ouedraogo (IMF).[1]

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Abstract

The literature on the effects of natural resources on education is mixed and inconclusive. In this paper, we adopt an innovative approach by exploring the effects of mineral discoveries and productions on intergenerational educational mobility (IM), linking parents to the children education levels for more than 14 million individuals across 28 African countries and 2,890 districts. We find that mineral discoveries and productions positively affect educational IM for primary education in Africa for individuals exposed to the mineral sites and living in districts with discoveries. Specifically, the probability of upward primary IM increases by 2.7 percentage points (pp.) following mineral discoveries and 6.7 pp. following mineral productions. Downward primary IM decreases by 1.2 pp. following both mineral discoveries and productions. These positive effects are increasing for individuals born later after discoveries and productions, for males, and individuals living in the urban area. However, no significant effects are found for secondary and tertiary educational IM. Finally, we explore the income and returns to education channels through which mineral discoveries and productions affect educational IM. In terms of recommendation policies, this paper suggests to governments to support the local development through the creation of jobs with better linkages between international mining firms and SMEs, to implement targeted policies to reduce gender and urban-rural inequalities; and to redistribute the mineral revenues equally between regions through the creation of a fund.

Keywords: Africa; Educational Intergenerational Mobility; Mineral discoveries and productions; Generalized Difference-in-differences; Natural experiment
JEL Codes: C55; I21; I25; I26; N9; O10; O55; Q32

4.1 Introduction

Pre-COVID-19, Africa emerged out of decades of stagnant and unstable economic growth since mid-1990s, with significant progress made on education and human capital. According to Young (2012), Sub-Saharan living standards have, for the past two decades, been growing about 3.4 to 3.7 percent per annum, reflecting the African "growth miracle". This "growth miracle" has been accompanied by significant improvements in education. Indeed, in Sub-Saharan Africa (SSA), gross enrollment in primary education almost doubled from 54 percent in 1970 to 99 percent in recent years. For secondary and tertiary education, it has been more than three and six times higher in recent years compared to 1970, from 13 to 43 percent and 1.4 to 9.4 percent, respectively (WorldBank 2020). These improvements have been observed for both rural and urban areas as well as females and males. As a result, intergenerational mobility (IM) in education—which measures the levels of children education relative to their parents—has also significantly increased across African countries, above the level in Latin America. But it remains lower in the region compared to Western, Asian, and Eastern Europe countries (Hertz et al. 2008; Azomahou and Yitbarek 2020; Henn and Robinson 2021). As shown by Henn and Robinson (2021), actual and perceived social and educational intergenerational mobility constitute one of the three Africa's latent assets that will drive its economic prosperity and bright future.

Taking stock of this progress in education, we analyze the potential effects of mineral discoveries and productions on educational IM across 28 African countries and 2,890 districts. Few studies have investigated the determinants of educational intergenerational mobility in Africa. They found that individuals and local characteristics (e.g., gender, race, urbanization, etc.), access to markets, quality of education, globalization, and investments in physical and human capital affect educational mobility (Alesina et al. 2021; Azomahou and Yitbarek 2020; Baah and Eshun 2020; Nimubona and Vencatachellum 2007). To the best of our knowledge, only Alesina et al. (2021) discussed the effects of natural resources on educational IM. They show a weak association between oil, gas, and diamond discoveries and educational IM. They explain this weak association by opposing mechanisms as natural resources might be a curse, and they may also represent a wealth spurring human capital accumulation and structural transformation. Still, their analysis of the effects of natural resources on educational IM is very limited and discussed in a short paragraph as this is not their focus.

In this paper, we fill this gap in the existing and inconclusive literature. Mineral discoveries are generally known as being a curse or sources of difficulties and fragility for most African countries as illustrated by the resource curse literature. The growth in the mining sector does not necessary shift an economy towards better industry processing, services, i.e., structural transformation, education, health, job creation, and inclusive growth and development. In contrast, they might have some positive effects, especially on educational IM. Mining activities may create new opportunities that will increase households' income (Becker and Tomes 1979; Weber-Fahr 2002; Loayza et al. 2013), enabling them to invest more in children education. They may also favor a structural transformation in the districts with natural resources (Cavalcanti et al. 2019), and therefore an increase of the returns to education, i.e., income or wealth induce by education (Torche 2014; Bütikofer et al. 2018). Finally, they may also support the provision of infrastructures (in education in particular) financed by the revenues from the resources (Witter and Jakobsen 2017). This analysis is particularly relevant as the African continent is home to an abundance of mineral resources.[2] It hosts 30 percent of the world's mineral reserves, 40

[2]These mineral resources include gold, silver, diamonds, emerald, ruby, iron, copper, coal, bauxite, cobalt, uranium, platinum and more.

percent of the world's gold and up to 90 percent of some minerals like chromium and platinum.[3] According to Minex Consulting database (2019),[4] 969 normal to super-giant mineral discoveries occurred in Africa between 1950 and 2019, and 396 of them (40 percent) since 2000. Moreover, the exploitation of mineral resources makes a significant contribution to the development of African economy. According to the IMF, the mining sector accounted for 8.8 percent of GDP and 51.2 percent of total exports in Sub-Saharan countries over the period 2009–19.

There is a vast and inconclusive literature on the effects of natural resources. At the macro level, most papers found that natural resources have been a curse than a blessing, as well illustrated by the resource curse literature (e.g., Corden and Neary 1982; Sachs and Warner 1995, 2001; Kretzmann and Nooruddin 2005).[5] Others studies have found positive effects on foreign direct investments in non-resource sectors (Toews and Vezina 2017), or ambiguous effects on macroeconomic activity and financial conditions (Arezki et al. 2017a; Seri 2021). At the local level, a positive effect of natural resources has emerged in recent analyses focusing on African countries or other developing countries (e.g., Fisher et al. 2009; Cust and Mensah 2020; Bhattacharyya and Mamo 2021). Specifically, the literature of the effects of natural resources on education is also inconclusive. Some papers found that natural resources exert a decrease in education level in developing countries (Leamer et al. 1999; Gylfason 2001; Ahlerup et al. 2020), while others have revealed that natural resources are positively associated with human capital accumulation, notably through the increase of public spending in education (Kim and Lin 2017; Pegg 2010; Stijns 2006). Other studies underscore that the effects depend on the quantity or the quality of education, the levels of education or the characteristics of individuals (e.g., Farzanegan and Thum 2020; Gradstein and Ishak 2020).

Our paper complements these studies by exploring the effects of mineral discoveries and productions on educational IM. We use a large dataset of more than 14 million individuals from 28 African countries, 2,890 districts. To do so, we rely on two main sources: i) the Integrated Public Use Microdata Series (IPUMS), and ii) the Minex Consulting datasets. We first start by providing a panorama of the trends, dynamics, and disparities of educational IM across countries, regions of the continent, and the characteristics of the individuals, using the conditional absolute measure of IM as in Alesina et al. (2021). Second, we empirically study the effects of mineral discoveries and productions on primary and secondary/tertiary educational IM by employing a generalized difference-in-differences method in a quasi-natural experiment. Our quasi-natural experiment on the plausible exogeneity of mineral discoveries that revert specific

[3] https://www.unep.org/regions/africa/our-work-africa

[4] https://minexconsulting.com/

[5] See Collier and Hoeffler (2005); Kretzmann and Nooruddin (2005); Ross (2004, 2006); Tsui (2011); Van Der Ploeg (2011); Keen (2012); Lei and Michaels (2014); Van Der Ploeg and Poelhekke (2017); Smith and Wills (2018); Harding et al. (2020) for more details on resource curse's literature.

characteristics, specifically the unpredicted time of discoveries, the unpredicted geographical location, and the lag between the natural resources discoveries and beginning of production (Horn 2011; Khan et al. 2016; Arezki et al. 2017a; Cavalcanti et al. 2019). Third, we explore the channels through which mineral resources discoveries and productions may affect educational IM such as job creation, and the returns to education.[6]

We find that mineral discoveries and productions positively affect educational IM for primary education in Africa. Indeed, the probability of upward primary educational IM, i.e. the probability for a child born from uneducated parents or parents with less than primary education attainment to achieve at least primary education, increases by 2.7 pp. following mineral discoveries and 6.7 pp. following mineral productions. The probability of downward primary educational IM, i.e. the probability for a child born from parents with at least primary education attainment to be uneducated or have less than primary education attainment, decreases by 1.2 pp. following both mineral discoveries and productions. About the size of the effects, it is relatively small when compared to the increase of educational IM across the different cohorts, signaling that, other factors have also played a significant role in improving IM in Africa.

To put our findings into perspective and extrapolate them to Africa, we show that the number of individuals born up to 15 years after mineral discoveries and who have completed at least primary education while their parents have not, increases by 662 thousand in Africa over the period 1950-2000. This figure stands at 581 thousand for individuals born up to 15 years after mineral productions. Similarly, the number of individuals born up to 15 years after mineral discoveries and who have not completed at least primary education while their parents have completed it, decreases by 371 thousand. This figure stands at 124 thousand for individuals born up to 15 years after mineral productions. These figures would have been even higher to millions of individuals if we would have considered all the individuals born after the discoveries and productions, and not only those born up to 15 years after the event. However, our results show that the effects of mineral resource discoveries and productions on the probability of upward and downward secondary and tertiary educational IM are not statistically significant.

Moreover, we also explore the dynamic effects of mineral discoveries and productions on educational IM, i.e. whether the effects vary with the distance between individuals' birth years and the year of mineral discoveries and productions, and test the assumption of parallel trend of the GDID model by estimating a leads and lags model following Angrist and Pischke (2009) and

[6]To further reinforce the returns to education channel, we also test whether mineral discoveries and productions affect the reallocation of individuals across the broad sectors, i.e., agriculture, manufacturing, and services, with population exposed to the mineral discoveries and productions more like to work in the manufacturing and services sectors. We also test a third channel of the provision of infrastructures but decide not to present them as we use an (imperfect) proxy—access to electricity and clean water—for the provisions of public goods. The results can be obtained upon request.

Maurer (2019). Our results show that mining activities positively affect primary educational IM for all age groups, but the effects are non-significant for secondary/tertiary educational IM, confirming our baseline findings. Interestingly, we find that the positive effects of mineral activities on educational IM are increasing for individuals born later after the discovery and beginning of mining production, while being non-significant or low for individuals born before the discovery or production, also confirming that the parallel trend assumption is verified. Our baseline results are robust to several robustness checks. We also analyze the sensitivity of our findings across African regions, size of mineral discoveries, gender, and urban-rural living area. Overall, our findings show that the effects of mining activities are different by African regions and size of the discoveries. Also, the positive effects are higher for males than females (only for primary education), and individuals living in urban than rural areas (both for primary and secondary/tertiary education).

Furthermore, we discuss two transmission channels through which the positive effects of mineral discoveries and productions on educational primary IM operate, including the income effect proxied by parents working in the mining sector, and the returns to education. First, our results show that the mining sector creates new job and income opportunities for parents, allowing them to invest more in their child's education attainment (Becker and Tomes 1979). Second, we uncover that the economic dynamism and creation of new jobs following the discoveries of mineral resources lead to an increase in the demand for skilled workers and thereby boosting the returns to education (Torche 2014).

Our paper unveils the potential impact of mineral discoveries and productions on educational IM in Africa. It shows that, on average, mineral discoveries and productions have led to an improvements of primary education and intergenerational mobility at local levels. It adds to the existing knowledge of the effects of natural resources in general, and on education in particular, and identifies some potential channels through which they impact educational IM. Our paper has many policy implications. We discussed them in the concluding section. In short, this paper calls for a better management of the resources by the government and companies. Adequate policies should be put in place to extract the benefits of the resources, including policies aiming at creating jobs and facilitating entreprise development, and ensuring equitable access to the benefits of the resources by all people independently of gender and location.

The rest of the paper is organized as follows. Section 4.2 reviews the literature and places this study among the existing papers. Section 4.3 discusses the data, explains the construction of the educational IM, and presents some stylized facts on educational IM in Africa by decade, gender, at district and country level. Section 4.4 provides stylized facts on both educational IM and mineral discoveries and productions. Section 4.5 describes the methodology. Section 4.6 presents our main findings. Section 4.7 explains the transmission channels. Section 4.8 and

Section 4.9 discuss the robustness checks and the sensitivity of our findings, respectively. Section 4.10 concludes and discusses potential policy implications.

4.2 Review of literature

Our paper closely relates to three strands of the literature, notably the general effects of natural resources, the relationship between natural resources and education, and the literature on the determinants of intergenerational mobility.

4.2.1 General effects of natural resources

At the macroeconomic level, most papers in this literature show that natural resources have been a curse than a blessing, as well illustrated by the resource curse literature. They found that natural resources are generally associated with the deterioration of economic and institutional conditions, the occurrence of conflicts, an appreciation of real exchange rate, which induces a loss of competitiveness and de-industrialization of the economy, as well as with weak fiscal policy stance and unsustainable debt accumulation (e.g., Corden and Neary 1982; Sachs and Warner 1995, 2001; Kretzmann and Nooruddin 2005; Collier and Hoeffler 2005; Ross 2004, 2006; Van Der Ploeg 2011; Keen 2012; Van Der Ploeg and Poelhekke 2017). However, the macroeconomic effects of natural resource discoveries of oil, gas, and minerals on economic activity seem to be mixed. While some papers find negative impacts of giant discoveries on fiscal policy, debt, conflict, poverty, and inequality (Kretzmann and Nooruddin 2005; Harding et al. 2020; Lei and Michaels 2014; Tsui 2011; Smith and Wills 2018), others show positive effects on foreign direct investments in non-resource sectors Toews and Vezina (2017), or ambiguous effects on macroeconomic activity and financial conditions (Arezki et al. 2017b; Seri 2021).

At the local level, a positive effect of natural resources has emerged in more recent analysis focusing on African countries or other developing countries. They show that natural resources are associated with a reduction of inequality, poverty, and an increase of living standards, income, and welfare. In fact, Goderis and Malone (2011) find that resource exploitation booms reduce income inequality in resource-rich countries, while Fisher et al. (2009) show an evidence of the reduction of poverty in the mineworkers' population in Tanzanian artisanal mines of gold and diamond. Zabsonré et al. (2018) reveal for Burkina Faso that gold exploitation led to better living standards, an increase in per capita household expenditures, and a reduction of poverty in the mining areas. Marlet (2020), using mining exploitation in Ghana, finds that mining activities tend to increase migration flows up to 200 km from the treated district by reducing migration costs through the construction of roads and infrastructures. Moreover, they also induce an increase of income and improvement of welfare by 1.3 percent. In contrast, some papers find that mining activities can create some environmental issues by increasing pollution and metal toxicity (e.g., von der Goltz and Barnwal 2019; Hausermann et al. 2018).

The literature also supports the benefits and positive role of natural resources discoveries on local economic development, governance and conflicts, provisions of public goods and welfare. Cavalcanti et al. (2019) find evidence of a positive impact of oil and gas discoveries on local development and urbanization in Brazil. Cust and Mensah (2020) reveal that oil, gas, and mineral discoveries positively impact the citizen's expectations, which is materialized by a decrease in outward migration and an increase in fertility in the short term. Bhattacharyya and Mamo (2021) show that oil and mineral discoveries reduce the likelihood of conflict in 48 African countries, which is mainly driven by an improvement of economic development and efficient political distribution patronage in districts with discoveries.

4.2.2 Natural resources and education

The literature on the effects of natural resources on education is also inconclusive, but it identifies channels through which natural resources may affect education. While some papers find that natural resources favor a decrease in education levels in developing countries, others rather point out to a positive effect. On the negative effects, Leamer et al. (1999) find that the abundance of natural resources entails a delay of industrialization, and it lowers education levels in Latin American resource-rich countries as workers do not need high skills to work in the natural resources sector. Gylfason (2001), Cockx and Francken (2016) and Ahlerup et al. (2020) show that natural resources crowd out investments in education in resource-rich countries, decrease public education expenditures relative to GDP, and reduce educational attainment, respectively. On the positive effects, some papers find that natural resources abundance is positively associated with human capital accumulation, notably through the increase of public spending in education (see, e.g., Stijns 2006; Kim and Lin 2017) and Pegg (2010). A possible channel is that the mining activity may create new opportunities that will increase households' income (Becker and Tomes 1979; Weber-Fahr 2002; Loayza et al. 2013), enabling them to invest more in children education. It may also favor a structural transformation in the district with natural resources (Cavalcanti et al. 2019), and therefore an increase of the returns to education, i.e., income or wealth induce by education (Torche 2014; Bütikofer et al. 2018). Finally, it may also support the provision of infrastructures (in education in particular) financed by the revenues from natural resources (Witter and Jakobsen 2017). We test these channels for the effects of mineral discoveries and productions on educational IM.

Other studies find that the effects of natural resources on education may diverge depending on whether the focus is the quantity or the quality of education, the levels of education, and characteristics of individuals (age, gender). In fact, Farzanegan and Thum (2020) show a positive effect of oil rents on the quantity of education measured by government spending in primary and secondary education, particularly in countries with sound quality of institutions. In contrast, they find a negative effect of oil rents on the quality of education, defined as "an increase in cognitive skills obtained from an additional year of schooling". This negative effect is driven by the low demand and supply for high-quality education. On the demand side, the phenomenon of resource curse in those countries, by leading to an increase in the size of the non-tradable sector, requires less skilled workers with lower level of human capital. On the supply side, the lower incentive to attract local qualified teachers and the lack of long-term opportunities for foreign or migrant teachers reduce the quality of education. Moreover, Gradstein and Ishak (2020), using IPUMS data on 18 African countries, find that oil price booms occurring in early childhood (ages 0-4) enhance educational attainment and other derived outcomes, but reduce them when occurring in the adolescence (ages 10-14), especially for girls.

4.2.3 Intergenerational mobility in education and its determinants

Very few papers exclusively focus on educational IM in Africa. Focusing on South Africa, Nimubona and Vencatachellum (2007) show that educational IM is higher for white than black people. They find that access to credit market and quality of schools are the main determinants of lower educational IM for black people. Baah and Eshun (2020) reveal that economic and educational IM in Ghana is one of the lowest in the world. In addition, they find that globalization enhances IM, thereby recommending policies aiming at expanding globalization. Moreover, they find that FDI and expansionary fiscal policy improve IM while unemployment has an exactly opposite effect on it. Other papers have conducted cross-country analysis based on several African countries. Alesina et al. (2021) employ measures of absolute mobility to estimate educational intergenerational mobility since independence using census data on 27 African countries. After maping IM cross-country and within country variation, they find that colonial investments in the transportation network and missionary activities were associated with higher upward mobility. Intergenerational mobility was also higher in regions close to the coast and national capitals as well as in rugged areas without malaria. Upward mobility is higher and downward mobility is lower in regions that were more developed at independence, with higher urbanization and employment in services and manufacturing. Finally, they also reveal that early exposure of children to regions with higher (lower) upward IM significantly improve (decrease) the likelihood of completing primary schooling. In addition, Azomahou and Yitbarek (2020) analyze the educational IM across 9 Sub-Saharan African countries over

50 years, using two measures of intergenerational educational persistence. They reveal that educational intergenerational persistence has reduced among the birth cohorts in all countries, particularly after the 1960s due to huge investments in human capital following independence and drastic changes in the educational systems. Even in the light of declining educational intergenerational persistence in the region, countries such as Ghana, Guinea, Nigeria, and Uganda experienced higher intergenerational mobility while Comoros and Madagascar had the lowest. Also, intergenerational persistence in education was found to be stronger from mothers to their children, and daughters' education is more correlated with their parents' education than that of sons.

More generally, the trends and drivers of intergenerational mobility or persistence in education have been studied in the literature (see e.g., Corak 2013; Chetty et al. 2014; Howell 2019; Engzell and Tropf 2019). Overall, the intergenerational mobility in education has increased over time, but some heterogeneities and disparities across regions remain. Hertz et al. (2008) analyze trends in the intergenerational persistence of education over 50 years in 42 countries, including 19 developing countries and 3 SSA countries.[7] They find that the educational IM has improved in almost all regions of the world.[8] The western developed countries have higher educational IM than in any region of the world, especially for the Nordic countries. They are followed by the Eastern bloc countries and Asian countries. However, educational IM is lower in Latin American countries and African countries. Interestingly, Henn and Robinson (2021), using the 2015 World Bank Intergenerational Database, find that educational IM is higher in Africa than in South Asia, MENA, and Latin American countries, with countries like Botswana, Kenya, Mauritania, and Cape Verde displaying approximately the same educational IM as high-income countries.[9]

4.3 Data sources and construction of the IM index

Our data mainly come from two sources. We use data on education and individual characteristics from Integrated Public Use Microdata Series (IPUMS) and data on mineral discoveries and production from Minex Consulting Dataset (2019).[10]

[7] A higher intergenerational persistence implies lower intergenerational mobility, and inversely.

[8] They also show that the regression coefficient representing the transmission of educational attainment from parent to child has decreased over the past 50 years, reflecting an improvement of mobility over time, while the IM's correlation coefficient has not changed.

[9] See other papers on developed countries (Black and Devereux 2010; Corak 2006, 2013; Chetty et al. 2014) and developing countries (Azam and Bhatt 2015; Daude and Robano 2015; Neidhöfer et al. 2018) for further discussions on the dynamics, disparities across countries and regions, and determinants of educational IM.

[10] https://www.ipums.org/ ; https://minexconsulting.com/

4.3.1 Data sources

4.3.1.1 IPUMS data

The Integrated Public Use Microdata Series (IPUMS) database covers 82 national censuses surveys from 28 African countries: Benin, Botswana, Burkina Faso, Cameroon, Egypt, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Liberia, Malawi, Mali, Mauritius, Morocco, Mozambique, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, South Sudan, Sudan, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.[11] It contains information on more than 130 million of individuals, including on their demographic characteristics, occupation, household members, the relationship between household members, and place of residence. Regarding education, IPUMS reports data on the total years of schooling and whether the individuals completed primary, secondary, tertiary education levels. For this study, we follow Alesina et al. (2021) and use the educational attainment for both parents and children instead of the years of schooling given their higher coverage. Our sample is based on the availability of information on district level and residency, education and individuals characteristics (gender, age) as well as whether individuals co-reside with their biological/step parents or immediate older generation. We have harmonized the boundaries of districts following Alesina et al. (2021) to deal with administrative boundaries changes.[12] We focus on the individuals aged between 16 and 50, and born between 1950 and 2000.[13] The final sample covers more than 14 million individuals across 2,890 districts. Table D.1 and Table D.2 describe the data for each census and country.

4.3.1.2 Mineral discoveries data

Our data on mineral discoveries and productions in Africa come from Minex Consulting Dataset (2019). This dataset provides geolocalized information on discoveries, their size (moderate, major, giant, super-giant), the status of the mine (closed, feasibility study, operating, underdeveloped), and the type of minerals.[14] After merging this dataset with the IPUMS data, we

[11]The population of the 28 countries covered in our analysis represents around 75 percent of the total population in Africa. As such our results can be extrapolated to the continent.

[12]We drop Burkina Faso (1985), Kenya (1979), Liberia (1974), Togo (1960, 1970) since they do not cover all local regions or do not have any identifier to match children to parents. Moreover, we have harmonized the countries boundaries and district names for countries such as Botswana, Burkina Faso, Ethiopia, Ghana, Guinea, Lesotho, Malawi, Mauritius, Morocco, Nigeria, South Africa, and Uganda. For Nigeria, data come from households' survey rather than census surveys, therefore the number of observations is small as compared to other countries.

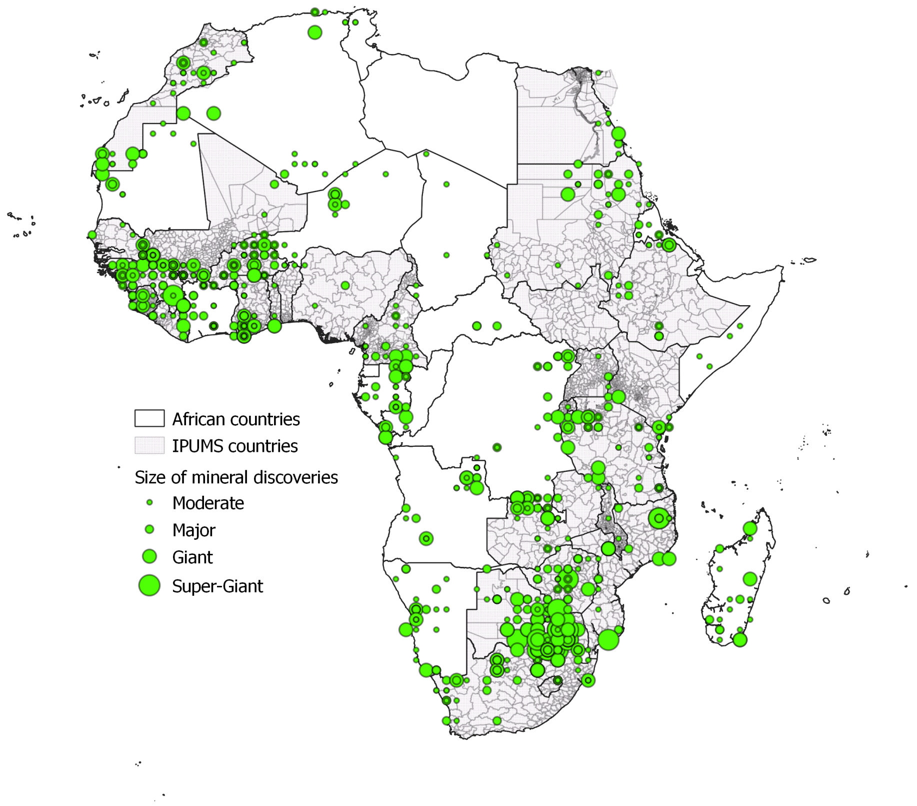
[13]We assume that primary level of education is most of the time completed for individuals above 16 years, and secondary for individuals above 25 years.

[14]According to Bhattacharyya and Mamo (2021), mineral discoveries are defined as giant if they generate an amount of at least US$500 million of revenue per annum for 20 years or more. They are qualified as major if they generate an annual revenue stream superior or equal to US$50 million over a shorter lifetime than in the case of giant discoveries.

identify 331 districts out of the total of 2890 in which mineral sites were discovered or entered in production. Figure C.1 displays the evolution of the number of discoveries over time in all African countries. 969 mineral discoveries occurred in Africa between 1950 and 2019, of which 573 (60 percent) between 1950 and 2000. This study covers 406 mineral discoveries in 28 African countries over the period 1950–2000 (i.e., 71 percent of the 573 mineral discoveries). We therefore cover a large share of mineral discoveries in Africa.

Figure D.1 maps the location of these discoveries across Africa by the size of mineral discoveries. We observe that mineral discoveries have been concentrated in Southern Africa (48.3 percent) and Western and Central Africa (34.2 percent). A relatively few discoveries occurred in Eastern Africa (11.9 percent) and Northern Africa (5.7 percent). Looking at the sizes of mineral discoveries, they have been mostly moderate (45.3 percent), followed by major (29.8 percent), giant (21.7 percent) and super-giant giant (3.2 percent). Moderate and major discoveries were mainly found in Western and Central Africa while giant and super-giant were located in Southern Africa. The minerals discovered were mostly gold (34 percent), bulk metals (18.4 percent), precious minerals (15.8 percent), and base metals (15 percent). Table C.4 and Table C.5 present some statistics on the mineral discoveries by regions, size, and types.

Figure 4.1: Location of mineral discoveries by size for all African countries, 1950-2019



Source: Authors' calculations based on Minex Consulting datasets (2019)

4.3.2 Construction of the educational IM

In this paper, we use absolute educational IM measures as in Alesina et al. (2021).[15] We define both an upward and downward educational IM for the primary and secondary/tertiary education levels. First, upward primary educational IM is defined as the probability for a child born from uneducated parents or parents with less than primary education attainment to achieve at least primary education. Downward primary educational IM is defined as the probability for a child born from parents with at least primary education attainment to be uneducated or have less than primary education attainment. Second, upward secondary/tertiary educational IM is defined

[15] For the use of relative educational IM measures, see, Hertz et al. (2008), Black and Devereux (2010), Chetty et al. (2014), Bütikofer et al. (2018), Azomahou and Yitbarek (2020). These measures are based on continuous type variables such as years of schooling or rank based on years of schooling. We rather use data on education attainment and construct absolute measures of education IM, as they are more available than years of schooling, and therefore increase the coverage of our analysis and reduce the attrition bias. Moreover, as shown by Alesina et al. (2021), data on educational attainment are less subject to measurements errors and allow to identify a common reference group for children (e.g., parents without primary education completed), as compared to years of schooling.

as the probability for a child born from parents with at most primary education background to at least secondary education. Downward secondary/tertiary educational IM is defined as the probability for a child born from parents with at least secondary education background to achieve primary education or be uneducated.[16] To identify the old generation benchmark for each child, we use the average of education attainment for their biological/step parents, rounded to the nearest integer. In the robustness section, we use the minimum or maximum of the education levels of the biological/step parents as benchmark. We also consider the immediate older generation and broaden the definition of parental authority to include uncles/aunts (in law), parents-in-law, grand-parents, and grand-uncles/aunts in the reference group, to take into account fostered, abandoned, or orphan children.

Practically, first, for each individual (parents and children), we compute two educational attainment variables P_{jith} and ST_{jith} measuring the primary and secondary/tertiary educational attainment, respectively. P_{jith} takes that value of one if the individual j born in district i and year h, and surveyed in year t has completed at least the primary education, and zero otherwise. Similarly, ST_{jith} takes that value of one if the individual j born in district i and year h, and surveyed in year t has completed at least the secondary education. Second, for each child j, we computed two averaged measures of parents' educational attainment, PP_{jith} and PST_{jith} as the average of P_{jith} and ST_{jith} rounded to the nearest integer, respectively, for the two biological/step-parents if both cohabit with the child, or if only the father/step-father or mother/step-mother if the child lives with only one of its parents. Third, we compare the educational attainment of each child j cohabiting with at least one parent to the average educational attainment of the parents and obtain our absolute measures of educational as follows:[17]

i) Upward primary IM: $$IMUP_{jith} = \begin{cases} 1 \text{ if } P_{jith} = 1 \text{ and } PP_{jith} = 0 \\ 0 \text{ if } P_{jith} = 0 \text{ and } PP_{jith} = 0 \end{cases}$$

ii) Downward primary IM: $$IMDP_{jith} = \begin{cases} 1 \text{ if } P_{jith} = 0 \text{ and } PP_{jith} = 1 \\ 0 \text{ if } P_{jith} = 1 \text{ and } PP_{jith} = 1 \end{cases}$$

iii) Upward secondary/tertiary IM: $$IMUST_{jith} = \begin{cases} 1 \text{ if } ST_{jith} = 1 \text{ and } PST_{jith} = 0 \\ 0 \text{ if } ST_{jith} = 0 \text{ and } PST_{jith} = 0 \end{cases}$$

iv) Downward secondary/tertiary IM: $$IMUST_{jith} = \begin{cases} 1 \text{ if } ST_{jith} = 0 \text{ and } PST_{jith} = 1 \\ 0 \text{ if } ST_{jith} = 1 \text{ and } PST_{jith} = 1 \end{cases}$$

[16] Our analysis does not cover the tertiary education exclusively given the few numbers of observations for the tertiary level.

[17] By replacing biological/step parents in the last sentences with immediate older generation, we obtain our alternative measures of absolute educational IM including other relatives on top of the biological/step parents. We will use these alternative definitions of IM in the robustness section.

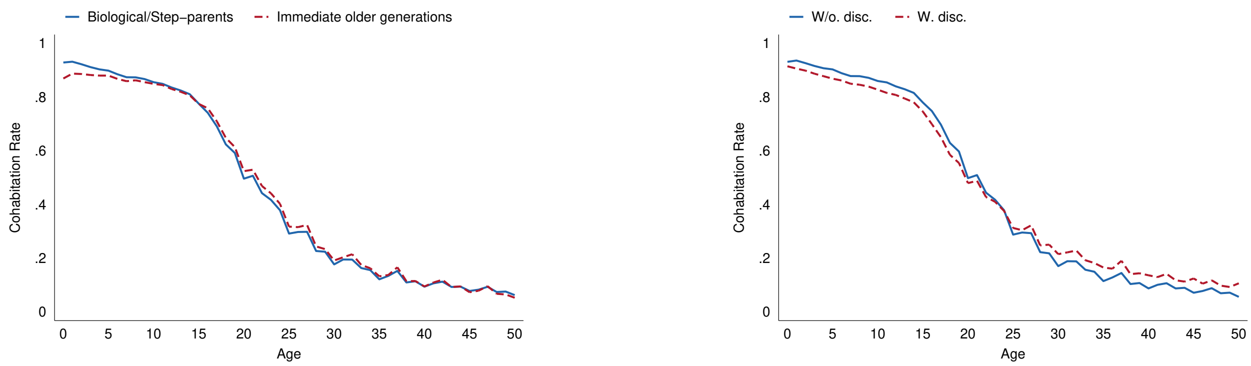
4.3.3 Cohabitation-selection issues

Our analysis might be subject to cohabitation-selection issues, as our sample includes both youth children and adults, and individuals' educational attainment is also determined by their cohabitation with their parents or not.[18] For adults, the cohabitation-selection issues are more severe as the intensity of self-selection is increasing with age. Moreover, it is more accentuated for adults' women, especially for those who got married at younger age, as some African countries are patrilocal (Heckert et al. 2021). Since our focus is also on secondary education, our sample must include adults at age where secondary education is mostly completed despite the likelihood of co-residing with parents at this age being low (see Figure 4.2).

Interestingly, we show in Figure 4.2 that the cohabitation selection is independent from the discoveries of natural resources. Both districts with and without discoveries exhibit the same patterns of cohabitation by age and gender, therefore the cohabitation selection issues might have limited impact on our analysis.[19] If the cohabitation rate was higher in districts with discoveries than districts without discoveries, it would have caused our estimates of the effects of discoveries on upward (downward) IM to be upward (downward) bias. Indeed, as we expect discoveries to have a positive effect on educational IM and given that individuals living with their parents are likely to have higher educational attainments, then, higher cohabitation rates in districts with discoveries than without discoveries would have resulted in higher positive estimates of the effects of discoveries on educational IM.

Figure 4.2: Cohabitation rates

(A) By age for biol./step-parents and immediate older generations (B) By age, gender, and district with or without disc. only for biol./step-pare



Source: Authors' calculations based on IPUMS dataset

[18]For instance, Hamoudi and Thomas (2014) show that lower-educated children are more likely to co-reside with elderly parents as they have a lower opportunity cost of providing elderly care. See also, Alesina et al. (2021) for discussion on cohabitation-selection issues.

[19]We also verify that cohabitation rates are similar between rural and urban areas, across ages and districts with and without discoveries (available upon request).

We further investigate the potential bias of the cohabitation selection. We do so in Table 4.1 by computing the differences in educational attainment for both individuals co-residing with biological/step parents (selected individuals) and those that do not, both in districts with and without discoveries, separately. We test the significance of the differences through a Khi-2 test. We show that the unconditional likelihood of not completing primary education is higher for individuals not co-residing with their biological/step parents than those who do. This difference is more accentuated in districts without discoveries than districts with discoveries. Similarly, the likelihood of completing primary and secondary education is higher for those living with their biological/step parents than those who do not, also more pronounced in districts without discoveries. These differences are significant as indicated by the Khi-2 tests. As a result, if we were to consider individuals not co-residing with parents in our study, the level of educational attainment would have been on average lower in districts without discoveries than districts with discoveries. Thus, if the cohabitation selection creates any biases, our estimates of the effects of discoveries on upward (downward) IM would be downward (upward) bias. Therefore, as we expect discoveries to have a positive effect on IM (i.e., increase upward IM and decrease downward IM), these effects should be considered as a lower bound.

Table 4.1: Differences in educational attainment between individuals living with biological parents or step-parents or not

	(A) With discoveries			(B) Without discoveries		
	(1) Without relatives	(2) With relatives	(3) Differences	(4) Without relatives	(5) With relatives	(6) Differences
Less than primary completed	47.31	40.52	-6.79	56.63	40.08	-16.55
Primary completed	36.06	42.38	6.32	27.19	37.22	10.03
Secondary completed	14.4	15.72	1.32	13	19.42	6.42
Tertiary completed	2.23	1.37	-0.86	3.18	3.28	0.1
Total	100	100		100	100	
Khi-2 tests p-value		0.000			0.000	

4.3.4 Stylized facts on educational IM in Africa

In this section, we briefly describe the trends of educational IM in Africa as well as their disparities across countries, gender, and residency. To do so, we calculate conditional educational IM, netting country/districts, cohort and census effects. Specifically, we regress educational IM indices on country or district fixed effects α_i, cohort fixed effects γ_t, and census-year fixed effects δ_t. The model is as follows:

$$IM_{jit} = \alpha_i + \gamma_t + \delta_t + \varepsilon_{jit} \tag{4.1}$$

Country or district fixed effects α_i reflect the conditional likelihood of each type of educational IM at the country or district levels, netting the cohort and census effects. Cohort fixed effects γ_t reflect the conditional likelihood of each type of educational IM, netting the country/district and census effects. We do so to better compare the educational IM across individuals, cohorts, districts, and over time, especially by purging the differences between countries/districts, cohorts, and census-year specific effects. In addition, we estimate conditional educational IM by country and gender, country and individuals' residency (urban and rural), by cohort and gender, cohort and residency, and cohort and discovery dummy by introducing country and gender fixed effects, country and residency fixed effects, cohort and gender fixed effects, cohort and residency fixed effects, and cohort and discovery fixed effects, respectively.[20]

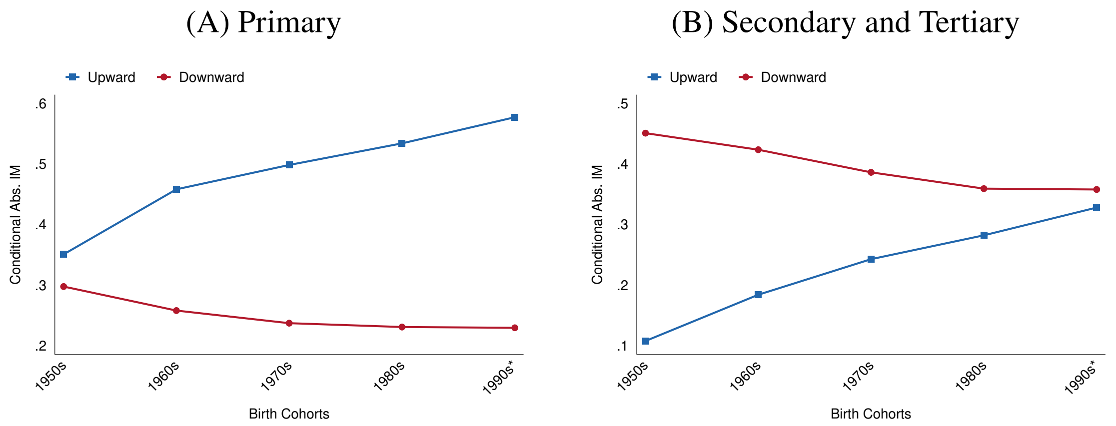
4.3.4.1 Trends of IM by decade

Overall, we observe that primary and secondary/tertiary educational IM have significantly improved in Africa over time, independently of gender and residency (urban/rural areas). The average trends of primary and secondary/tertiary educational IM are displayed in Figure D.2 for both upward and downward mobility, respectively, and for five cohorts between 1950 and 2000. We show that upward primary IM has steadily increased across cohorts, from 35.1 percent for the 1950s cohort to 57.7 percent for the 1990s cohort. Similarly, downward primary IM has steadily decreased, but at a slower pace, from 29.8 to 23 percent between the 1950s and 1990s cohorts, respectively. Moreover, secondary and tertiary educational IM have experienced similar trends. Upward secondary and tertiary educational IM has steadily increased from 10.8 to 32.9 percent, while downward secondary and tertiary educational IM has steadily decreased from 45.1 to 35.8 percent between the 1950s and 1990s cohorts, respectively. In contrast to primary education level, downward IM has always been elevated than upward IM for secondary and tertiary levels, but the gap has closed over time. Finally, upward (downward) educational IM has been higher (lower) at primary level than secondary and tertiary level.

We next look at these trends by gender in Figure D.3. In general, both males and females have had an increase in the probability of upward educational IM and a decline of the probability of downward educational IM for both primary and secondary/tertiary levels. We also observe that the gender gap in favor of males has narrowed over time, for instance, with the probability of upward (downward) secondary/tertiary educational IM for females being higher (lower) than that of males in the last decades.

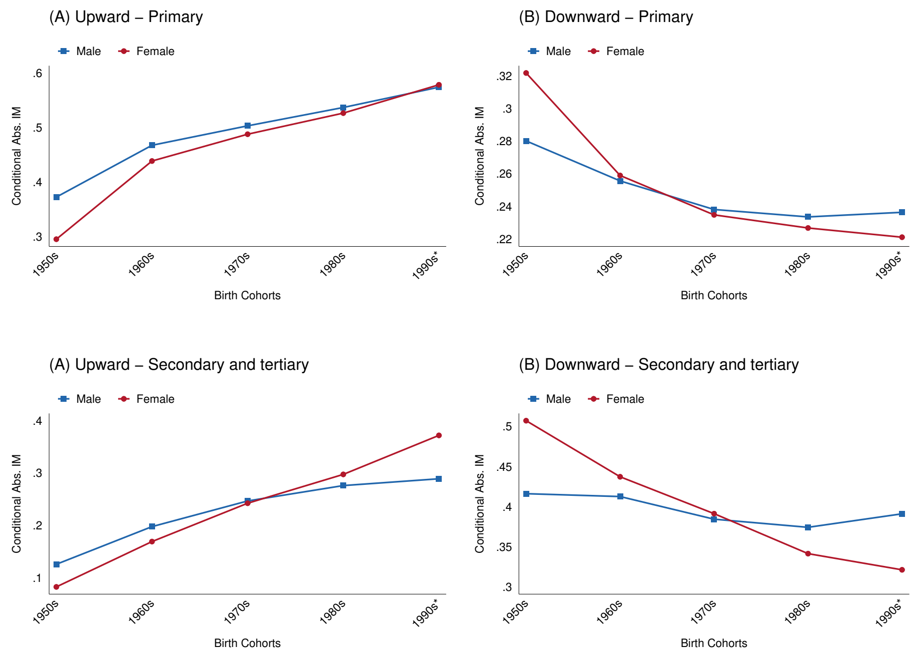
[20] We present the dynamics of country-level educational IM by district with and without discoveries in Section 4.4 where we discuss the stylized facts on both educational IM and mineral discoveries and productions.

Figure 4.3: Country-level educational IM by birth cohorts



Source: Authors' calculations based on IPUMS dataset

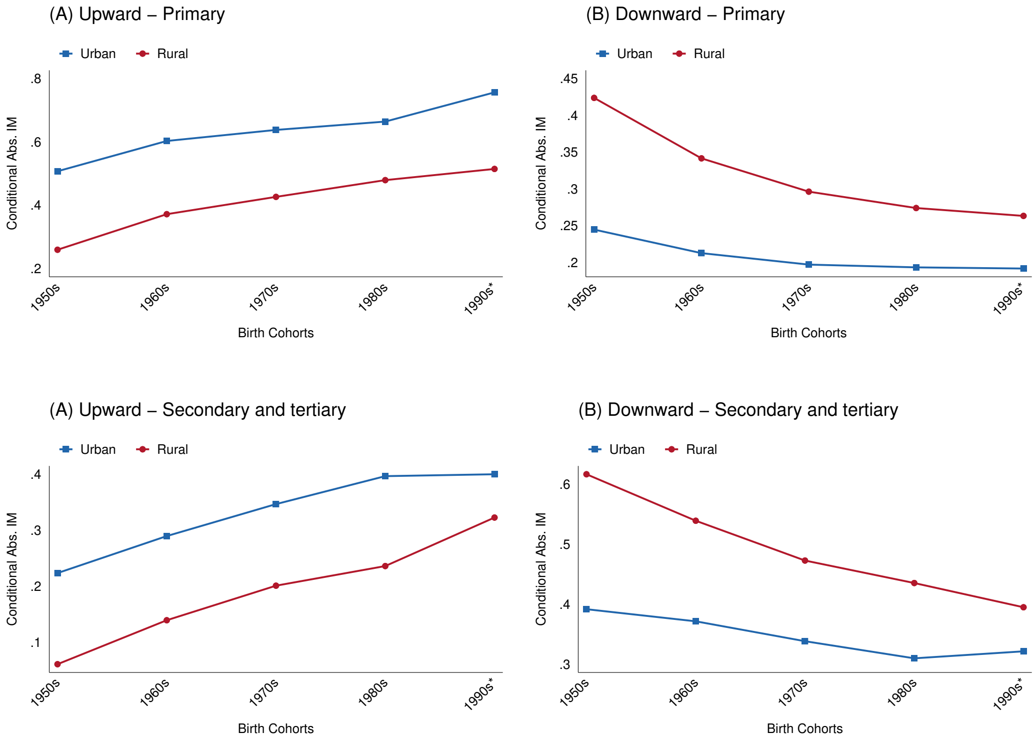
Figure 4.4: Country-level educational IM by birth cohorts and gender



Source: Authors' calculations based on IPUMS dataset

Finally, we explore the trends by residency as presented in Figure 4.5. We find that the general trends are also confirmed for both individuals living in urban and rural areas. More specifically, we show that educational IM has always been higher in urban areas than in rural areas. Although the residency gap has diminished over time, it has remained significant across cohorts.

Figure 4.5: Country-level educational IM by birth cohorts and gender



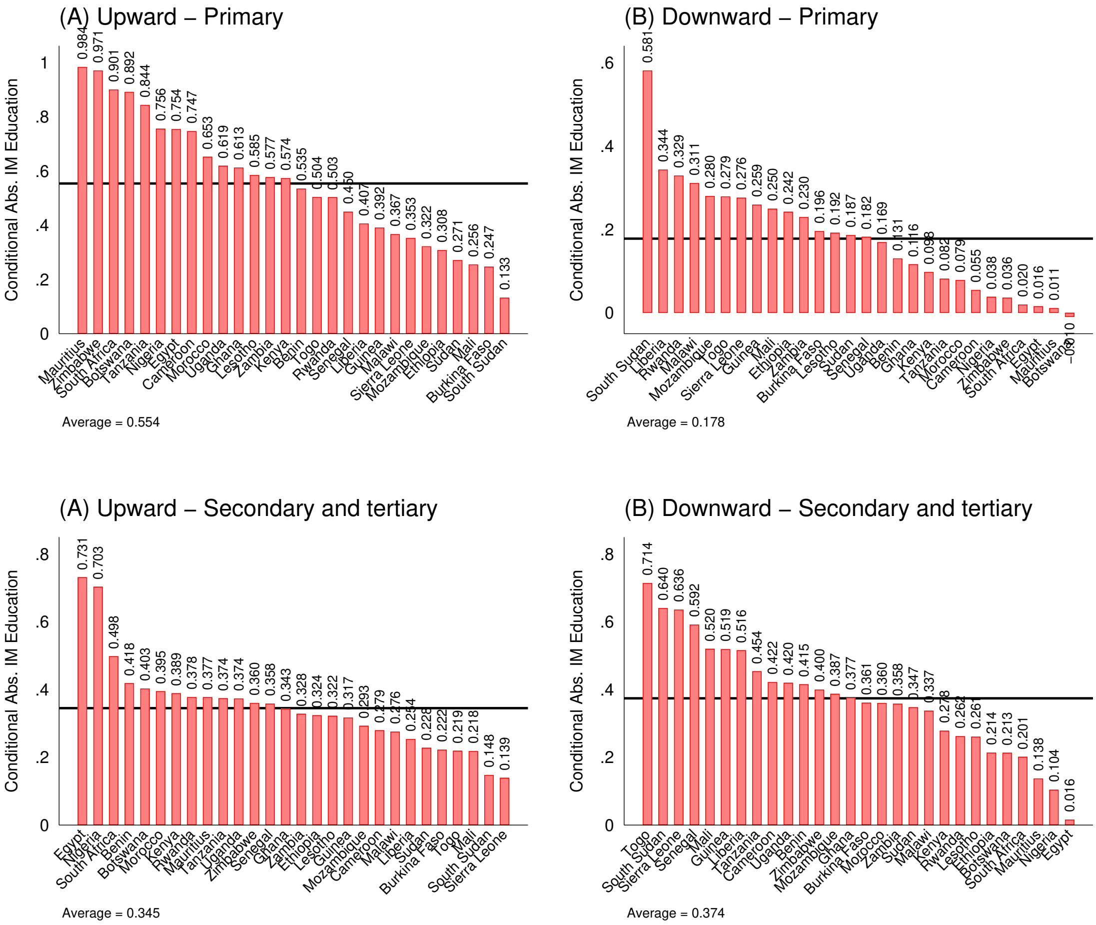
Source: Authors' calculations based on IPUMS dataset

4.3.4.2 Educational IM at country and district level

a) Country-level educational IM

We display in Figure D.2, the country-level educational IM. It shows that educational IM is uneven across countries, and that upward and downward IM are negatively correlated, i.e., countries with the highest upward IM tend to have the lowest downward IM, and inversely. These findings hold for both primary and secondary/tertiary education levels. Upward primary IM ranges between 13 percent in South Sudan and 98 percent in Mauritius, and downward primary IM between close to zero for Egypt, Mauritius and Botswana and 58 percent in South Sudan. Upward secondary/tertiary IM ranges about 14 percent in Sierra Leone and Sudan and more than 70 percent in Egypt and Nigeria, while downward secondary/tertiary IM is between 1 percent in Egypt and 71 percent in Togo.

Figure 4.6: Ranking: Country-level educational IM



Source: Authors' calculations based on IPUMS dataset

b) Country-level educational IM by gender

We also present the country-level gender gap in educational IM in Figure C.2 and Figure C.3. First, we show that gender gap, in favor of males for the primary level, is more pronounced for individuals living in countries with lowest values of upward IM, and in countries with highest values of Downward IM. More specifically, upward primary IM is higher for males than females in Togo (14.9 percent), Liberia (11.6 percent), Sierra Leone, Zambia, Uganda (around 8–9 percent).[21] It is rather higher for females than males in Lesotho (25.9 percent), Botswana (15.5 percent), Nigeria (5 percent), and South Africa (4.2 percent). Similarly, downward primary IM is higher for females than males in Togo (9.8 percent), Liberia (7 percent), Guinea (6.2 percent), and Sierra Leone, Benin, and South Sudan (4–6 percent). It is rather higher for males than females in Lesotho (16.1 percent), and Botswana, Burkina Faso (5.4 percent). Second, in contrast, gender gap in favor of males, for the secondary/tertiary level, is less related to whether

[21] The differences are reported in parentheses.

individuals are living in countries with highest values of upward or downward educational IM. For instance, upward secondary/tertiary IM is higher for males than females in Rwanda, Egypt, Liberia (8–9 percent), Uganda, Malawi and Zambia (6–6.5 percent). It is rather higher for females and males in South Africa, Morocco (4.5–5 percent), Sudan, Lesotho (3.9 percent), Mauritius (3 percent), Nigeria (2.5 percent), and Burkina Faso (2 percent). Moreover, downward secondary/tertiary IM is higher for females than males in Botswana (14.2 percent), Malawi (11.3 percent), Togo, Sierra Leone (around 9 percent), Ghana, and Benin (around 8 percent). It is rather higher for males than females in Morocco (7.2 percent), Mauritius (6.8 percent), South Africa (5.8 percent), Zimbabwe, Burkina Faso (around 4.5 percent), Sudan, Lesotho and Mozambique (3 percent).

c) Country-level educational IM by residency

We also report the country level residency gap in educational IM in Figure C.4 and Figure C.5. First, we show that upward (downward) IM are higher (lower) for individuals living in urban than rural areas, for both primary and secondary/tertiary levels, and for all countries. Second, individuals living in urban areas tend to do far better than those in rural areas in countries with the lowest values of upward IM and the highest values of downward IM. Indeed, the countries with the highest values of upward primary IM for individuals living in urban than rural areas are Ethiopia (57.6 percent), Sudan (44.8 percent), Burkina Faso (42.3 percent), and Guinea (40.2 percent). The countries with the lowest residency gap for upward primary IM (always in favor of individuals living in urban areas) are Mauritius (5 percent), South Africa (7.6 percent), Nigeria (10.5 percent), and South Sudan (12.1 percent). Similarly, the countries with the highest values of downward primary IM for individuals living in urban than rural areas are Ethiopia (50.8 percent), Burkina Faso (43.3 percent), and Sierra Leone (34.4 percent). The countries with the lowest residency gap for downward primary IM are Mauritius (0.9 percent), Nigeria, South Africa (close to 3 percent), and Egypt (4.7 percent). Third, we find that the residency gap for upward secondary/tertiary IM is higher in Ethiopia (32.9 percent), Malawi (21.8 percent), Morocco (21.6 percent), and Guinea (21.2 percent), while it is lower in South Sudan, Sierra Leone, and Botswana (5–6 percent). We also show that the residency gap for downward secondary/tertiary IM is higher in Burkina Faso (51.9 percent), Ethiopia (40.9 percent), and Morocco (34.9 percent), while it is lower in South Sudan (-2.8 percent), Nigeria (7.7 percent), and Egypt (9.1 percent).

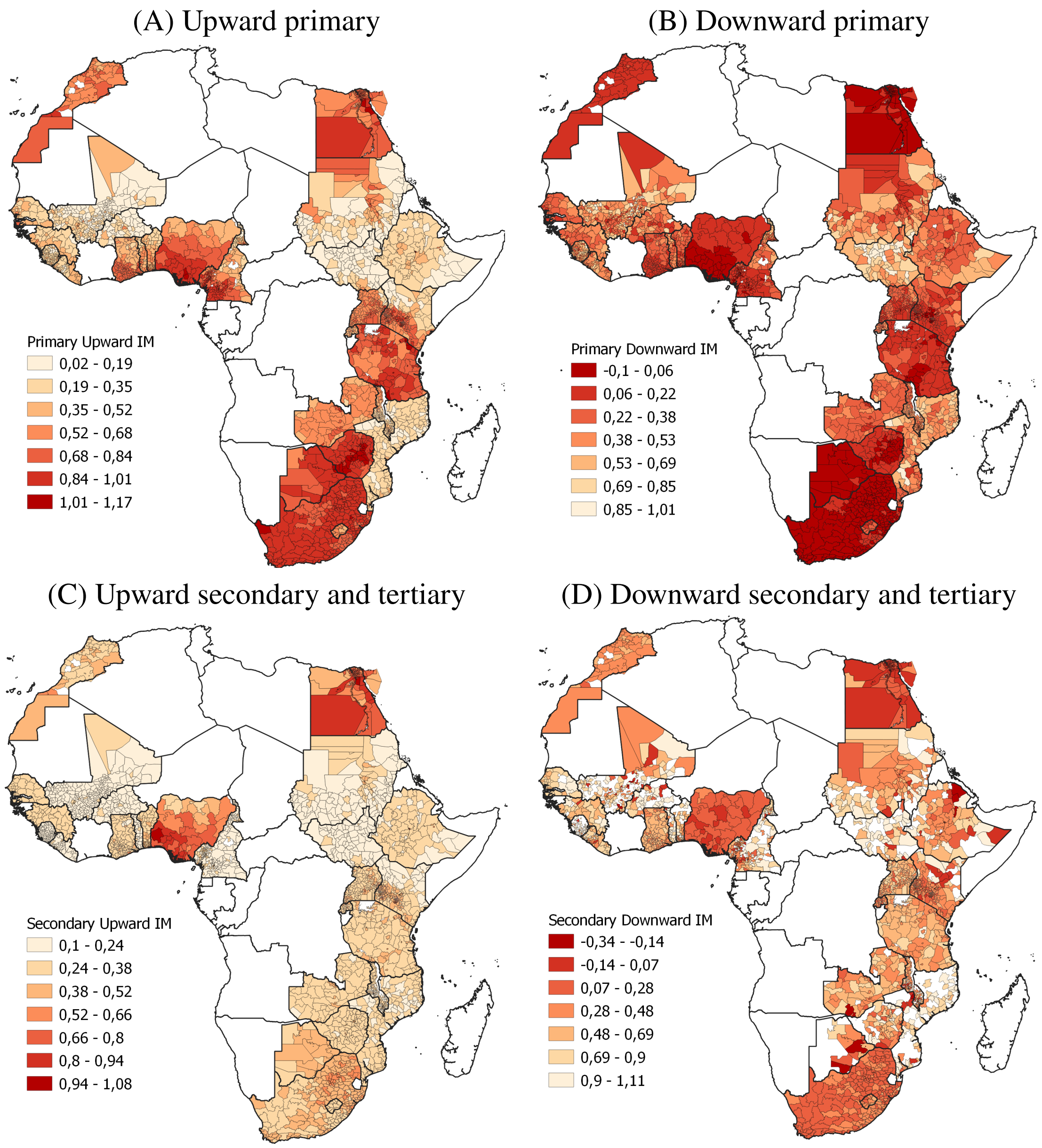
d) Mapping of district-level educational IM across Africa

Finally, we map educational IM across 2,890 districts in Africa in Figure D.3.[22] Table C.6 and Table C.7 also report the summary statistics of district-level educational IM by country for primary and secondary/tertiary levels, respectively. They show both large within country and cross-districts variations. Overall, we find that within country disparities are larger in countries with lower educational mobility, with some exceptions. First, we show that upward primary IM is more unequal in South Sudan, Sudan, Ethiopia, and Burkina Faso (countries with lower average upward primary IM) and less unequal in Mauritius, South Africa, and Zimbabwe (most countries with higher average upward primary IM).[23] Regarding the probability of downward primary IM, it is more unequal in Botswana, Mauritius, and Egypt, and less unequal in South Sudan, Rwanda, Liberia, and Lesotho. Moreover, upward primary IM varies less across regions than downward primary IM (coefficient of variation is 1.6 times higher for the latter than the former). Second, we find that upward secondary/tertiary IM varies more across districts in Ethiopia, Sudan, Malawi, and Cameroon (many countries with lower average upward secondary/tertiary IM). It varies less across districts in Botswana, Mali, Lesotho, and Senegal (most countries with higher or milder average upward secondary/tertiary IM). Moreover, downward secondary/tertiary IM varies more across districts in Botswana, Egypt, Ethiopia, and Malawi (paradoxically, most countries with lower average downward secondary/tertiary IM). It varies less across districts in Senegal, Ghana, Morocco, and Tanzania (paradoxically, most countries with higher or milder average downward secondary/tertiary IM).

[22] For some districts, educational IM are either negative, close to zero, higher than one, or close to one, due to a small number of observations at district level. Moreover, we show that while country-level and district-level estimates of educational IM may differ, they are strongly correlated and provide a quite similar ordering of countries by educational IM.

[23] For instance, in South Sudan, the probability of upward primary educational IM is between 35 and 52 percent for individuals living in the South against only less than 19 percent for those living in the North. In South Africa, the lowest and highest probability of upward primary educational IM are recorded in the North Central (between 84 and 101 percent) and in the West (between 101 and 117 percent) respectively.

Figure 4.7: District-level educational IM



Source: Authors' calculations based on IPUMS dataset

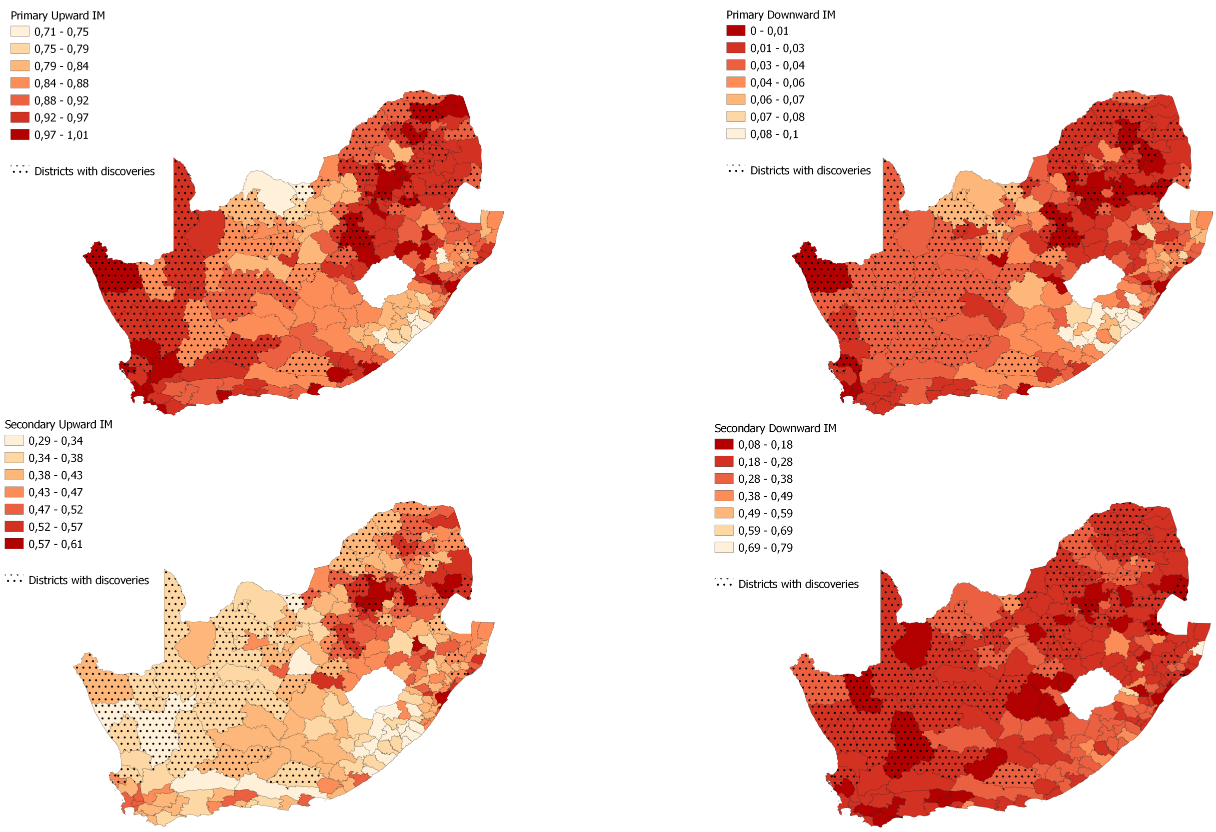
4.4 Stylized facts on educational IM and mineral discoveries and productions

As a foretaste of the effects of mineral resource discoveries and productions on intergenerational educational IM, we present in this section some stylized facts on both conditional IM in education and mineral discoveries and productions. South Africa, the country with the highest number of discoveries in our sample (108 total discoveries), illustrates well the case of countries where educational IM is higher in districts with discoveries/productions (see Figure 4.8). In the 60 districts where mineral sites were found, upward IM was 92 and 46 percent for primary and secondary/tertiary levels, respectively, higher by 2–3 pp. than in the 156 districts without any discoveries. Similarly, downward IM was 2 and 25 percent in districts with discoveries for primary and secondary/tertiary levels, respectively, lower by 1–2 pp. than in districts without discoveries.

We also show the mean differences of district-level conditional IM between districts with and without discoveries over the period of study (see Table C.8 and Table C.9).[24] We find that upward (downward) IM for primary education is, on average, higher (lower) in districts with discoveries than in districts without discoveries by around 4 pp. The opposite result holds for secondary education: upward (downward) IM is on average lower (higher) in districts with discoveries than districts without discoveries by around 4–6 pp. Second, we also present the summary statistics of IM by districts with and without discoveries for each country in Table C.8 and Table C.9. Upward IM is on average higher in districts with discoveries than districts without discoveries in 12 and 7 countries out of 26 countries (with both districts with and without discoveries) for primary and secondary levels, respectively. Downward IM is, on average, lower in districts with discoveries than districts without discoveries in 11 and 9 countries out of 26 for primary and secondary levels, respectively (see also Figure C.10).

[24]One caveat is worth noting. The differences in the mean differences between districts with and without discoveries in Table C.8 and Table C.9 (district level) as compared to Figure 4.9 (country level) are mainly explained by the differences in the specification of the conditional IM. For the former, we use district-fixed effects whereas for the latter we use country-fixed effects. While the specifications with the district-fixed effects better capture the invariants characteristics at the district level (the most disaggregated level), those with the country-fixed effects offer insightful comparisons across countries, cohorts, gender, and residency.

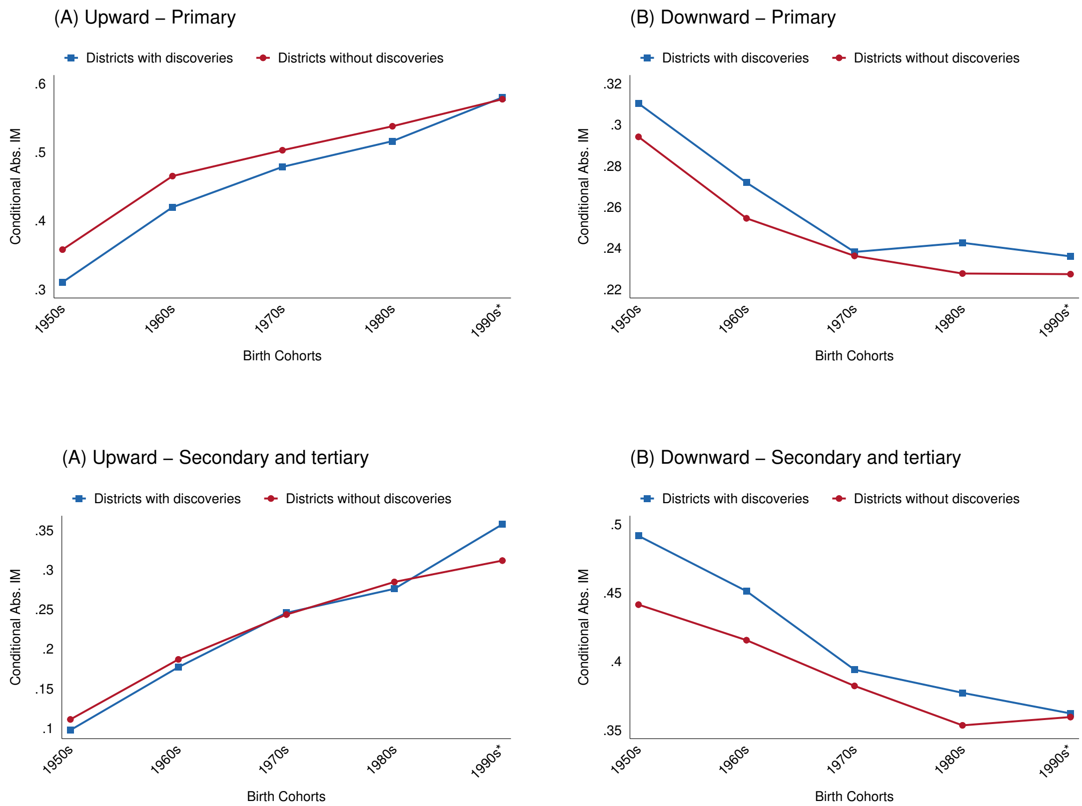
Figure 4.8: District-level educational IM in South Africa



Source: Authors' calculations based on IPUMS dataset and Minex Consulting dataset (2019)

However, these stylized facts could hide differences in the dynamics of IM in districts with and without discoveries, and particularly progress that has happened in districts with discoveries. Figure 4.9 shows that while upward IM for primary and secondary/tertiary education was lower in districts with discoveries among the old cohorts (1950s and 1960s), it has significantly increased and closed the gap in these districts for more recent cohorts (1980s and 1990s) to stand above the one in districts without discoveries. Similarly, downward IM for primary and secondary/tertiary education was higher in districts with discoveries than without discoveries for old cohorts, and the gap has narrowed over time and for more recent cohorts. Therefore, IM has been significantly more dynamic in districts with discoveries. As a result, mineral discoveries and productions seem to have contributed to change the geography of the land of opportunities across African regions.

Figure 4.9: District-level educational IM

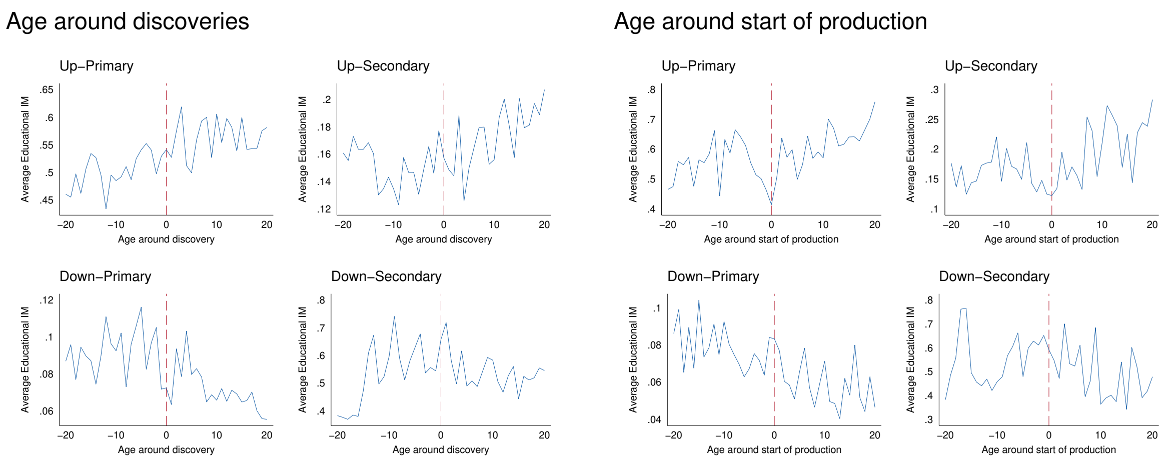


Source: Authors' calculations based on IPUMS dataset and Minex Consulting dataset (2019)

In addition, we find that improvements in IM have occurred for both females and males, with females doing better than males in districts with discoveries (see Figure C.6 and Figure C.7). The gender gap of upward primary IM in favor of males has closed early in districts with discoveries (for 1970s cohort) than districts without discoveries (for 1990s cohort). The gender gap of secondary and tertiary IM in favor of males quickly turns to be in favor of females in districts with discoveries (for cohorts 1960s–1990s), which happened 20 years later in districts without discoveries (for cohorts 1980s–1990s). Likewise, downward IM for primary and secondary/tertiary was higher for females than males in districts without discoveries contrary to districts with discoveries. Still, the gap has closed or widened for recent cohorts in districts without and with discoveries, respectively, with females performing better than males. We also find that IM improvements have occurred both in urban and rural areas in all districts (see Figure C.8 and Figure C.9). However, the gap between urban and rural areas has remained significant despite greater improvements in rural areas. There are, however, no significant differences in the dynamics of IM for rural and urban districts with and without discoveries.

Finally, we look at the dynamics of IM for individuals born around the first discovery and beginning of production. They are presented in Figure 4.10. These dynamics show that the timing of mineral discoveries and productions may constitute structural breaks in IM dynamics for individuals born before and after the discovery or production. Indeed, we show that the likelihood of upward IM for primary and secondary education has significantly increased after mineral discoveries and productions for individuals born after the discovery or production. Similarly, the likelihood of downward IM for primary and secondary education has decreased after the mineral discoveries and productions for individuals born after the discovery or production, while it is has sometimes increased for individuals born in years running up to discovery or production. While we cannot plot the dynamics of the counterfactuals, we show that IM has on average significantly accelerated after mineral discoveries and productions.

Figure 4.10: Dynamics of Unconditional IM around the first discovery and start of production



Source: Authors' calculations based on IPUMS dataset and Minex Consulting dataset (2019)

4.5 Empirical methodology

To estimate the potential effects of mineral discoveries and productions on educational IM, we adopt an experimental approach and exploit the exogeneity of natural resource discoveries. First, it is plausible that the timing of mineral resource discoveries is exogenous due to the uncertainty related to the timing of the discovery and exploration success. While the technology used for exploration has improved over time, it is still highly improbable to predict the timing and success likelihood of finding a mineral field in a particular region (Khan et al. 2016; Arezki et al. 2017b; Cavalcanti et al. 2019; Seri 2021). Moreover, the exact location of mineral resources discoveries is purely exogenous as it depends on random geographical factors of the area. Therefore, while some regions may be endowed with mineral resources, it is improbable to find any resources in others. Second, mineral discoveries provide a significant source of revenues and represent a major economic shock that can affect the trajectory of the development in countries and districts they are found. They can also change the habit of individuals and their expectations about their own and children's future. Third, as shown by Horn (2011) and Arezki et al. (2017b), there is a significant lag between the discoveries of natural resources and the beginning of their production, around five to six years. This allows us to study the effects of both mineral discoveries and productions on educational IM, separately. These features stand at the heart of our identification strategy and allow capturing a causal effect of mineral discoveries and productions on educational IM in African countries. Throughout the paper, we analyze both the effects of the first discoveries and productions on upward and downward mobility, and later in the robustness section, of multiple and successive discoveries and productions.

We employ a generalized difference-in-differences (GDID) strategy in a quasi-natural experiment and estimate treatment effects by comparing the changes in educational IM between a treatment group (people with exposure to the mineral discoveries and productions) and a control group, across pre-discovery/production and post-discovery/production. By doing so, our goal is to identify how educational IM has evolved following discovery/production for a group of people with exposition compared to a group of people born in the same district and around the discovery or production but not exposed to it, while controlling for the dynamics of educational IM in other districts without any discovery/production.

To capture the effects of the discovery/production, first, we focus in our baseline on a period spanning 30 years around it, i.e., we consider in the regressions, individuals born 15 years before and after the discovery or production. In the robustness, we expand this window and consider larger window periods of 40, 50, 60 years around the discovery or production. We define different expositions to the discovery or production as well as various control groups. First, focusing on a window of 30 years, we consider all the individuals born the year of the discovery or production to up to 15 years after it to be in the treatment group. In an alternative specification, we assume that individuals born 5 years before the discovery or production will still be exposed to it as they start their education around the date of the discovery or production; therefore, the treatment group comprises individuals born five years before the discovery or production to up to 15 years after. Second, in the first specification, we consider as control groups (i) individuals born in districts with a discovery or production and between 15 years before to one year before the discovery or production, and (ii) individuals born in districts without any discovery or production over the period of study. Similarly, the second specification includes in the control groups, (i) individuals born in districts with a discovery or production and born between 15 years to 5 years before the discovery or production, and (ii) individuals born in districts without any discovery or production.

Given the nature of our data, multiple discoveries or productions and multiple treatments and control groups within and across districts, our GDID model allows for (i) specific IM across districts by introducing district fixed-effects α_i, (ii) the common change in IM to vary across cohorts (decade in baseline, and each year of birth in the robustness) and years of census/survey by introducing cohort fixed-effects or year-birth fixed effects γ_t and census-year fixed effects δ_t respectively, and (iii) different timing of the discovery or production for different treated groups. This allows to filter out all rigid characteristics specific to districts, cohorts or years of birth, and census year found to be critical in explaining education IM by Alesina et al. (2021). The model is estimated using a linear probability specification and obtained as follows:

$$IM_{jith} = \alpha_i + \gamma_t + \delta_t + \beta d_h + X_{jit}\theta + \varepsilon_{jit} \tag{4.2}$$

Where IM_{jith} is our measure of upward (and downward) mobility for primary or secondary/tertiary levels that takes the value one if the child j in district i has on average a higher (lower) education than its biological/step-parents knowing that its biological/step-parents have not completed (have completed) primary or secondary/tertiary education, respectively. d_h is a dummy that takes the value of one if the individual is in the treated group (e.g., born between the year of the discovery or production to up to 15 years later) and zero if the individual is in the control group (e.g., either born between 15 years to one year before the discovery or production, or born in districts without any discovery or production). β is the coefficient of interest. It captures the treatment effect of mineral discovery/production on upward and downward educational IM by comparing educational IM in the treated and control groups. X_{it} is a set of control variables including the gender of individuals and of their household head, the occupation of household head, the dummies of cohabitation with biological/step-parents (i.e, with only biological/step-father, only biological/step-mother, or both biological/step-father and mother), the size of the household, and urban/rural residency. ε_{jit} is the idiosyncratic term.

Our model requires the parallel trends assumption to hold, i.e., in the absence of the discovery or production, the change of educational IM would have been the same in both the treated and control groups. This assumption is violated when there are unobserved factors that are correlated with both the exposition to the discovery or production and the timing of the discovery or production. As discussed above, we have good reasons to believe that the timing of mineral discoveries is exogenous. Regarding the exposition to the discovery or production, since we focus on a relatively short period around the discovery or production in our baseline and include either cohort fixed effects or year-birth fixed effects, we limit the risks that other shocks or interventions polluted our findings. However, since we cannot test for the parallel trends' assumption in our GDID, we apply the following strategy to test the robustness of our findings and implicitly verified whether this assumption holds. First, we analyze the dynamic effects and conduct a standard leads-and-lags test following the literature (see e.g., Angrist and Pischke 2009; Maurer 2019). This allows testing whether the effects of discoveries occurred after the discovery or production and tend to intensify thereafter. Second, we cross validate our findings by using different control groups while dropping from the control group all individuals in (i) countries without mineral discoveries (Mauritius and South Sudan) and (ii) in districts without mineral discoveries. This reduces the heterogeneity and differences in characteristics between our treated and control groups.

4.6 Results

In this section, we present our main findings, starting with the baseline results for the primary and secondary/tertiary levels of education, before discussing the dynamic effects of mineral discoveries and productions on educational IM.

4.6.1 Baseline results

4.6.1.1 Educational Primary IM

Table 4.2 reports the baseline results for the various sample compositions and definitions of the variables. The dependent variable is the occurrence of upward (columns 1–4) or downward (columns 5–8) educational IM. As explained in the previous section, we consider a time window of 15 years before and after the mineral discoveries or productions. We start with the results in Panel (A) where control variables are not included in the estimates.

In columns (1) and (5), the treatment group includes individuals born after the mineral discoveries or productions. The estimates then provide the differences in the likelihood of upward or downward primary educational IM for individuals in districts with mineral discoveries or productions born after (treatment group) and before (control group) the discovery within the exposure window period of 15 years. We do so by controlling for the likelihood of educational IM in districts without mineral discoveries/productions. The results show that the probability of experiencing an upward educational IM is 2.7 pp. higher for an individual born after a discovery of a mining site compared to an individual born before the discovery (column 1). In other words, individuals who are born from parents who are uneducated have better chances of achieving at least primary education if exposed and living to a district with a mining discovery. Inversely, the likelihood of experiencing a downward educational IM for individuals born after the discovery of a mining site is 1.2 pp. lower than those before the mining discovery (column 5). That said, individuals who are born from educated parents are less likely to do less than their parents if exposed and living to a district with a mining discovery. About the size of the effects, it is relatively small when compared to the increase of IM across the different cohorts, signaling that, other factors have also played a significant role in improving IM in Africa. To put our findings into perspective and extrapolate them to Africa, we show that the number of individuals born up to 15 years after mineral discoveries and who have completed at least primary education while their parents have not, increases by 662 thousand in Africa over the period 1950-2000. This figure stands at 581 thousand for individuals born up to 15 years after mineral productions. Similarly, the number of individuals born up to 15 years after mineral discoveries and who have not completed at least primary education while their parents have completed it, decreases by 371 thousand. This figure stands at 124 thousand for individuals born up to 15 years after mineral productions. These figures would have been even higher to millions of individuals if we would have considered all the individuals born after the discoveries and productions, and not only those born up to 15 years after the event.

Table 4.2: Baseline results, primary education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Upward mobility				Downward mobility			
	Disc-B/A	Disc-5	Prod-B/A	Prod-5	Disc-B/A	Disc-5	Prod-B/A	Prod-5
Panel (A) Without control variables								
Mining	0.027***	0.026***	0.067***	0.056***	-0.012***	-0.005***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	8306024	8306024	8537407	8537407	4374423	4374423	4478390	4478390
R-squared	0.251	0.251	0.252	0.252	0.124	0.124	0.123	0.123
# Treated	148633	192236	53986	67663	98793	123151	36768	49337
Control variables	No	No	No	No	No	No	No	No
Panel (B) With control variables								
Mining	0.028***	0.027***	0.070***	0.059***	-0.013***	-0.007***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	8306024	8306024	8537407	8537407	4374423	4374423	4478390	4478390
R-squared	0.269	0.269	0.270	0.270	0.134	0.134	0.133	0.133
# Treated	148633	192236	53986	67663	98793	123151	36768	49337
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the baseline results for the probability of upward (columns 1–4) and downward (columns 5–8) educational IM as a function of mining discoveries and production without (Panel A) and with (Panel B) a number of other control variables. Standard errors are in parentheses. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Disc-5 is when individuals born 5 years before the discovery are included in the treatment group; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production; Prod-5 is when individuals born 5 years before mining production are included in the treatment group. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

In columns (2) and (6), we expand the treatment group to include individuals who are born 5 years before the discovery. In fact, these individuals may have not started their education at the time of the discovery as they do not meet the minimum years of schooling in most African countries. The coefficient of interest in column (2) remains broadly the same as in column (1), suggesting that the change in the time exposition to the mining discovery does not after the likelihood of upward primary educational IM. However, the coefficient is significantly lower in column (6) than in column (5), implying that individuals born after the discovery of the mining sites would have a lower likelihood of downward mobility than those born just before (five years before) the discovery.

In columns (3) and (7), we use an alternative definition of mining activity where the binary variable is now equal to one for districts where mining production has started and zero otherwise. The estimates compare the likelihood of upward or downward educational IM between individuals born after and before the beginning of the mining production. We find that the probability of experiencing an upward educational IM is 6.7 pp. higher for an individual born after the mining production compared to those born before the beginning of the mining production. The coefficient associated with mining is higher in column (3) than in column (1), implying that mining productions tend to have, on average, higher positive effects on the likelihood of upward primary educational IM than the discoveries. These higher effects could be explained by the increase in investments required to start production, which may create more jobs and income opportunities for district residents than the proceeds associated with the exploration and discovery of mining sites. Indeed, the start of the production reveals a new information that would affect the parents own and child's life expectation. We also observe that our coefficient of interest remains broadly unchanged in column (7) compared to column (5), suggesting that individuals born after the discovery and the beginning of the mining production have the same likelihood of experiencing downward primary educational IM. We also include the individuals born 5 years before the beginning of production in the treatment group in columns (4) and (8). We find that the coefficient associated with mining production is lower in column (4) than in column (3), while remaining the same in columns (7) and (8).

In Panel (B), we control for several covariates that can affect the likelihood of upward and downward educational IM as presented in the previous section (see Table D.3 for the coefficients associated with each control variable). We find that the coefficients associated with mining are highly significant at 1 percent level in all columns, and their magnitude are broadly equal to those found in Panel (A). Thus, our findings remain unchanged when we control for individual characteristics.

4.6.1.2 Educational secondary/tertiary IM

We now turn to secondary/tertiary education level. The results are reported in Table 5.2. We find that the coefficient associated with mineral discoveries and productions is not statistically significant in all columns, except the slightly significance in column (5) at 10 percent level. The result suggests that the likelihood for individuals born after the mineral discoveries and productions to experience an upward or downward secondary/tertiary educational IM is not statistically different from that of individuals born before the start of mining activities discovery or production. The insignificance of the effects of mining activities on secondary and tertiary educational IM could be due to the presence of mixed effects, both positive and negative, that are offsetting each other. For instance, as illustrated by Gradstein and Ishak (2020), a positive oil price shock is found to have a positive effect on educational attainment for children (ages 0–4), and a negative effect for adolescents (ages 10–14). Indeed, when youth children or adults reach secondary and tertiary education levels, they face a significant trade-off between education and employment. They are now able to do some domestic tasks or work outside of the household, and therefore be forced or decide to drop out of school. This situation could be particularly prone when there is a mining site within the district. For instance, Ahlerup et al. (2020) found that individuals who had gold mines within their district when they were adolescent have significantly lower educational attainment. This is explained by some myopic educational decisions when employment in gold mining is an alternative. However, some other papers reveal a positive effect of subsoil wealth on average years of primary, secondary, and tertiary education level (Stijns 2006). In addition, the same reasons driving the benefits of mineral discoveries and productions on the primary education may still be playing a role, therefore re-balancing the negative effects at higher levels of education.

In Panel (B), we include the control variables (see Table D.5 for the coefficient associated with each control variables). The results remain unchanged. The coefficients associated with mineral discoveries and productions are still statistically not significant in all columns, except column (5). In the latter, the coefficient is positive and significant at 5 percent level, suggesting that the likelihood of downward secondary/tertiary educational IM of individuals born after mining discoveries tend to be higher than those born before the discoveries. However, this finding does not hold when we expand the treatment group by including individuals born 5 years before the discovery in column (6), meaning it is not robust.

Table 4.3: Baseline results, secondary and tertiary education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Upward mobility				Downward mobility			
	Disc-B/A	Disc-5	Prod-B/A	Prod-5	Disc-B/A	Disc-5	Prod-B/A	Prod-5
Panel (A) Without control variables								
Mining	-0.006	-0.000	0.016	0.006	0.034*	0.012	-0.002	0.015
	(0.012)	(0.011)	(0.020)	(0.019)	(0.019)	(0.018)	(0.022)	(0.022)
Observations	3335415	3335415	3461167	3461167	323998	323998	331618	331618
R-squared	0.195	0.195	0.195	0.195	0.155	0.155	0.155	0.155
# Treated	67525	89986	38002	43715	6197	7491	2813	3380
Control variables	No	No	No	No	No	No	No	No
Panel (B) With control variables								
Mining	-0.007	-0.000	0.016	0.007	0.037**	0.015	-0.010	0.007
	(0.013)	(0.011)	(0.021)	(0.020)	(0.019)	(0.018)	(0.024)	(0.022)
Observations	3335415	3335415	3461167	3461167	323998	323998	331618	331618
R-squared	0.217	0.217	0.217	0.217	0.169	0.169	0.169	0.169
# Treated	67525	89986	38002	43715	6197	7491	2813	3380
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the baseline results for the probability of upward (columns 1–4) and downward (columns 5–8) educational IM as a function of mining discoveries and production without (Panel A) and with (Panel B) a number of other control variables. Standard errors are in parentheses. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Disc-5 is when individuals born 5 years before the discovery are included in the treatment group; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production; Prod-5 is when individuals born 5 years before mining production are included in the treatment group. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.6.2 Dynamic effects of mineral discoveries and productions on educational IM

In this subsection, we explore the dynamic effects of mining activities based on the time distance between the years of discoveries or productions and the birth years of individuals to test the parallel trends' assumption. As explained previously, we conduct a leads-and-lags test following the literature (Angrist and Pischke 2009; Maurer 2019) to analyze whether the effects of mineral discoveries on IM tend to intensify the years after the shock. To do so, we estimate the likelihood of upward and downward educational IM for individuals born 0–5, 6–10 and 11–15 years after the discoveries or the beginning of mining production, and those born 5–10 and 10–6 years before the discoveries or the first year of mining production. The reference group is given by individuals born 11–15 years before the discoveries or the beginning of mining productions. The results are reported in Table 4.4 for upward IM (columns 1–2 and 5–6) and downward IM (columns 3–4 and 7–8).

Table 4.4: Dynamic effects of mining activities on educational IM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Discovery	Production	Discovery	Production	Discovery	Production	Discovery	Production
Born 10-6 years before Disc/Prod	0.002	0.011***	-0.004**	-0.005*	0.010	-0.006	0.006	0.006
	(0.003)	(0.004)	(0.002)	(0.003)	(0.011)	(0.008)	(0.014)	(0.023)
Born 5-1 years before Disc/Prod	0.025***	0.035***	-0.005*	-0.006**	0.009	0.005	0.000	0.028
	(0.003)	(0.004)	(0.003)	(0.003)	(0.010)	(0.015)	(0.019)	(0.021)
Born 0-5 years after Disc/Prod	0.032***	0.075***	-0.014***	-0.013***	-0.004	0.009	0.032	0.020
	(0.003)	(0.005)	(0.003)	(0.003)	(0.016)	(0.020)	(0.024)	(0.020)
Born 6-10 years after Disc/Prod	0.042***	0.076***	-0.015***	-0.020***	-0.002	0.011	0.042	0.009
	(0.003)	(0.006)	(0.003)	(0.004)	(0.016)	(0.026)	(0.030)	(0.030)
Born 11-15 years after Disc/Prod	0.062***	0.153***	-0.029***	-0.028***	0.016	0.043	0.044	-0.012
	(0.004)	(0.006)	(0.003)	(0.005)	(0.019)	(0.034)	(0.030)	(0.024)
Observations	8306024	8537407	4374423	4478390	3335415	3461167	323998	331618
R-squared	0.269	0.270	0.134	0.133	0.217	0.217	0.169	0.169
# Treated, born 15-11 years before Disc/Prod	60590	27285	56998	17420	26819	14564	1540	1139
# Treated, born 10-6 years before Disc/Prod	55420	21713	42734	20391	27051	10265	1498	1130
# Treated, born 5-1 years before Disc/Prod	54183	17231	31550	15229	27820	7903	1587	764
# Treated, born 0-5 years after Disc/Prod	60051	22312	38694	15473	23993	12752	1602	769
# Treated, born 6-10 years after Disc/Prod	49568	15278	29402	11164	22707	11520	2192	799
# Treated, born 11-15 years after Disc/Prod	39014	16396	30697	10131	20825	13730	2403	1245
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the dynamic effects of mineral discoveries and productions on primary (columns 1–4) and secondary/tertiary (columns 5–8) educational IM. Standard errors are in parentheses. Disc stands for mining discovery. Prod stands for mining. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

The results are two folds. First, we find that mining activities affect the likelihood of primary educational IM for all age groups, while the effect is not statistically significant for secondary/tertiary educational IM. In fact, the results show that the coefficients associated with mineral discoveries and productions are positive and significant in columns 1–2, suggesting that mining activities tend to increase the likelihood of upward primary educational IM for all age groups of individuals. Inversely, the coefficients associated with mineral discoveries and productions are negative and significant in columns 3–4, meaning that mining activities are correlated with lower likelihood of downward primary educational IM for all age groups. On the other hand, the coefficients associated with mineral discoveries and productions are not statistically significant for all age groups of individuals in columns 5–8. This is in line with our findings in Table 5.2 that mining activities do not affect the likelihood of upward and downward secondary and tertiary educational IM. Second and more importantly, we find that the coefficients associated with mineral discoveries and productions are higher for individuals born later after the discovery and the beginning of mining production. For instance, the probability of upward primary educational IM is 7.6 pp. higher for individuals born 6–10 years after the beginning of mining production against only 1.1 pp. higher for those born 10–6 years before the beginning of mining production, as compared to those born 15–11 years before the beginning of mining of production (column 2). This higher probability could be explained by the fact that it takes time for mining activities to have an impact on the local communities, particularly in terms of infrastructure provision. It also supports that the parallel trend assumption might be verified, and therefore the effects we are capturing can be fully attributed to mineral discoveries and start of productions.

4.7 Transmission channels

We explore the channels through which mining activities affect the likelihood of educational IM. We focus on two channels including the income effect proxied by parents working in the mining sector, and the returns to education.[25] First, the increase of income for parents working in the mining sector, due to novel abundant opportunities, will allow them to invest more in their children education attainment Becker and Tomes (1979). Second, this new economic dynamism, creation of new jobs, will lead to an increasing demand for skilled workers. Thus, the higher returns or benefits to education in terms of wealth and income will motivate individuals to increase their educational attainment relative to their parents (Torche 2014).

To capture the income effect, we include an interactive variable between the discovery or production variable and a dummy equals to one if individuals have one of their parents working in the mining sector, and the latter itself as additional variables. For the return to education channel, we employ a two-step strategy where, in the first step, the effects of the mining discovery or production on the transmission channel variable is analyzed, and in the second step, we check the correlation between the transmission channel variable and upward/downward educational IM. This allows us to test whether the effect of mineral discoveries and productions on the probability of upward and downward educational IM transits through our transmission channel variable.

4.7.1 Income channel: parents working in the mining sector

We first test whether the income effect proxied by parents working in the mining sector could be a channel through which mining activities affect the likelihood of upward/downward educational IM. One would expect that mining activities will create jobs in the local communities, therefore

[25] We also test a third channel of the provision of infrastructures but decide not to present them as we use an (imperfect) proxy—access to electricity and clean water—for the provisions of public goods. The results can be obtained upon request. Indeed, following a mineral discovery, large scale investments in mining infrastructures and other transport infrastructures related to the exploitation and transportation of the resources are needed. Moreover, the revenues generated by the resources offer an opportunity for the region and the country to address infrastructure gaps and enhance economic development. Among the types of infrastructures, the general or local government may increase their public spending in education through better access to all primary and secondary education for all aged-children (Witter and Jakobsen 2017). Our findings show that for individuals exposed to the mineral discoveries and productions, the likelihood of having access to electricity and clean water increase by around 4 percent, and access to electricity and clean water is strongly and positively (negatively) correlated with the upward (downward) primary educational IM.

generating a source of income which could allow parents to invest more in their children education. We define a binary variable taking the value of one if one of the parents of the child is working in the mining sector, and zero otherwise and interact it with the treatment variable of mineral discoveries or productions. The results are displayed in Table 4.5, with the estimates about primary education in columns 1–4, and secondary and tertiary education in columns 5–8. We find that the coefficients associated with mineral discoveries or productions and the interactive term in columns 1–4 are statistically significant and have the expected sign. First, the mineral discoveries and productions increase (decrease) the likelihood of upward (downward) primary IM. Second and more importantly, these benefits of mining discovery or production are accentuated for individuals those one of the parents works in the mining sector. We find that having one of the parents working in the mining sector raises the likelihood of upward primary IM by 2.2 and 6.3 pp. following mineral discoveries and productions, respectively. Moreover, it diminishes the likelihood of downward primary IM by 1.1 pp. following mineral discovery. For secondary and tertiary IM, we find no significant effects of both the mineral discovery or production and its interactive term with parents working in mining. This suggests that the insignificant effects of mineral discoveries and productions hold for all individuals, independently of whether they have a parent working in the mining sector or not.

Table 4.5: Income channel: parents working in the mining sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Yes Parents work in mining	-0.018***	-0.019***	-0.003*	-0.005***	-0.015***	-0.016***	-0.007	-0.005
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.007)	(0.007)
Yes Mining	0.029***	0.078***	-0.015***	-0.014***	-0.007	0.010	0.032	0.024
	(0.002)	(0.004)	(0.002)	(0.002)	(0.014)	(0.026)	(0.032)	(0.044)
Yes Parents work in mining X Yes Mining	0.022**	0.063***	-0.011**	-0.006	0.006	0.030*	0.013	0.003
	(0.010)	(0.014)	(0.004)	(0.006)	(0.010)	(0.016)	(0.018)	(0.021)
Observations	7891058	7891058	4307002	4307002	10621699	10621699	1576361	1576361
R-squared	0.278	0.278	0.137	0.137	0.204	0.204	0.266	0.266
# Treated; with parents in mining	20171	20171	29589	29589	39923	39923	9837	9837
# Treated	270002	87980	237652	106496	436000	157564	71654	36912
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on primary (columns 1–4) and secondary/tertiary (columns 5–8) educational IM, conditional on having of the parents working in the mining sectors. Standard errors are in parentheses. *Yes Parents work in mining* is a dummy taking the value of one for individuals with one of the parents working in the mining sector. *Yes Mining* is the treatment dummy variable for either discovery or production (depending on the columns). Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level

4.7.2 Return to education: Wealth index and LIDO score

We further test a second channel of return to education to check whether individuals in districts with mineral discoveries and productions increase their level of education to get a higher wealth and income. Indeed, individuals exposed to the mineral discoveries and productions have a higher likelihood to work in the manufacturing and services sectors, and a lower likelihood to work in the agriculture sector. Given that the manufacturing and services sector may require a higher educational attainment and skills, individuals would have to increase their education level to work in these sectors, and thus having a better socio-economic status. To study the effect of mineral discoveries and productions on the returns to education, we first estimate a Mincer-like equation using a GDID model. The dependent variables are a proxy of wealth and income, given the lack of data on income and consumption in our database. The explanatory variables include the educational levels (primary and secondary/tertiary), the mineral discoveries and productions dummy, and their interactive term.

To do so, we construct the wealth index using a principal component analysis on several variables at the household level reflecting the economic status of household, following closely the Demographic and Health Survey wealth index (Rutstein and Staveteig 2014).[26] Second, we apply the lasso-adjusted industry, demographic, and occupational (LIDO) scores computed using actual data of labor market for the United States in 1950 by Saavedra and Twinam (2020) to our individuals in Africa. This LIDO score is an occupational income ranking score used as an alternative measure of income, socioeconomic status, and labor market outcome. It is dependent on (i) the fine categories of sectors of employment based on the industry classification (e.g., agriculture, mining and extraction, manufacturing, construction, hotels and restaurants, etc.), (ii) the occupation within employment based on the occupation classification (e.g., legislators, senior officials and managers, technicians and associate professionals, service works and market sales, elementary occupations), and (iii) individuals characteristics (e.g., age, gender). When applies to workers in Africa, the cross-individual, district and country differences at each period and over time would only come from the differences in the labor market conditions (sectors of activities, and occupation within employment) and demographics. We neutralize the effects of the demographic variables in the estimations by controlling for gender and age. We show in the Figure C.11 and Figure C.12 that the LIDO Score and Wealth index are strongly correlated with PPP GDP per capita at the country level, thereby implying that they are good proxies of income in Africa.

The results for the LIDO score and Wealth score are reported in Table 4.6 in columns 1–3 and 4–6, respectively. We find that an increase in the levels of education are associated with a higher LIDO score and Wealth index in all districts (with or without mineral discoveries) and all individuals (exposed to mineral discoveries/productions or not). This implies higher

[26]The variables used to construct the Wealth index include: (i) whether the household (HH) has at least one domestic servant, (ii) whether any HH member owns a dwelling unit, (iii) HH services and possessions such as drinking water, electricity, fuel cook, and their sources or types, (iv) characteristics of the dwelling such as characteristics of the floor, wall, and roof. The choice of variables is constrained by the availability of data for all countries included in the analysis.

returns to education in Africa. More importantly, we find that the returns to education are higher in districts with mineral discoveries or productions (columns 1 and 4), and they are even greater for individuals exposed to the mineral discoveries and productions (columns 2–3 and 5–6, respectively). In a second step equation, we look how the LIDO score and Wealth index correlate with the educational IM. Table 4.7 shows a strong and positive (negative) association between the LIDO score and Wealth index with the upward (downward) primary educational IM. Thus, our findings suggest that in districts with mineral discoveries and productions, and specifically for individuals born after the mineral discoveries and productions, the returns to higher education has played a key role as an incentive to achieve higher educational levels and greater educational IM.

To further reinforce this channel, we also test whether mineral discoveries and productions affect the reallocation of individuals across the broad sectors, i.e., agriculture, manufacturing, and services. Specifically, the mineral discoveries and productions, by creating new opportunities, may change the economic prospects at the local level. They can accelerate the demand for skilled workers by more capital-intensive and better paid activities in the manufacturing and services sectors, whereas individuals may be less prone to work in labor-intensive agriculture sector. The results are reported in Table 4.8. First, we show that the likelihood to work in the agriculture sector decreases by 1.1 pp. for individuals exposed to the mineral discoveries or productions (see columns 1–2). Second, we also find that the likelihood to work in the manufacturing or services sector increases by around 0.8–1.4 pp., respectively (see columns 3–4 and 5–6). These findings suggest that mineral discoveries and productions lead to the shift from lower skilled to higher skilled jobs, and therefore boost the demand for better educated people in Africa.

Table 4.6: Return to education channel: Mincer-type equation

	(1)	(2)	(3)	(4)	(5)	(6)
	LIDO Score			Wealth Index		
	With Disc.	Disc-B/A	Prod-B/A	With Disc.	Disc-B/A	Prod-B/A
Primary completed	0.021***	0.021***	0.021***	0.041***	0.041***	0.041***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary and/or tertiary completed	0.048***	0.049***	0.049***	0.097***	0.097***	0.098***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary completed X Yes Mining	0.001***	0.003***	0.007***	0.013***	0.027***	0.045***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Secondary and/or tertiary completed X Yes Mining	0.009***	0.010***	0.012***	0.017***	0.042***	0.064***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Yes Mining		0.003***	0.001		-0.012***	-0.052***
		(0.001)	(0.001)		(0.001)	(0.002)
Observations	4615725	4665165	4665165	4254638	4254638	4254638
R-squared	0.518	0.520	0.520	0.789	0.789	0.789
# Treated	396901	136323	46519	387670	178970	66437
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents a mincer-type equation where the effects of mineral discoveries and productions on the LIDO score (columns 1–3) and Wealth index (columns 4–6), conditional on educational attainment. Standard errors are in parentheses. Yes Mining is a dummy for district with discovery or not (columns 1 and 2) or the treatment dummy variable for either discovery (columns 2 and 5) or production (columns 3 and 6). With Disc. means with discovery. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 4.7: Returns to education channel: primary educational IM and LIDO score, Wealth index

	(1)	(2)	(3)	(4)
	Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Mining	0.014**	0.118***	-0.014*	-0.003
	(0.006)	(0.009)	(0.008)	(0.018)
LIDO score, 0-1	0.592***	0.592***	-0.352***	-0.351***
	(0.007)	(0.007)	(0.009)	(0.009)
Wealth index, 0-1	0.433***	0.434***	-0.252***	-0.252***
	(0.004)	(0.004)	(0.005)	(0.005)
Observations	1032317	1032317	369737	369737
R-squared	0.227	0.228	0.177	0.177
# Treated	48751	23733	15531	4664
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions as well as of LIDO score and wealth index on primary upward (columns 1–2) and secondary/tertiary (columns 3–4) educational IM. Standard errors are in parentheses. Mining is the treatment dummy variable for either discovery or production (depending on the columns). Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 4.8: Returns to education channel: effects of mineral discoveries and productions on sectoral employment

	(1)	(2)	(3)	(4)	(5)	(6)
	Agriculture		Manufacturing		Services	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Mining	-0.011***	-0.010***	0.008***	0.012***	0.003***	0.014***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	7167154	7167154	7167154	7167154	7167154	7167154
R-squared	0.659	0.659	0.145	0.145	0.220	0.220
# Treated	335257	138082	335257	138082	335257	138082
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on the likelihood to work in the agricultural (columns 1–2), manufacturing (columns 3–4), and services (columns 5–6) sectors. Standard errors are in parentheses. Mining is the treatment dummy variable for either discovery or production (depending on the columns). Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.8 Robustness checks

We undertake various robustness tests to check the validity of our results to alternative samples and specifications.

4.8.1 Use of alternative control groups (only countries/districts with discoveries)

We start by using an alternative definition of the control groups. In our baseline, we compared the likelihood of upward and downward educational IM between individuals born after the discovery or the beginning of mining production, and those born before the discovery or beginning of production or in regions and countries without discoveries, regardless of their residing countries or districts. In this robustness check, we restrict the control group to individuals living in countries or districts where mining sites are discovered or with production activities. The results are reported in Table 4.9, with the estimates for primary educational IM being in Panel (A) and those for secondary and tertiary educational IM in Panel (B). As in the baseline, we find that the coefficients associated with mining activities are significant for primary educational IM, and insignificant for secondary and tertiary educational IM. Therefore, mining activities affect the likelihood of upward and downward primary educational IM in countries and districts with mineral resources, while the effect on secondary and tertiary educational IM is not statistically significant. Our results remain unchanged and are robust to the change of control groups and samples.

4.8.2 Use of alternative structures of fixed effects and time variable

We then perform a series of consistency checks based on the structure of the fixed effects. The results are in Table 4.10, with Panel (A) being for primary education and Panel (B) for secondary and tertiary education. In columns 1–4, we replace the cohort fixed effects by birth year fixed effects and therefore compare individuals born within the same year instead of cohort since they may have experienced different shocks in 10 years. In columns 5–8, we include both the birth year fixed effects and the common time trend to capture the evolution of IM and rule out the possibility that individuals born before and after the discoveries or the beginning of mining production were already on differential growth trajectories in their education outcomes, i.e., a change in the educational IM indices that would have happened even in the absence of the mining activities. These factors could include particularly the family background of individuals (rich, poor and others). In columns 9–12, we control for cohort fixed effects and common

Table 4.9: Robustness check: Using different control groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Countries with mining activities				Districts with mining activities			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Panel (A) Primary education								
Mining	0.027***	0.069***	-0.013***	-0.012***	0.045***	0.072***	-0.012***	-0.005**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
Observations	8226648	8458031	4320910	4424877	318826	550209	230075	334042
R-squared	0.266	0.267	0.130	0.130	0.342	0.326	0.121	0.116
# Treated	148633	53986	98793	36768	148633	53986	98793	36768
Panel (B) Secondary and tertiary education								
Mining	-0.007	0.015	0.038**	-0.010	0.011	0.017	0.024	-0.008
	(0.013)	(0.021)	(0.019)	(0.024)	(0.008)	(0.020)	(0.020)	(0.024)
Observations	3289349	3415101	321879	329499	149215	274967	10822	18442
R-squared	0.217	0.217	0.168	0.168	0.152	0.169	0.119	0.127
# Treated	67525	38002	6197	2813	67525	38002	6197	2813
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM on a sample of countries (columns 1–4) and districts (columns 5–8) with mining activities. Standard errors are in parentheses. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

time trend to filter out all persistent cohort related differences that could affect the likelihood of educational IM of individuals born before and after the discoveries of mining sites: for example, the availability of school infrastructure and change in the education system. Table 4.10 shows that our main findings remain unchanged even after accounting for all these different structures of fixed effects and time variable.

4.8.3 Use of alternative time window around the mineral discoveries and productions

Another important element of our analysis is the time window around the mineral discovery and production. In the baseline, we used a time window of 30 years (15 years before and after the discovery or the beginning of production). We test the robustness to alternative time windows, including 40 years (i.e., 20 years before and after), 50 years (25 years before and after) and 60 years (30 years before and after the discovery/production) to account for the individuals who take more time to complete their education and the potential long-lasting effect of mining activities. The results are reported in Table 4.11, with Panel (A) for primary education, and Panel (B) for secondary and tertiary education. We find that the coefficients associated with our variable of interest are significant for the primary education, while insignificant for the secondary and

Table 4.10: Robustness check: Inclusion of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Upward mobility		Downward mobility		Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Panel (A) Primary education												
Mining	0.016***	0.039***	-0.009***	-0.009***	0.016***	0.039***	-0.009***	-0.009***	0.014***	0.052***	-0.009***	-0.008***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	8306024	8537407	4374423	4478390	8306024	8537407	4374423	4478390	8306024	8537407	4374423	4478390
R-squared	0.273	0.274	0.135	0.134	0.273	0.274	0.135	0.134	0.272	0.273	0.134	0.133
# Treated	148633	53986	98793	36768	148633	53986	98793	36768	148633	53986	98793	36768
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Common Time-Trend	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District X Cohort FE	No	No	No	No	No	No	No	No	No	No	No	No
Panel (B) Secondary and tertiary education												
Mining	-0.017	0.011	0.050***	-0.001	-0.017	0.011	0.050***	-0.001	-0.017	0.011	0.048**	-0.001
	(0.012)	(0.020)	(0.019)	(0.024)	(0.012)	(0.020)	(0.019)	(0.024)	(0.012)	(0.020)	(0.019)	(0.025)
Observations	3335415	3461167	323998	331618	3335415	3461167	323998	331618	3335415	3461167	323998	331618
R-squared	0.221	0.221	0.171	0.171	0.221	0.221	0.171	0.171	0.221	0.221	0.170	0.170
# Treated	67525	38002	6197	2813	67525	38002	6197	2813	67525	38002	6197	2813
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Common Time-Trend	No	No	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes
District X Cohort FE	No	No	No	No	No	No	No	No	No	No	No	No

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM, using different sets of fixed effects reported at the bottom of the table. Standard errors are in parentheses. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

tertiary education, thus in line with the findings in the baseline estimates. This confirms that our baseline results are not driven by the choice of the time window around the discovery or the beginning of mining production. Moreover, the effects of mineral discoveries or productions tend to be long-lasting, also for cohorts born years after the discovery or production.

Table 4.11: Robustness check: Using alternative time window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Window of 40 years				Window of 50 years				Window of 60 years			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Panel (A) Primary education												
Mining	0.030***	0.074***	-0.015***	-0.018***	0.032***	0.074***	-0.016***	-0.019***	0.033***	0.073***	-0.016***	-0.016***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	8397851	8397851	4459701	4459701	8487171	8487171	4534408	4534408	8563949	8563949	4603751	4603751
R-squared	0.270	0.270	0.134	0.134	0.271	0.271	0.134	0.134	0.271	0.271	0.134	0.134
# Treated	182250	37372	128892	27622	211230	50369	154302	38299	242877	66867	180868	55795
Panel (B) Secondary and tertiary education												
Mining	-0.003	0.026	0.039**	-0.021	-0.001	0.029	0.040**	-0.021	-0.001	0.022	0.040**	-0.011
	(0.012)	(0.016)	(0.019)	(0.023)	(0.012)	(0.020)	(0.020)	(0.023)	(0.012)	(0.019)	(0.019)	(0.022)
Observations	3388392	3388392	329884	329884	3442816	3442816	337347	337347	3495819	3495819	343205	343205
R-squared	0.217	0.217	0.168	0.168	0.218	0.218	0.167	0.167	0.217	0.217	0.166	0.166
# Treated	88176	26107	7715	1948	106151	36649	9003	2871	126826	50705	11022	4475
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM, considering different time windows around discovery or production. Standard errors are in parentheses. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.8.4 Use of alternative time exposition to the mineral discoveries or productions

We further explore whether our results are robust to the change in the time exposition to the mining activities. We expand the definition of the treatment group to account for individuals who may not have completed their education before the discovery or the beginning of mining production. Our baseline estimates compare the likelihood of individuals born before and after the start of mining activities. However, some individuals born before the start of mining activities may complete their education after the beginning of mining activities. In this case, those individuals will benefit from the economic and social impact from the exploitation of mining resources. We have already tried to account for these individuals by including in the treatment group the individuals born 5 years before the discovery/production in Table 4.2 and Table 5.2. In this robustness check, we include in the treatment group individuals born 10 and 15 years before the discovery or the start of mining production. To this end, we consider a longer time window of 60 years (30 years before and after the discovery/production). The results are reported in Table 4.12, with the primary educational IM in Panel (A), and secondary and tertiary educational IM in Panel (B). In all cases, we confirm our findings that mining activities have a statistically significant positive (negative) effect on the probability of upward (downward) primary educational IM, while the effect on the probability of secondary/tertiary educational IM is not statistically significant.

4.8.5 Use of alternative IM definitions

We also check the robustness of our findings to alternative definitions of our dependent variables. In the baseline, we considered children living with their biological/step parents and the average values of parents' education achievements to construct the intergenerational mobility indices. In this subsection, we first broaden the definition of parental authority to include all other immediate relatives from older generations such as uncles/aunts (in law), parents-in-law, grand-parents, and grand-uncles/aunts to account for abandoned or orphan children sent to relatives, and biological parents deliberately sending their children to relatives or places where education conditions are better. The results are reported in Table 4.13, columns 1–4. Panel (A) is for primary education and Panel (B) is for secondary and tertiary education. Second, we use the minimum and the maximum of the parents' education attainment instead of the average education attainment to better capture potential parents' education inequalities as women tend to have lower education attainment then men in Africa. In this case, a child will experience upward (downward) educational IM if his/her education attainment is higher (lower) than the minimum or the

Table 4.12: Robustness check: Use of alternative time exposition to mining activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	10 years				15 years			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-10	Prod-10	Disc-10	Prod-10	Disc-15	Prod-15	Disc-15	Prod-15
Panel (A) Primary education								
Mining	0.022***	0.052***	-0.008***	-0.012***	0.005**	0.048***	-0.003*	-0.013***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
Observations	8397851	8397851	4459701	4459701	8397851	8397851	4459701	4459701
R-squared	0.270	0.270	0.134	0.134	0.270	0.270	0.134	0.134
# Treated	281879	65666	194290	56478	341347	90201	248730	74213
Panel (B) Secondary and tertiary education								
Mining	0.009	0.003	0.012	0.022	0.009	-0.001	-0.007	-0.002
	(0.010)	(0.015)	(0.015)	(0.032)	(0.009)	(0.016)	(0.019)	(0.026)
Observations	3388392	3388392	329884	329884	3388392	3388392	329884	329884
R-squared	0.217	0.217	0.168	0.168	0.217	0.217	0.168	0.168
# Treated	138784	38651	10596	3304	165254	51506	11988	4546
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM, considering different treated group expositions. Standard errors are in parentheses. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

maximum of his/her parents' education attainment.[27] The results of the estimates are displayed in Table 4.13, columns 5-12. We still find that mining discoveries and productions increase (reduce) the likelihood of upward (downward) primary educational IM in Panel (A), while the effects on secondary/tertiary educational IM is insignificant in Panel (B). That said, the use of alternative intergenerational mobility definitions does not alter our findings.

[27] We also use the minimum and maximum for the immediate older generation as a robustness check. Similarly, to the results presented for the biological/step parents, our findings remain unchanged. The results are available upon request.

Table 4.13: Robustness check: Using alternative IM definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All immediate older generations				Minimum parents' education				Maximum parents' education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Panel (A) Primary education												
Mining	0.022***	0.070***	-0.016***	-0.008***	0.028***	0.067***	-0.008***	-0.006***	0.028***	0.070***	-0.013***	-0.012***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	9317365	9583522	4759270	4876916	9656297	9920198	3024150	3095599	8306024	8537407	4374423	4478390
R-squared	0.279	0.280	0.137	0.136	0.280	0.281	0.0917	0.0909	0.269	0.270	0.134	0.133
# Treated	168029	63557	112392	41220	172451	62158	74975	28596	148633	53986	98793	36768
Panel (B) Secondary and tertiary education												
Mining	-0.009	0.011	0.028	-0.011	-0.009	0.017	0.031*	0.011	-0.012	-0.001	0.025*	-0.003
	(0.012)	(0.018)	(0.022)	(0.022)	(0.013)	(0.021)	(0.017)	(0.032)	(0.010)	(0.006)	(0.013)	(0.008)
Observations	4026641	4178603	381313	390657	3472544	3601346	186869	191439	3390543	3609255	330215	345236
R-squared	0.220	0.219	0.183	0.183	0.234	0.233	0.162	0.162	0.216	0.216	0.167	0.166
# Treated	80221	45703	7960	3549	69345	38973	4377	1842	86544	45422	7904	3240
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM, using alternative definitions of IM to account for fostered, abandoned, or orphan children. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.8.6 Use of all mineral discoveries and productions

We test for robustness to the coverage of all mineral discoveries and productions. As explained in Section 4.5, we focused on the first discovery and the first production to cancel out any potential anticipation and duplication effects as resource-rich districts are more likely to experience several discoveries or have many production sites. In this subsection, we use all discoveries and productions of mineral resources. The results are displayed in Table 4.14. We still find that mining activities affect the likelihood of primary educational IM, while the effect on secondary and tertiary educational IM is not statistically significant. Therefore, the change in coverage of mineral discoveries and productions does not alter our baseline findings.

Table 4.14: Robustness check: Using all mining sites

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Mining	0.014***	0.028***	-0.008***	-0.007***	-0.012	-0.001	0.025*	-0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.010)	(0.006)	(0.013)	(0.008)
Observations	8432049	8797840	4485265	4679709	3390543	3609255	330215	345236
R-squared	0.270	0.272	0.134	0.133	0.216	0.216	0.167	0.166
# Treated	185161	64163	136094	45205	86544	45422	7904	3240
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM, using all mineral discoveries and productions. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.8.7 Use of conflicts as additional control variables

Finally, we verify if our baseline results hold after the inclusion of conflicts as additional control variables, given their negative association with mineral discoveries, extensively found in the literature. We have not included this variable in the baseline since geolocalized data on conflicts at district level is available from 1989, thereby restraining our sample of study. We use the Georeferenced Event Dataset (GED) on conflicts from Uppsala Conflict Data Program. We create a dummy equal to one if individuals aged 0–16 years old were exposed to a conflict with more than 25 deaths at the district level and use it as explanatory of primary educational IM. For secondary and tertiary educational IM, we rather consider individuals aged 0–25 years old for exposition to conflicts. The results are reported in Table 4.15. We show that conflicts are negatively associated with upward primary IM, while they have no significant effects on downward primary IM as well as both upward and downward secondary and tertiary IM. However, the effect of mining activities (discoveries or productions) on educational upward (downward) IM remain positive (negative) for the primary level, and not significant for the secondary and tertiary level. Then, additional conflicts as an explanatory of educational IM does not alter our baseline findings.

Table 4.15: Robustness check: Adding conflicts as explanatory of educational IM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Mining	0.028***	0.020***	-0.016***	0.001	0.012	0.024	0.019	0.002
	(0.003)	(0.005)	(0.003)	(0.002)	(0.026)	(0.029)	(0.037)	(0.022)
Conflict	-0.009***	-0.009***	-0.000	-0.000	0.010	0.010	-0.012	-0.014*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.010)	(0.009)	(0.008)	(0.007)
Observations	2240418	2327927	1529992	1566001	1051050	1094890	111055	115467
R-squared	0.380	0.382	0.162	0.161	0.180	0.180	0.100	0.100
# Treated	57972	11529	34160	21096	31019	12668	3016	2093
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note:This table presents the effects of mineral discoveries and productions on upward and downward educational IM, adding conflicts has an explanatory variable. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.9 Sensitivity tests

In this section, we undertake some sensitivity tests to explore whether our findings vary across African regions, size of the mining sites, gender, and urban-rural residency.

4.9.1 Depending on the African regions

We first explore whether the regional subdivision matters. We split the African continent into four regions: Eastern Africa, Northern Africa, Southern Africa, and Western and Central Africa. We then estimate the effects of mining activities on the probability of upward/downward educational IM for each region. The results reported in Table 4.16 show that there are some heterogeneities across regions. We find that the coefficients associated with mineral discoveries or productions are positive and strongly significant at the 1 percent level (columns 1–2), suggesting that mining activities tend to increase the probability of upward primary educational IM in all African regions. However, mining activities reduce the likelihood of downward primary educational IM only in Eastern Africa and Northern Africa, as the coefficients associated with mineral discoveries or productions are negative and significant only for these two regions (columns 3–4). Regarding secondary and tertiary educational IM, the results are more divergent. We find that the coefficient associated with mining activities are negative and significant in Eastern Africa and Northern Africa, while positive and significant in Southern Africa, and Western and Central Africa (columns 5–6). In other words, mining activities increase the probability of upward secondary and tertiary educational IM in Southern Africa, and Western and Central Africa, while reducing the probability of upward secondary and tertiary educational IM in Eastern Africa and Northern Africa. On the other hand, the coefficients associated with downward secondary and tertiary educational IM are not statistically significant in all regions, except some positive associations in Eastern and Northern Africa.

Table 4.16: Sensitivity: African Regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
Mining	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Eastern Africa	0.011***	0.054***	-0.024***	-0.017***	-0.013***	-0.029***	0.037*	0.036
	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)	(0.008)	(0.022)	(0.036)
Northern Africa	0.039***	0.105***	-0.008***	-0.012***	-0.016***	0.015	0.045***	0.030
	(0.003)	(0.006)	(0.002)	(0.004)	(0.005)	(0.010)	(0.016)	(0.036)
Southern Africa	0.044***	0.026**	-0.005	-0.008	0.048***	0.066***	0.003	-0.056*
	(0.008)	(0.011)	(0.005)	(0.006)	(0.010)	(0.009)	(0.060)	(0.032)
Western and Central Africa	0.078***	0.062***	0.007	0.007	0.063***	0.050***	-0.015	-0.063
	(0.016)	(0.017)	(0.011)	(0.007)	(0.016)	(0.018)	(0.060)	(0.058)
Observations	8306024	8537407	4374423	4478390	3335415	3461167	323998	331618
R-squared	0.269	0.270	0.134	0.133	0.217	0.217	0.169	0.169
# Treated; Eastern Africa	71453	32587	35765	11765	27505	19397	1880	541
# Treated; Northern Africa	57616	11335	45223	10666	25016	6121	2935	476
# Treated; Southern Africa	16186	7765	12252	10160	11255	10185	888	1457
# Treated; Western and Central Africa	3378	2299	5553	4177	3749	2299	494	339
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM across African regions. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.9.2 Depending on the size of mineral discoveries

We now study whether our results generalize to all sizes of mineral discoveries or if some subgroups of minerals have specific effects on education outcomes. The Minex Consulting Dataset (2019) splits mineral discoveries into four categories: moderate, major, giant and super-giant mining. We merge the last two categories as there was not sufficient observations to include each of them in the estimates. The results are in Table 4.17, columns 1–4 for primary education and columns 5–6 for secondary and tertiary education. We find that the coefficient associated with all sizes of mineral discoveries are positive and significant at the 1 percent in columns 1–2, suggesting that mineral discoveries or productions, regardless of its size, is positively correlated with higher likelihood of primary educational upward IM for individuals born after the discovery than those born before. However, we observe in columns 3–4 that the coefficients associated with giant and super-giant mining are not statistically significant, while those associated with moderate and major mining are significant and in line with our baseline findings. Therefore, individuals living in districts with moderate and major mining operations are less likely to experience downward primary educational IM. Furthermore, we find that the coefficients associated with major and moderate mining are higher in absolute terms than those associated with giant and super-giant mining. On the other hand, only the coefficients associated with giant and super-giant mining discoveries are statistically significant in columns 5–6, meaning that individuals exposed to the discoveries and productions of giant and super-giant mining have a higher likelihood of upward secondary and tertiary educational IM.

Table 4.17: Sensitivity: Size of mineral discoveries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Moderate Mining	0.011***	0.054***	-0.024***	-0.017***	-0.013	-0.029**	0.037	0.036**
	(0.003)	(0.005)	(0.004)	(0.003)	(0.024)	(0.013)	(0.037)	(0.017)
Major Mining	0.039***	0.105***	-0.008***	-0.012***	-0.016	0.015	0.045**	0.030
	(0.003)	(0.006)	(0.002)	(0.004)	(0.010)	(0.047)	(0.021)	(0.032)
Giant and Super-Giant Mining	0.051***	0.036***	-0.003	-0.003	0.053***	0.062***	-0.007	-0.057***
	(0.007)	(0.009)	(0.005)	(0.005)	(0.019)	(0.015)	(0.045)	(0.014)
Observations	8306024	8537407	4374423	4478390	3335415	3461167	323998	331618
R-squared	0.269	0.270	0.134	0.133	0.217	0.217	0.169	0.169
# Treated; Moderate	71453	32587	35765	11765	27505	19397	1880	541
# Treated; Major	57616	11335	45223	10666	25016	6121	2935	476
# Treated; Giant and Super-Giant	19564	10064	17805	14337	15004	12484	1382	1796
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Moderate <> Major, p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Moderate <> Giant / Super Giant, p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Major <> Giant / Super Giant, p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM by sizes of discoveries. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.9.3 Depending on the gender

We then look at whether the effect of mining activities varies based on the gender status of individuals. The models are separately estimated for males and females. The results are reported in Table 4.18 for both primary education (columns 1–4) and secondary and tertiary education (columns 5–6), with male gender being in Panel (A) and female gender in Panel (B). The p-values of the difference-in-means test between males and females are presented at the bottom of the table. Interestingly, the results in Table 4.18 show that the coefficient associated with mining in Panel (A) and (B) in column (1) are not statistically different, suggesting that mining discoveries affect by the same magnitude the probability of upward primary educational IM of males and females. However, the coefficient associated with mining in column (2) is nearly 2 times higher in Panel (A) than in Panel (B), reflecting the gender gap in benefits associated with mining production, in favor of males. Indeed, the probability for males to experience an upward primary educational IM is 8.4 percent, against 4.9 percent for females. We also find that the coefficients associated with mining in columns (3) and (4) are higher in absolute terms in Panel (A) than in Panel (B). Males are therefore less likely to experience downward primary educational IM than females. Regarding secondary and tertiary education, Table 4.18 shows that the coefficient associated with mining is mostly not statistically significant or inconsistently estimated both for males and females.

Table 4.18: Sensitivity: Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
	Panel (A) Male							
Mining	0.027***	0.084***	-0.016***	-0.017***	-0.006	0.017***	0.045**	-0.024
	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.006)	(0.018)	(0.026)
Observations	5101686	5241058	2361599	2417884	2089939	2165635	190636	194782
R-squared	0.257	0.258	0.126	0.125	0.232	0.232	0.172	0.172
# Treated	85358	32490	51792	19482	37088	23104	3269	1553
	Panel (B) Female							
Mining	0.027***	0.049***	-0.010***	-0.006*	-0.014***	0.014*	0.029	0.011
	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.008)	(0.018)	(0.027)
Observations	3204338	3296349	2012824	2060506	1245476	1295532	133362	136836
R-squared	0.308	0.308	0.153	0.153	0.217	0.217	0.194	0.194
# Treated	63275	21496	47001	17286	30437	14898	2928	1260
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean difference, p-value	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM by gender. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.9.4 Depending on the urban-rural living area

We split the sample into two subsamples based on the urban-rural residency, and then run the estimates of the effect of mining activities on the likelihood of upward and downward educational IM for each subgroup, separately. The results are reported in Table 4.19 for both primary education (columns 1–4) and secondary and tertiary education (columns 5–6). The estimates for urban residents are in Panel (A), while those of rural residents are in Panel (B). We report at the bottom of the table the p-value of the significance of the difference in coefficients between urban and rural areas. In columns 1–4, we find that the coefficients associated with mining are broadly higher in absolute terms in urban areas than in rural areas, suggesting that the effect of mining activities on the probability of educational IM tends to be high for individuals living in urban areas. In columns 5–6, we observe that the coefficients associated with our variable of interest are not statistically significant in rural areas, while there are significant in urban areas, meaning that the place of living also matters regarding the effect of mining activities on the probability of secondary and tertiary educational IM. Indeed, individuals living in rural areas face unique barriers to economic and educational opportunities (including poverty, access to public goods, lack of teachers, weaker local economy, etc.) than those living in urban areas. This supports that it is more likely that the preconditions for a positive effect of mineral discoveries and productions on educational IM are more likely to be reunited in urban than rural areas.

Table 4.19: Sensitivity: Urban Rural residency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary education				Secondary and tertiary education			
	Upward mobility		Downward mobility		Upward mobility		Downward mobility	
	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A	Disc-B/A	Prod-B/A
Panel (A) Urban								
Mining	0.055***	0.083***	-0.015***	-0.010***	-0.013**	0.020***	0.047***	-0.022
	(0.005)	(0.006)	(0.003)	(0.003)	(0.006)	(0.007)	(0.017)	(0.021)
Observations	2620209	2675545	2639013	2672691	1407813	1447625	258097	263176
R-squared	0.118	0.118	0.0772	0.0766	0.156	0.155	0.151	0.150
# Treated	31407	20106	41516	22049	23830	19390	3612	2319
Panel (B) Rural								
Mining	0.018***	0.060***	-0.005**	-0.009***	-0.007	0.006	0.046	0.050*
	(0.002)	(0.004)	(0.003)	(0.003)	(0.015)	(0.021)	(0.030)	(0.029)
Observations	5685815	5861862	1735410	1805699	1927602	2013542	65901	68442
R-squared	0.290	0.291	0.152	0.152	0.230	0.229	0.208	0.208
# Treated	117226	33880	57277	14719	43695	18612	2585	494
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean difference, p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: This table presents the effects of mineral discoveries and productions on upward and downward educational IM by urban-rural residency. Disc-B/A means that the treatment group is after the discovery and the control group is before the discovery; Prod-B/A means that the treatment group is after the beginning of production and the control group is before production. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

4.10 Conclusion and Policy implications

This paper sheds light on the effects of mineral discoveries and productions on the educational IM on more than 14 million individuals across 28 countries and 2,890 districts. Using this large and unique dataset, we compute absolute measures of intergenerational mobility and provide a panorama of stylized facts about the trend, dynamics, and disparities of educational IM across countries, and regions of the continent. We show that primary and secondary/tertiary educational

IM have significantly improved in Africa over time, with a more significant increase in primary IM (higher upward IM and lower downward IM) than in secondary/tertiary IM. We uncover that the gender gap in favor of males has narrowed over time, with sometimes females doing better than males in most recent cohorts. Regarding the living area, we show that although the residency gap has slightly diminished over time, educational IM has always been better in urban than rural areas and the gap still remains significant. We also provide country-specific characteristics regarding educational IM as well as cross-country and within-country disparities. In addition, we identify where is the land of opportunities by mapping the district-level educational IM to unveil the heterogeneities across the African continent.

We then empirically study the potential role of mineral discoveries and productions on educational IM in Africa given the abundance of mineral resources across the continent. To so do, we employ a generalized difference-in-differences method in a quasi-natural experiment to identify the causal relationship between mineral discoveries/production and educational IM. Our findings suggest that mineral discoveries and productions positively affect primary educational IM in Africa for individuals exposed to the mineral sites and living in districts with mineral discoveries and productions. However, no significant effects are found for secondary/tertiary educational IM. We also unveil two transmission channels through which the positive effects of mineral discoveries and productions on educational primary IM operate, including the income effect proxied by parents working in the mining sector and the returns to education.

Our paper has many policy implications. We show that mineral discoveries and productions have helped improved the social and educational intergenerational mobility in Africa by creating job opportunities, and the returns to education. For these opportunities to be seized, several conditions need to be in place. First, governments should implement accommodative policies that will support enterprise development and the full potential for the creation of jobs to be harnessed. These policies can include labor market flexibility and the creation of business linkages between large mining companies and local small and medium enterprises (SMEs) that will strengthen the sector's capacity to create jobs. Second, as shown in this paper, mineral discoveries and productions tend to profit males and females as well as people living in urban and rural areas differently. Targeted policies that aim at reducing the inequality of opportunities, especially following mineral discoveries, are also welcome. In addition, our results suggest that districts with discoveries could benefit more from the discoveries or productions, therefore calling for the channeling of the mining revenues in a fund and redistributing it among the districts with the objective to reduce regional disparities.

As avenue for further research, it would be interesting to investigate in details how mineral discoveries and productions induce a local structural transformation, by analyzing their impact on intergenerational mobility in occupation. It might be that mineral discoveries and productions also incur an increase of the likelihood that children do better than their parents in terms of employment at local level.

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Appendix

C

Appendix to Chapter 4

C.1 Sample

Table C.1: Construction of sample from raw IPUMS data

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Country	**Year**	**Nall**	**Ndistrict**	**Neduc**	**Nliverelative**	**Nlivebiop**	**Nage**	**Nsex**	**Nurban**	**Ncont**	**NIMiog**	**NIMbiop**	**Inc.**
Benin	1979	331 049	331 049	246 094	96 925	80 434	22 566	22 566	0	0	0	0	no
Benin	1992	498 419	498 419	435 827	212 711	196 722	50 851	50 851	50 851	40 875	38 869	38 689	yes
Benin	2002	685 467	685 467	612 658	317 380	250 883	84 593	84 593	84 593	48 913	48 651	48 606	yes
Benin	2013	1 009 693	1 009 693	911 604	512 405	412 923	152 398	152 398	152 398	94 195	93 987	93 975	yes
Total		**2 524 628**	**2 524 628**	**2 206 183**	**1 139 421**	**940 962**	**310 408**	**310 408**	**287 842**	**183 983**	**181 507**	**181 270**	
Botswana	1981	97 238	97 238	73 096	32 554	25 225	9 359	9 359	0	0	0	0	no
Botswana	1991	132 623	132 623	113 172	49 711	41 258	16 624	16 624	16 624	13 877	13 058	13 037	yes
Botswana	2001	168 676	168 676	159 446	76 312	63 327	29 167	29 167	0	0	0	0	no
Botswana	2011	201 752	201 752	190 510	84 347	69 536	33 686	33 686	0	0	0	0	no
Total		**600 289**	**600 289**	**536 224**	**242 924**	**199 346**	**88 836**	**88 836**	**16 624**	**13 877**	**13 058**	**13 037**	
Burkina Faso	1985	884 797	884 797	484 993	0	0	0	0	0	0	0	0	no
Burkina Faso	1996	1 081 046	1 081 046	803 642	377 219	327 148	112 834	112 834	0	0	0	0	no
Burkina Faso	2006	1 417 824	1 417 824	1 244 906	609 130	543 338	127 886	127 886	127 886	103 987	103 605	103 518	yes
Total		**3 383 667**	**3 383 667**	**2 533 541**	**986 349**	**870 486**	**240 720**	**240 720**	**127 886**	**103 987**	**103 605**	**103 518**	
Cameroon	1976	736 514	736 514	605 857	224 570	210 439	40 560	40 555	0	0	0	0	no
Cameroon	1987	897 211	897 211	763 744	312 705	301 224	63 193	63 193	63 193	55 113	52 612	52 357	yes
Cameroon	2005	1 772 359	1 766 211	1 536 785	769 108	712 995	240 864	240 864	240 864	207 506	205 996	205 902	yes
Total		**3 406 084**	**3 399 936**	**2 906 386**	**1 306 383**	**1 224 658**	**344 617**	**344 612**	**304 057**	**262 619**	**258 608**	**258 259**	
Egypt	1986	6 799 093	6 799 093	5 421 801	2 825 392	2 552 405	1 297 832	1 297 829	1 297 829	1 131 225	1 100 397	1 098 502	yes
Egypt	1996	5 902 243	5 902 243	4 453 785	2 126 960	2 027 351	1 185 312	1 185 312	1 185 312	1 090 368	1 083 995	1 083 953	yes
Egypt	2006	7 282 434	7 282 434	5 739 722	2 553 381	2 450 443	1 610 591	1 610 591	1 610 591	1 515 467	1 514 369	1 514 364	yes
Total		**19 983 770**	**19 983 770**	**15 615 308**	**7 505 733**	**7 030 199**	**4 093 735**	**4 093 732**	**4 093 732**	**3 737 060**	**3 698 761**	**3 696 819**	
Ethiopia	1984	3 404 306	3 400 221	2 735 271	1 209 735	1 149 841	228 972	228 971	228 971	196 636	175 867	175 365	yes
Ethiopia	1994	5 044 598	5 044 598	4 201 617	2 015 604	1 979 879	566 246	566 246	566 246	539 043	524 827	524 590	yes
Ethiopia	2007	7 434 086	7 434 086	1 097 614	544 065	514 140	154 345	154 345	154 345	141 002	140 034	140 024	yes
Total		**15 882 990**	**15 878 905**	**8 034 502**	**3 769 404**	**3 643 860**	**949 563**	**949 562**	**949 562**	**876 681**	**840 728**	**839 979**	
Ghana	1984	1 309 352	1 309 352	1 050 813	545 036	545 036	187 288	187 288	0	0	0	0	no
Ghana	2000	1 894 133	1 894 133	1 730 902	727 288	671 959	243 122	243 122	243 122	212 320	208 074	208 010	yes
Ghana	2010	2 466 289	2 466 289	2 262 894	1 091 326	1 018 943	400 015	400 015	400 015	360 219	359 524	359 489	yes
Total		**5 669 774**	**5 669 774**	**5 044 609**	**2 363 650**	**2 235 938**	**830 425**	**830 425**	**643 137**	**572 539**	**567 598**	**567 499**	
Guinea	1983	457 837	457 837	364 823	106 728	105 679	30 830	30 815	30 749	30 444	29 418	28 999	yes
Guinea	1996	729 071	729 071	553 173	246 286	207 001	89 851	89 851	89 851	66 128	63 700	63 495	yes
Guinea	2014	1 050 916	1 050 916	951 617	539 972	444 014	184 293	184 293	184 293	126 181	125 892	125 830	yes
Total		**2 237 824**	**2 237 824**	**1 869 613**	**892 986**	**756 694**	**304 974**	**304 959**	**304 893**	**222 753**	**219 010**	**218 324**	
Kenya	1969	659 310	659 310	659 310	273 058	263 394	20 959	20 959	0	0	0	0	no
Kenya	1979	1 033 769	1 033 769	854 251	0	0	0	0	0	0	0	0	no
Kenya	1989	1 074 098	1 074 098	829 247	364 258	355 117	115 571	115 571	115 571	110 185	106 171	106 095	yes
Kenya	1999	1 407 547	1 407 547	1 191 268	487 645	482 717	160 587	160 587	160 587	156 553	154 897	154 879	yes
Kenya	2009	3 841 935	3 841 935	3 402 695	1 717 135	1 593 028	507 075	507 075	507 075	462 754	456 403	456 195	yes
Total		**8 016 659**	**8 016 659**	**6 936 771**	**2 842 096**	**2 694 256**	**804 192**	**804 192**	**783 233**	**729 492**	**717 471**	**717 169**	
Lesotho	1996	187 795	187 776	165 945	88 666	79 967	39 728	39 728	39 728	34 241	33 503	33 496	yes
Lesotho	2006	180 208	180 208	171 947	85 473	77 758	37 556	37 556	37 556	32 983	32 851	32 850	yes
Total		**368 003**	**367 984**	**337 892**	**174 139**	**157 725**	**77 284**	**77 284**	**77 284**	**67 224**	**66 354**	**66 346**	
Liberia	1974	150 256	150 256	127 442	0	0	0	0	0	0	0	0	no
Liberia	2008	348 057	348 057	294 517	126 770	118 977	47 631	47 631	47 631	44 199	44 012	44 007	yes
Total		**498 313**	**498 313**	**421 959**	**126 770**	**118 977**	**47 631**	**47 631**	**47 631**	**44 199**	**44 012**	**44 007**	
Malawi	1987	798 669	798 669	658 449	222 672	220 229	49 617	49 617	49 617	48 293	45 303	45 291	yes
Malawi	1998	991 393	991 393	826 197	292 284	286 039	77 453	77 453	77 453	73 746	72 671	72 668	yes
Malawi	2008	1 341 977	1 341 977	1 156 748	497 097	492 609	106 570	106 570	105 741	102 459	101 882	101 877	yes
Total		**3 132 039**	**3 132 039**	**2 641 394**	**1 012 053**	**998 877**	**233 640**	**233 640**	**232 811**	**224 498**	**219 856**	**219 836**	
Mali	1987	785 384	784 096	581 806	243 229	227 034	78 724	78 724	0	0	0	0	no
Mali	1998	991 330	991 330	737 487	340 903	318 695	117 063	117 063	117 063	98 261	96 126	95 816	yes
Mali	2009	1 451 856	1 451 856	1 285 750	741 784	648 243	209 408	209 408	209 408	157 779	156 175	155 877	yes
Total		**3 228 570**	**3 227 282**	**2 605 043**	**1 325 916**	**1 193 972**	**405 195**	**405 195**	**326 471**	**256 040**	**252 301**	**251 693**	

Table C.2: Construction of sample from raw IPUMS data (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Country	**Year**	**Nall**	**Ndistrict**	**Neduc**	**Nliverelative**	**Nlivebiop**	**Nage**	**Nsex**	**Nurban**	**Ncont**	**NIMiog**	**NIMbiop**	**Inc.**
Mauritius	1990	106 710	106 710	101 646	54 683	52 074	24 727	24 727	24 727	22 367	21 738	21 736	yes
Mauritius	2000	119 695	119 695	114 499	56 350	53 366	28 650	28 650	28 650	25 829	25 539	25 539	yes
Mauritius	2011	126 332	126 332	121 383	54 820	51 921	29 191	29 191	29 191	26 478	26 431	26 430	yes
Total		**352 737**	**352 737**	**337 528**	**165 853**	**157 361**	**82 568**	**82 568**	**82 568**	**74 674**	**73 708**	**73 705**	
Morocco	1982	1 012 873	1 012 873	948 008	546 732	511 677	178 034	178 034	0	0	0	0	no
Morocco	1994	1 294 026	1 294 026	1 293 467	835 569	783 915	338 124	338 124	0	0	0	0	no
Morocco	2004	1 482 720	1 482 720	1 482 716	928 290	864 824	442 157	442 157	0	0	0	0	no
Morocco	2014	3 341 426	3 340 830	3 340 830	1 939 870	1 803 530	935 976	935 976	933 662	808 379	808 249	808 242	yes
Total		**7 131 045**	**7 130 449**	**7 065 021**	**4 250 461**	**3 963 946**	**1 894 291**	**1 894 291**	**933 662**	**808 379**	**808 249**	**808 242**	
Mozambique	1997	1 551 517	1 551 517	1 248 483	515 184	472 203	146 861	146 861	146 861	120 325	118 632	118 617	yes
Mozambique	2007	2 047 048	2 047 048	1 616 853	718 962	664 244	197 113	197 113	197 113	164 534	163 418	163 380	yes
Total		**3 598 565**	**3 598 565**	**2 865 336**	**1 234 146**	**1 136 447**	**343 974**	**343 974**	**343 974**	**284 859**	**282 050**	**281 997**	
Nigeria	2006	83 700	83 700	82 740	46 326	44 662	10 436	10 436	10 436	9 802	9 738	9 708	yes
Nigeria	2007	85 183	85 183	84 123	47 618	45 235	10 557	10 557	10 557	9 761	9 715	9 696	yes
Nigeria	2008	107 425	107 425	105 944	62 622	60 823	15 199	15 184	15 142	14 469	14 323	14 306	yes
Nigeria	2009	77 896	77 896	77 666	41 179	39 621	9 690	9 673	9 673	8 920	8 883	8 876	yes
Nigeria	2010	72 191	72 191	59 173	30 890	29 756	11 240	11 240	11 240	10 584	10 392	10 377	yes
Total		**426 395**	**426 395**	**409 646**	**228 635**	**220 097**	**57 122**	**57 090**	**57 048**	**53 536**	**53 051**	**52 963**	
Rwanda	1991	742 918	742 918	0	0	0	0	0	0	0	0	0	no
Rwanda	2002	843 392	843 392	629 146	277 153	264 800	107 446	107 446	107 446	103 899	102 745	102 725	yes
Rwanda	2012	1 038 369	1 038 369	938 201	485 203	463 875	150 671	150 671	150 671	144 338	143 843	143 826	yes
Total		**2 624 679**	**2 624 679**	**1 567 347**	**762 356**	**728 675**	**258 117**	**258 117**	**258 117**	**248 237**	**246 588**	**246 551**	
Senegal	1988	700 199	700 199	527 680	207 551	181 977	76 093	76 093	0	0	0	0	no
Senegal	2002	994 562	994 562	911 891	477 330	440 205	192 555	192 555	192 555	168 266	167 086	166 999	yes
Senegal	2013	1 245 551	1 016 023	908 310	578 764	477 271	257 347	257 347	257 347	186 875	186 345	186 044	yes
Total		**2 940 312**	**2 710 784**	**2 347 881**	**1 263 645**	**1 099 453**	**525 995**	**525 995**	**449 902**	**355 141**	**353 431**	**353 043**	
Sierra Leone	2004	494 298	494 298	397 137	182 198	144 915	74 010	74 010	74 010	55 065	53 064	52 469	yes
Total		**494 298**	**494 298**	**397 137**	**182 198**	**144 915**	**74 010**	**74 010**	**74 010**	**55 065**	**53 064**	**52 469**	
South Africa	1996	3 621 164	3 621 164	3 083 346	1 385 515	1 255 578	621 444	621 444	621 435	562 421	538 506	537 039	yes
South Africa	2001	3 725 655	3 725 655	3 353 684	1 509 080	1 366 352	728 007	728 007	727 870	656 452	650 438	650 174	yes
South Africa	2007	1 047 657	1 047 657	842 103	384 555	347 943	197 500	197 500	197 500	179 236	177 447	177 401	yes
South Africa	2011	4 418 594	4 418 594	3 845 633	1 494 142	1 355 066	777 948	777 948	766 491	699 181	697 461	697 347	yes
South Africa	2016	3 328 793	3 328 793	3 023 034	1 345 876	1 186 490	674 872	674 872	674 872	603 780	591 480	590 681	yes
Total		**16 141 863**	**16 141 863**	**14 147 800**	**6 119 168**	**5 511 429**	**2 999 771**	**2 999 771**	**2 988 168**	**2 701 070**	**2 655 332**	**2 652 642**	
South Sudan	2008	542 765	542 765	542 333	300 590	273 961	71 220	71 220	71 220	60 552	60 416	60 399	yes
Total		**542 765**	**542 765**	**542 333**	**300 590**	**273 961**	**71 220**	**71 220**	**71 220**	**60 552**	**60 416**	**60 399**	
Sudan	2008	5 066 530	5 066 530	3 902 071	2 048 229	1 936 664	792 810	792 810	792 810	714 673	699 070	697 097	yes
Total		**5 066 530**	**5 066 530**	**3 902 071**	**2 048 229**	**1 936 664**	**792 810**	**792 810**	**792 810**	**714 673**	**699 070**	**697 097**	
Tanzania	1988	2 310 424	2 310 424	1 916 737	683 484	679 664	183 596	183 596	0	0	0	0	no
Tanzania	2002	3 732 735	3 732 735	3 123 724	1 245 172	1 186 155	366 594	366 594	366 594	336 996	333 681	333 660	yes
Tanzania	2012	4 498 022	4 498 022	3 918 823	1 763 397	1 661 165	503 981	503 981	503 981	466 289	464 823	464 806	yes
Total		**10 541 181**	**10 541 181**	**8 959 284**	**3 692 053**	**3 526 984**	**1 054 171**	**1 054 171**	**870 575**	**803 285**	**798 504**	**798 466**	
Togo	1960	13 759	13 759	13 758	5 005	4 238	0	0	0	0	0	0	no
Togo	1970	23 680	23 680	23 672	12 267	11 999	712	712	0	0	0	0	no
Togo	2010	584 859	584 859	517 900	120 225	115 641	33 730	33 730	33 730	32 274	31 926	31 889	yes
Total		**622 298**	**622 298**	**555 330**	**137 497**	**131 878**	**34 442**	**34 442**	**33 730**	**32 274**	**31 926**	**31 889**	
Uganda	1991	1 548 460	1 529 024	1 226 290	450 737	442 411	131 819	131 819	131 819	124 996	121 888	121 856	yes
Uganda	2002	2 497 449	2 497 449	2 042 838	847 255	838 411	213 799	213 799	213 799	208 499	207 355	207 284	yes
Uganda	2014	3 506 546	3 506 546	3 145 894	1 600 477	1 506 609	400 450	400 450	400 450	374 435	373 919	373 908	yes
Total		**7 552 455**	**7 533 019**	**6 415 022**	**2 898 469**	**2 787 431**	**746 068**	**746 068**	**746 068**	**707 930**	**703 162**	**703 048**	
Zambia	1990	787 461	787 461	664 239	304 994	304 281	106 751	106 751	106 751	106 406	104 920	104 920	yes
Zambia	2000	996 117	996 117	825 110	417 749	341 108	145 247	145 247	145 247	98 694	97 967	97 933	yes
Zambia	2010	1 321 973	1 321 973	1 028 628	537 693	465 478	177 428	177 428	0	0	0	0	no
Total		**3 105 551**	**3 105 551**	**2 517 977**	**1 260 436**	**1 110 867**	**429 426**	**429 426**	**251 998**	**205 100**	**202 887**	**202 853**	
Zimbabwe	2012	654 688	654 688	587 748	222 825	204 736	65 518	65 518	65 518	60 166	59 615	59 599	yes
Total		**654 688**	**654 688**	**587 748**	**222 825**	**204 736**	**65 518**	**65 518**	**65 518**	**60 166**	**59 615**	**59 599**	
Total All		**130 727 972**	**130 466 872**	**104 306 886**	**48 454 385**	**45 000 794**	**18 160 723**	**18 160 667**	**16 214 531**	**14 459 893**	**14 263 922**	**14 252 719**	**61/82**

Notes: This table shows how we construct our final sample from the raw IPUMS data. Columns (1) and (2) give the country and census year, respectively. Columns (3) shows the initial number of observation in IPUMS data. Columns (4) gives the number of observations with available information on district. Columns (5) gives the number of observations with available information on educational attainment and district. Columns (6) gives the number of observations for individuals living with at least one relative and for which information on educational attainment and district is available. Columns (7) gives the number of observations for individuals living with at least one biological or step- parents and for which information on educational attainment and district is available. Columns (8) gives the number of observations for individuals aged 16-50 years old and born after 1950 living with at least one relative and for which information on educational attainment and district is available. Columns (9) gives the number of observations for individuals aged 16-50 years old and born after 1950 living with at least one relative and for which information on gender, educational attainment and district is available. Columns (10) gives the number of observations for individuals aged 16-50 years old and born after 1950 living with at least one relative and for which information on residency (urban or rural areas), gender, educational attainment and district is available. Columns (11) gives the number of observations for individuals aged 16-50 years old and born after 1950 living with at least one relative and for which information on residency (urban or rural areas), gender, educational attainment, district, and other control variables is available. Columns (12) gives the final sample with immediate older generation used as reference group for individuals. Columns (13) gives the final sample with biological or step- parents (baseline) used as reference group for individuals. Columns (14) gives the census/survey used in the final sample.

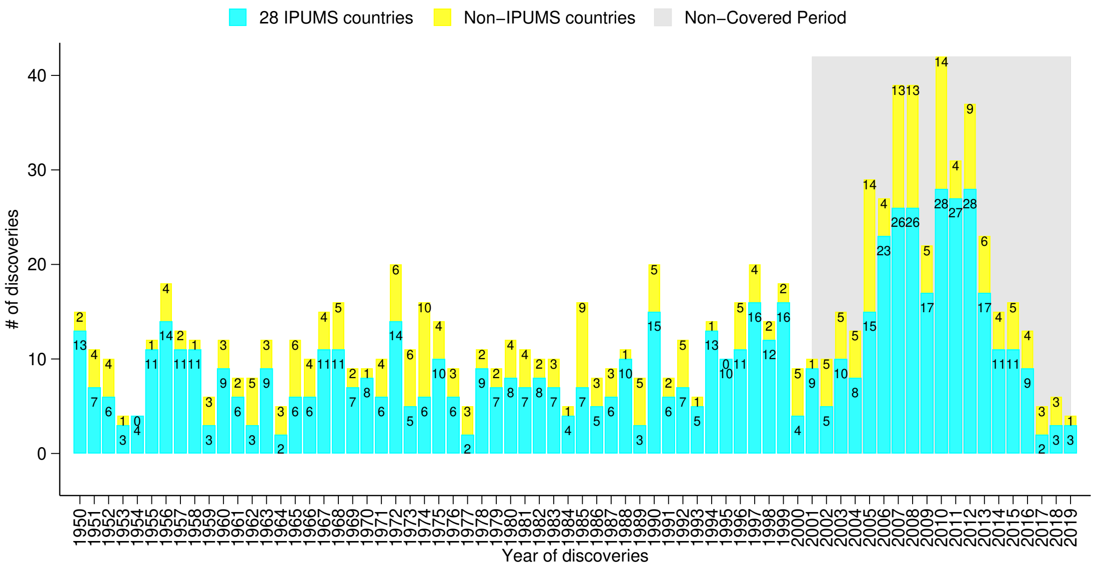
C.2 Summary statistics of educational IM

Table C.3: Summary statistics of Educational IM

	(1)	(2)	(3)	(4)	(5)	(6)
	Obs.	Mean	Sd	Obs.	Mean	Sd
	Panel (A) Primary			**Panel (B) Secondary and tertiary**		
(I) Upward mobility						
(a) Biological or step- parents						
IM (Mean)	9 258 374	0,508	0,500	12 447 352	0,204	0,403
IM (Min)	10 727 953	0,550	0,497	13 228 050	0,221	0,415
IM (Max)	9 258 374	0,508	0,500	12 447 352	0,204	0,403
(b) Immediate older generation						
IM (Mean)	9 280 274	0,507	0,500	12 462 921	0,204	0,403
IM (Min)	10 811 989	0,552	0,497	13 275 780	0,222	0,415
IM (Max)	9 132 978	0,505	0,500	12 370 537	0,204	0,403
(II) Downward mobility						
(a) Biological or step- parents						
IM (Mean)	4 994 345	0,099	0,299	1 805 367	0,438	0,496
IM (Min)	3 524 766	0,064	0,245	1 024 669	0,384	0,486
IM (Max)	4 994 345	0,099	0,299	1 805 367	0,438	0,496
(b) Immediate older generation						
IM (Mean)	4 983 648	0,097	0,296	1 801 001	0,435	0,496
IM (Min)	3 451 933	0,062	0,241	988 142	0,375	0,484
IM (Max)	5 130 944	0,104	0,305	1 893 385	0,449	0,497

C.3 Additional stylized facts on mineral discoveries

Figure C.1: Number of mineral discoveries for all African countries, 1950-2019



Source: Authors' calculations based on Minex Consulting dataset (2019)

Table C.4: Summary statistics of mineral discoveries, IPUMS countries, 1950-2000

Characteristics	**# of disc.**	**Percentage**
by African regions		
Eastern Africa	48	11,82
Northern Africa	23	5,67
Southern Africa	196	48,28
Western and Central Africa	139	34,24
by Size of mineral discoveries		
Moderate	184	45,32
Major	121	29,8
Giant	88	21,67
Super-Giant	13	3,2
by Mineral categories		
Gold	141	34,73
Bulk	75	18,47
Precious	64	15,76
Base Metal	61	15,02
Other	34	8,37
Mineral Sands	17	4,19
Uranium	14	3,45
Total	406	100

Table C.5: Composition of minerals in each metal category

Class of mineral categories	Composition
Gold	Gold
Bulk	Bauxite, Coal, Iron ore, Phosphate, Potash
Precious	Diamond, Emerald, PGE, Platinum, Ruby, Rutile, Silver
Base Metal	Copper, Lead, Nickel, Zinc
Other	Andalusit, Chromium, Cobalt, Flourine, Graphite, Lithium, Manganese, Niobium, Rare earth, Tantalum, Tanzanite, Tin, Tungsten, Vanadium
Mineral Sands	Mineral sands, Zircon
Uranium	Uranium

C.4 Additional stylized facts on country-level educational IM

C.4.1 Ranking: Country-level educational IM by gender

Figure C.2: Primary level

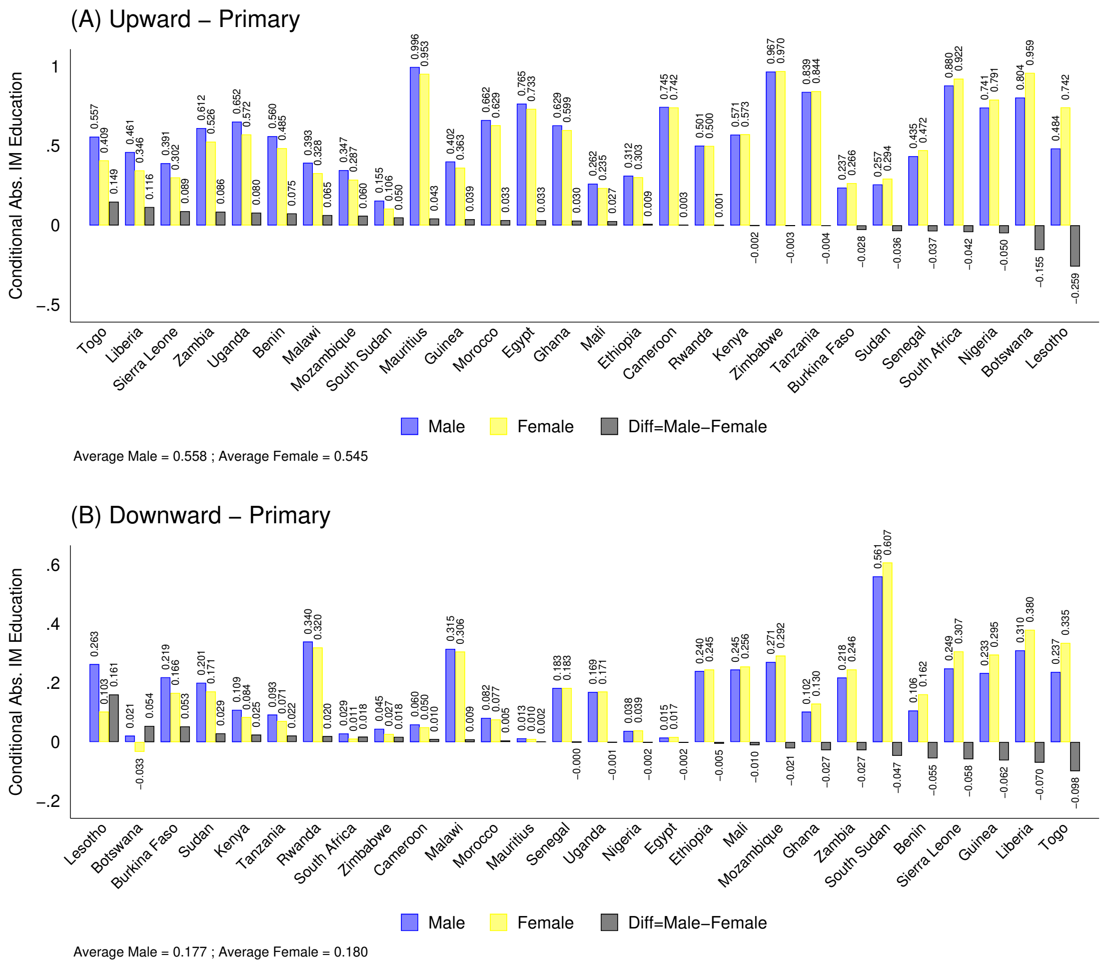
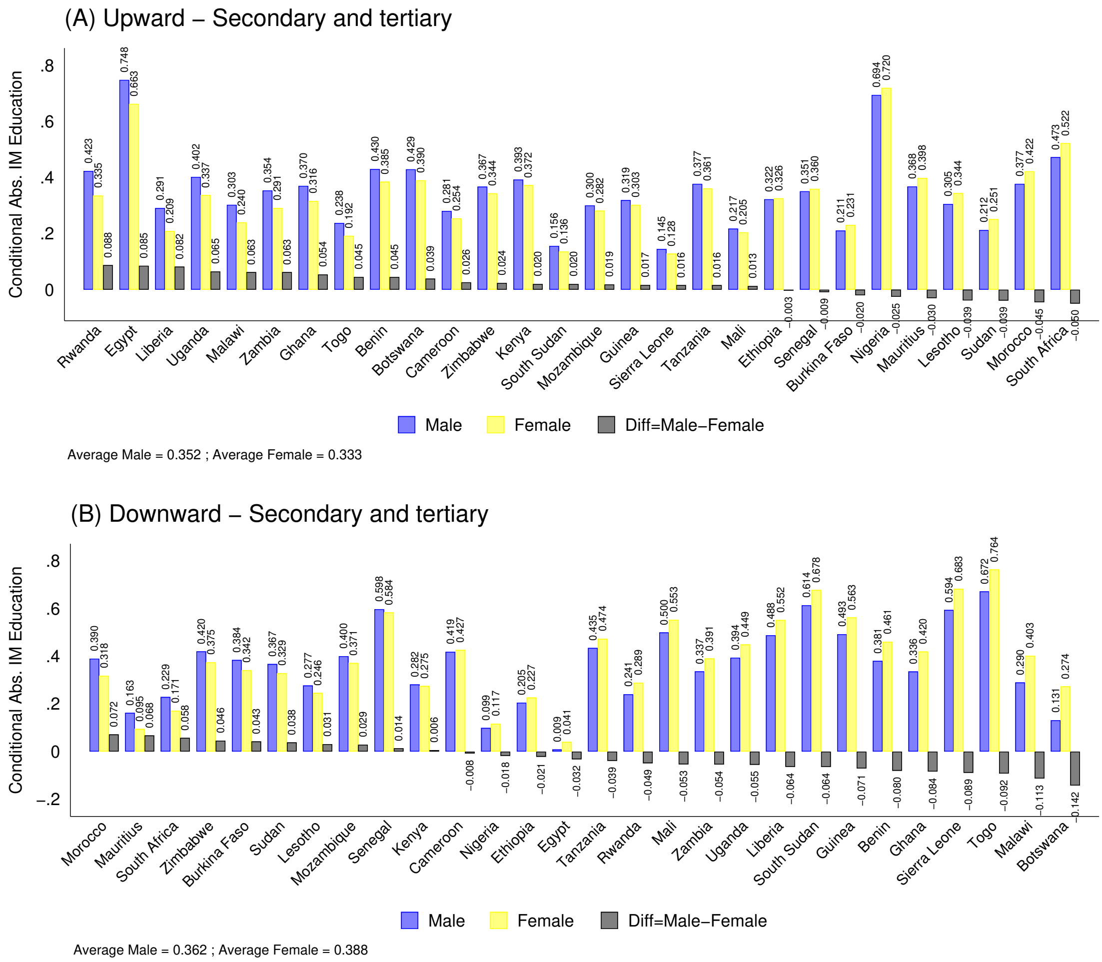


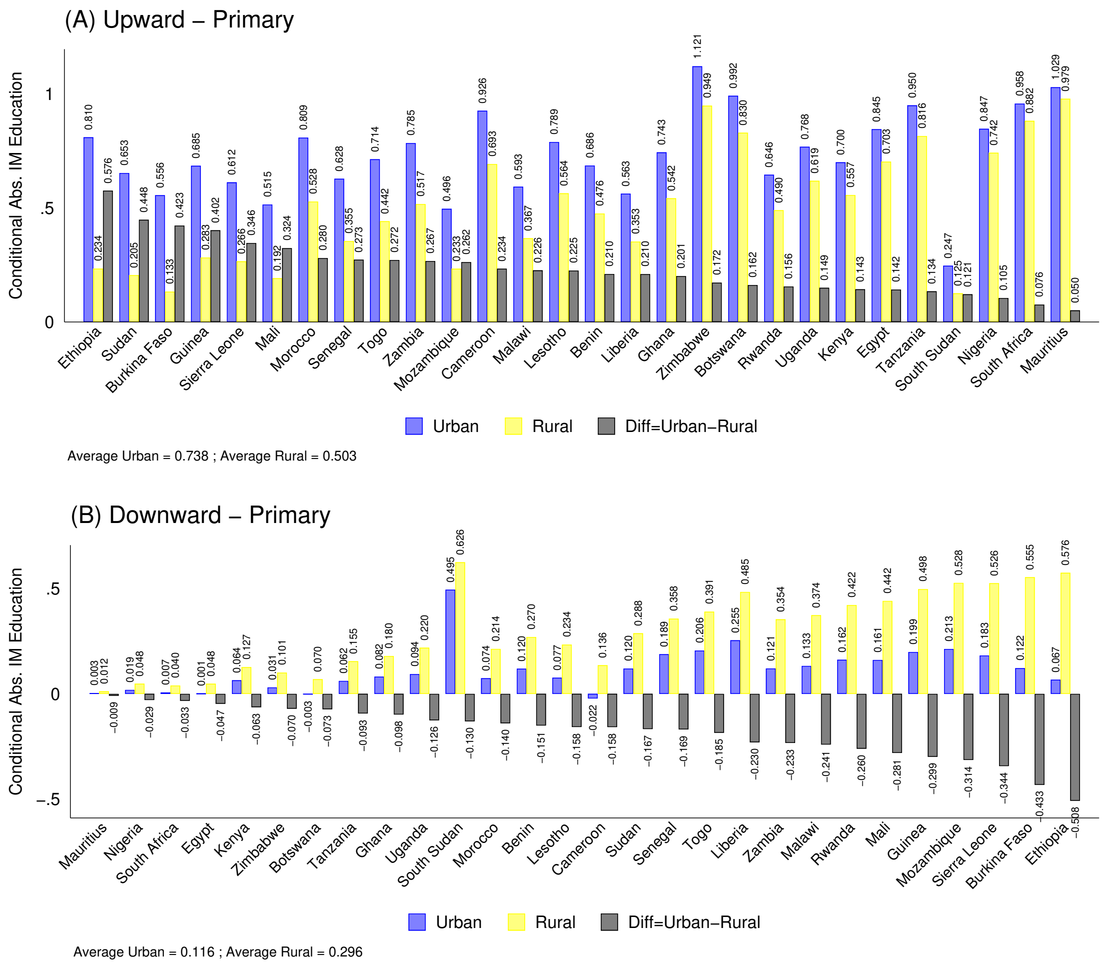
Figure C.3: Secondary and Tertiary level



Source: Authors' calculations based on IPUMS dataset

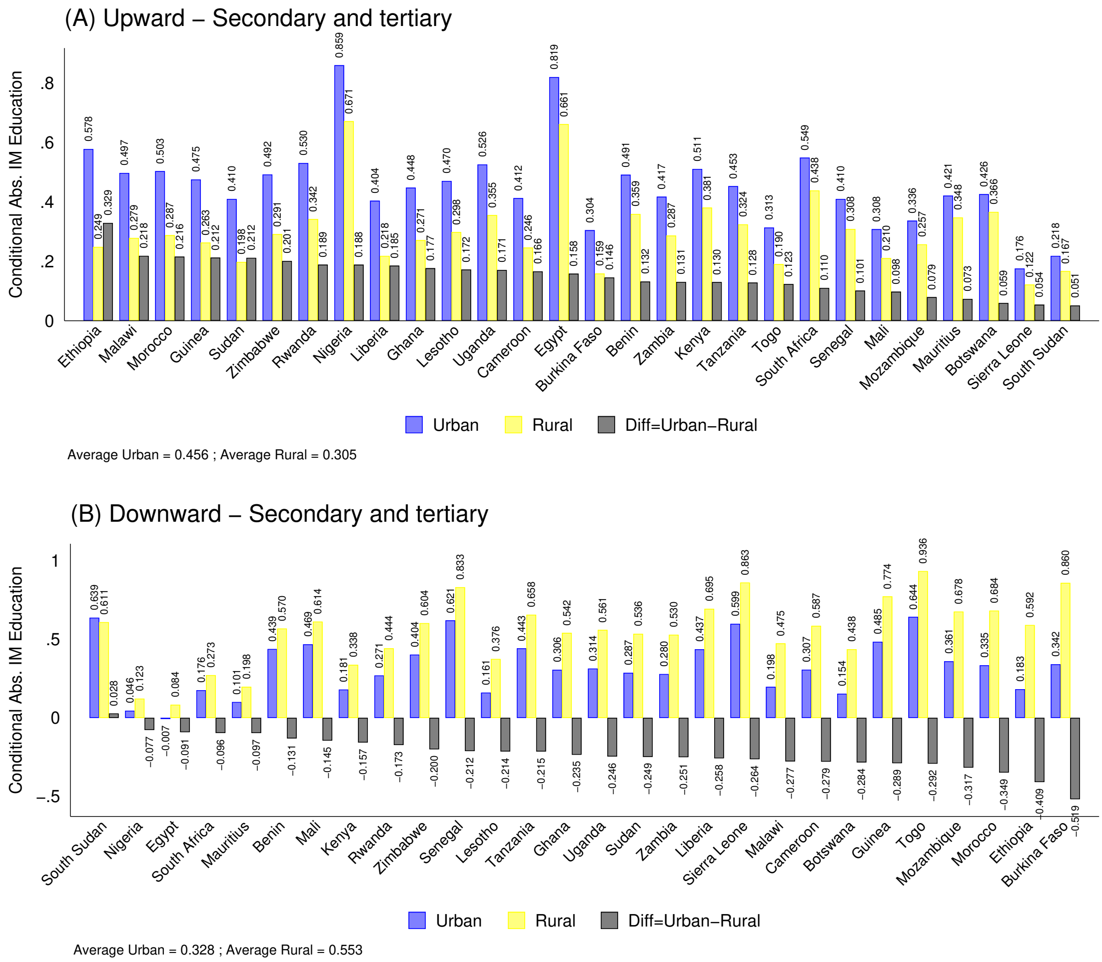
C.4.2 Ranking: Country-level educational IM by urban-rural residency

Figure C.4: Primary level



Source: Authors' calculations based on IPUMS dataset

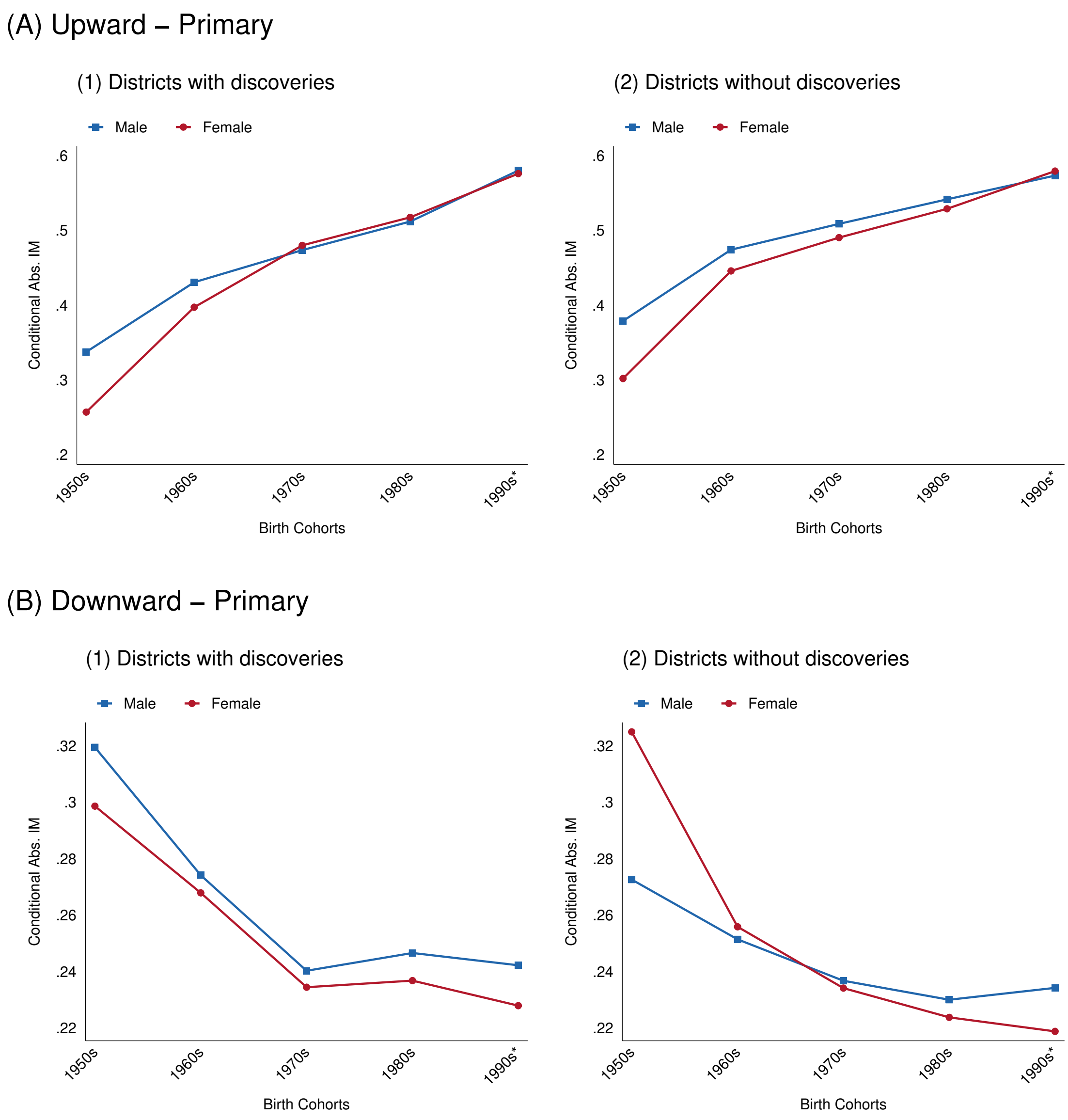
Figure C.5: Secondary and Tertiary level



Source: Authors' calculations based on Minex Consulting dataset (2019)

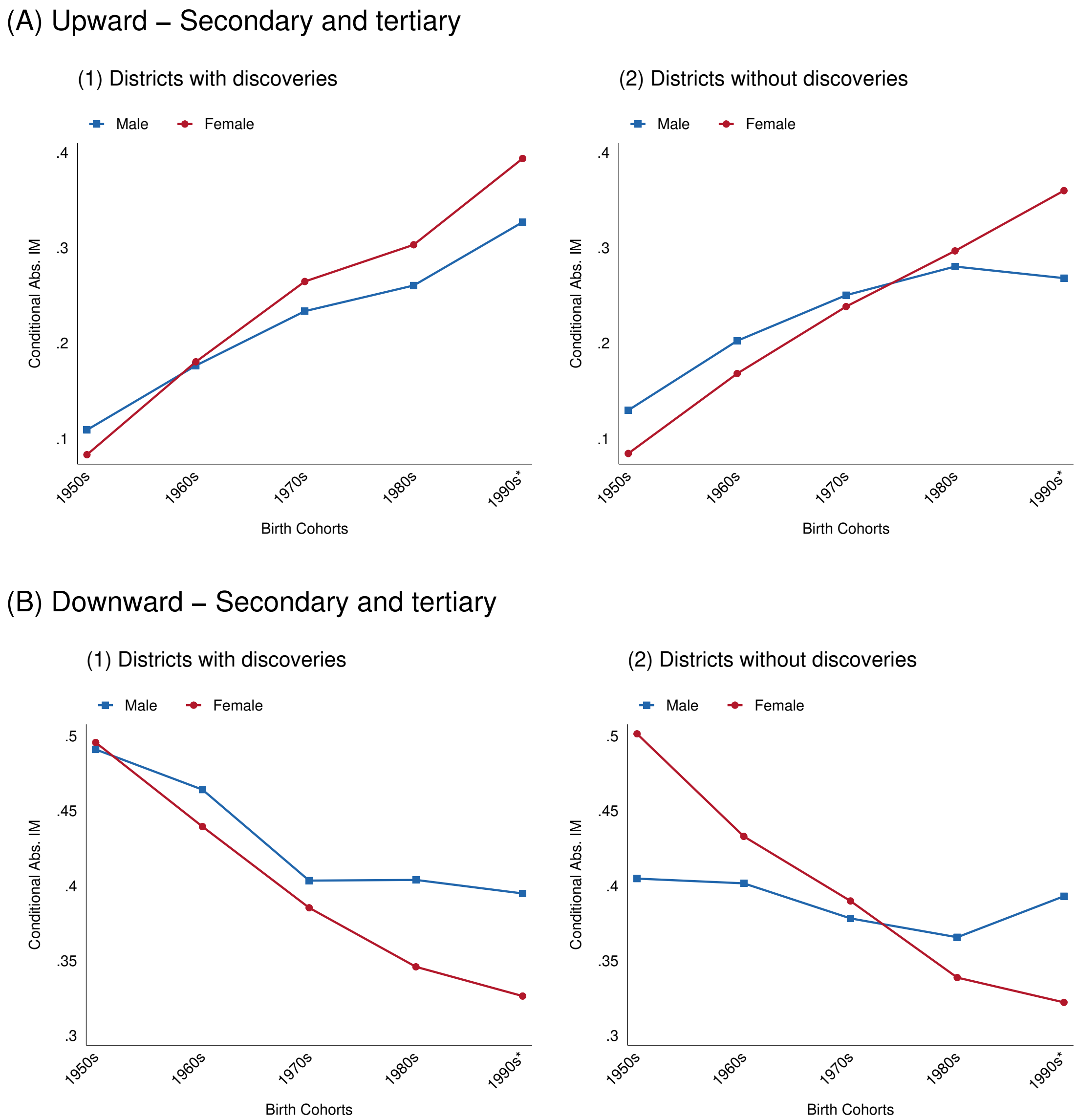
C.4.3 Dynamics of IM by districts with and without discoveries, cohorts and gender

Figure C.6: Primary level



Source: Authors' calculations based on IPUMS and Minex Consulting dataset (2019)

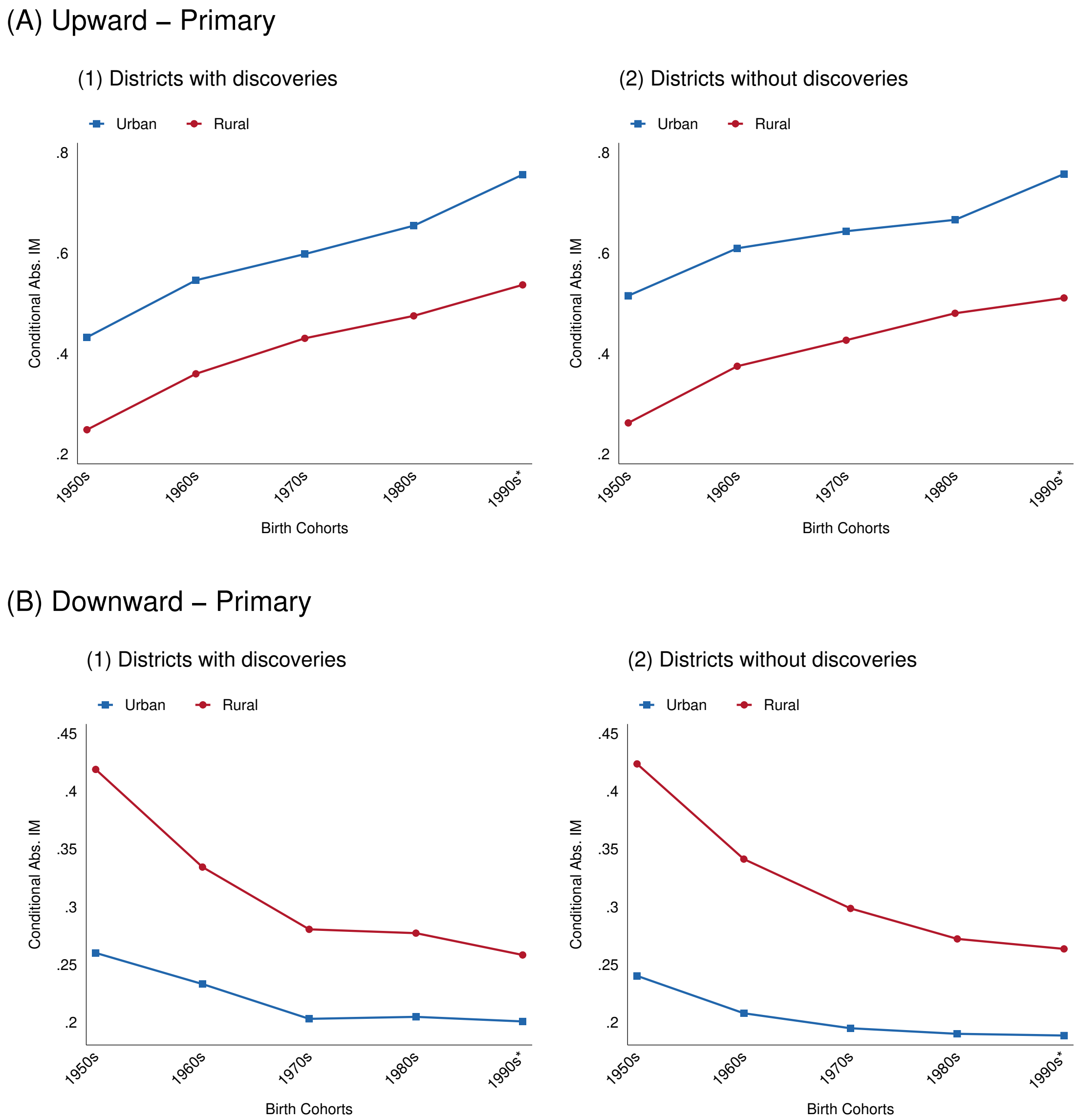
Figure C.7: Secondary and Tertiary level



Source: Authors' calculations based on IPUMS and Minex Consulting dataset (2019)

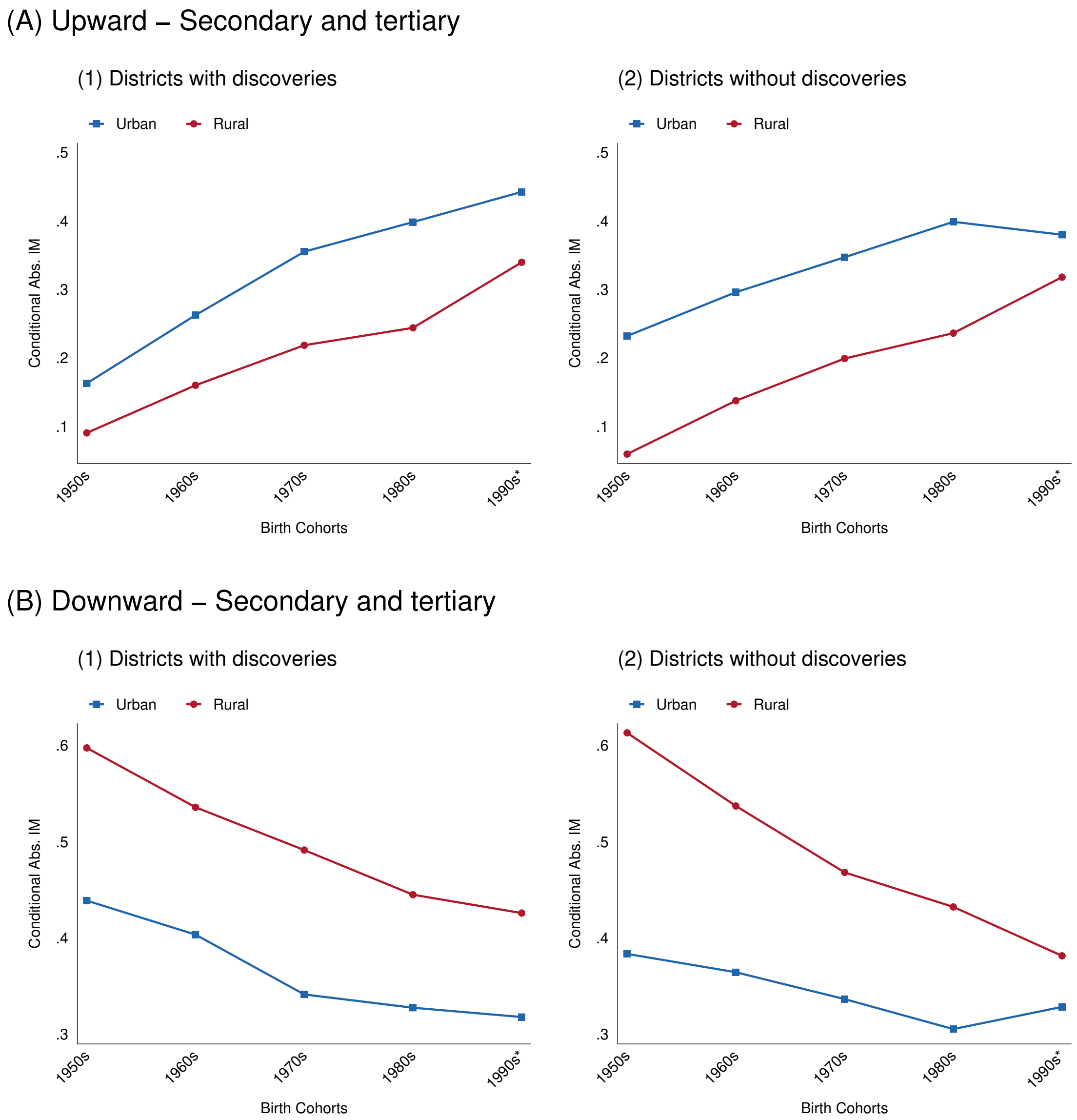
C.4.4 Dynamics of IM by districts with and without discoveries, cohorts and urban-rural residency

Figure C.8: Primary level



Source: Authors' calculations based on IPUMS and Minex Consulting dataset (2019)

Figure C.9: Secondary and Tertiary level



Source: Authors' calculations based on IPUMS and Minex Consulting dataset (2019)

C.5 Additional stylized facts on district-level educational IM

C.5.1 Supplementary tables

Table C.6: District-Level Primary IM by country

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel (A): Upward			Panel (B): Downward		
Country	# districts	mean	cv	# districts	mean	cv
Benin	77	0,509	0,278	77	0,240	0,357
Botswana	21	0,924	0,119	21	-0,002	-16,700
Burkina Faso	45	0,174	0,519	45	0,399	0,416
Cameroon	229	0,685	0,356	229	0,204	0,899
Egypt	236	0,793	0,149	236	0,027	1,143
Ethiopia	97	0,374	0,684	95	0,336	0,575
Ghana	110	0,659	0,228	110	0,182	0,472
Guinea	34	0,357	0,320	34	0,383	0,291
Kenya	173	0,671	0,321	173	0,136	0,661
Lesotho	10	0,574	0,122	10	0,228	0,277
Liberia	47	0,346	0,310	47	0,461	0,274
Malawi	227	0,412	0,359	227	0,355	0,384
Mali	242	0,191	0,462	242	0,519	0,386
Mauritius	42	1,047	0,051	45	0,005	2,224
Morocco	55	0,675	0,167	55	0,103	0,346
Mozambique	144	0,279	0,457	144	0,476	0,380
Nigeria	37	0,787	0,259	37	0,057	0,772
Rwanda	30	0,500	0,143	30	0,354	0,268
Senegal	34	0,437	0,376	34	0,280	0,398
Sierra Leone	107	0,358	0,439	107	0,455	0,419
South Africa	216	0,902	0,072	216	0,033	0,658
South Sudan	72	0,141	0,803	70	0,712	0,265
Sudan	129	0,282	0,782	129	0,395	0,505
Tanzania	113	0,859	0,140	113	0,092	0,644
Togo	37	0,497	0,301	37	0,371	0,308
Uganda	161	0,656	0,200	161	0,210	0,407
Zambia	72	0,605	0,209	72	0,313	0,349
Zimbabwe	88	0,999	0,103	88	0,056	0,868
Total	2885	0,562	0,520	2884	0,259	0,861

Notes: This table shows the average conditional district-level educational IM by country. Columns (2)-(5), (3)-(6), and (4)-(7) give the number of districts, the average educational IM, and the coefficient of variation of education IM, for each country, respectively.

Table C.7: District-Level Secondary and tertiary IM by country

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel (A): Upward			Panel (B): Downward		
Country	# districts	mean	cv	# districts	mean	cv
Botswana	21	0,400	0,113	14	0,194	1,539
Egypt	236	0,745	0,165	236	0,053	1,305
Ethiopia	97	0,326	0,483	76	0,397	0,837
Malawi	227	0,311	0,419	203	0,436	0,666
Mauritius	44	0,362	0,283	41	0,161	0,617
Nigeria	37	0,691	0,254	37	0,121	0,581
Zimbabwe	88	0,366	0,313	74	0,529	0,561
Kenya	173	0,395	0,299	169	0,346	0,550
Cameroon	229	0,231	0,331	172	0,558	0,535
Burkina Faso	45	0,170	0,195	27	0,720	0,517
Mali	242	0,195	0,118	128	0,681	0,507
Mozambique	144	0,261	0,190	81	0,655	0,467
Rwanda	30	0,388	0,191	30	0,321	0,447
Sudan	129	0,207	0,429	106	0,583	0,440
South Sudan	72	0,155	0,262	45	0,754	0,405
Benin	77	0,388	0,148	59	0,649	0,398
Lesotho	10	0,307	0,124	10	0,385	0,382
Zambia	72	0,309	0,165	68	0,511	0,372
South Africa	216	0,438	0,168	216	0,254	0,327
Liberia	47	0,218	0,301	47	0,672	0,310
Guinea	34	0,292	0,181	32	0,685	0,289
Togo	37	0,198	0,209	29	0,870	0,287
Uganda	161	0,378	0,180	161	0,544	0,283
Sierra Leone	107	0,135	0,197	64	0,809	0,271
Tanzania	113	0,391	0,175	113	0,507	0,253
Morocco	55	0,393	0,210	55	0,411	0,246
Ghana	110	0,311	0,205	110	0,502	0,220
Senegal	34	0,342	0,137	33	0,757	0,172
Total	2887	0,342	0,517	2436	0,457	0,658

Notes: This table shows the average conditional district-level educational IM by country. Columns (2)-(5), (3)-(6), and (4)-(7) give the number of districts, the average educational IM, and the coefficient of variation of education IM, for each country, respectively.

Table C.8: District-Level Primary IM by country and discovery

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Panel (A): Upward				Panel (B): Downward			
Country	discovery	disc. high	# districts	mean	cv	disc. high	# districts	mean	cv
Benin	yes	no	3	0,35	0,38	yes	3	0,25	0,31
Benin	no		74	0,52	0,27		74	0,24	0,36
Botswana	yes	no	12	0,89	0,13	yes	12	0,01	3,66
Botswana	no		9	0,97	0,10		9	-0,02	-2,60
Burkina Faso	yes	no	28	0,16	0,46	yes	28	0,40	0,43
Burkina Faso	no		17	0,20	0,56		17	0,40	0,41
Cameroon	yes	yes	13	0,73	0,31	no	13	0,14	0,57
Cameroon	no		216	0,68	0,36		216	0,21	0,90
Egypt	yes	no	3	0,78	0,03	yes	3	0,05	0,15
Egypt	no		233	0,79	0,15		233	0,03	1,16
Ethiopia	yes	no	9	0,26	0,17	yes	9	0,39	0,27
Ethiopia	no		88	0,39	0,69		86	0,33	0,60
Ghana	yes	yes	22	0,69	0,18	no	22	0,18	0,35
Ghana	no		88	0,65	0,24		88	0,18	0,50
Guinea	yes	no	21	0,34	0,27	yes	21	0,39	0,30
Guinea	no		13	0,38	0,38		13	0,37	0,29
Kenya	yes	no	8	0,65	0,14	yes	8	0,17	0,20
Kenya	no		165	0,67	0,33		165	0,14	0,68
Lesotho	yes	no	2	0,54	0,16	yes	2	0,24	0,24
Lesotho	no		8	0,58	0,12		8	0,22	0,30
Liberia	yes	yes	6	0,37	0,14	yes	6	0,48	0,23
Liberia	no		41	0,34	0,33		41	0,46	0,28
Malawi	yes	yes	5	0,44	0,23	yes	5	0,37	0,16
Malawi	no		222	0,41	0,36		222	0,36	0,39
Mali	yes	yes	19	0,22	0,35	no	19	0,45	0,32
Mali	no		223	0,19	0,47		223	0,53	0,39
Mauritius	no	-	42	1,05	0,05	-	45	0,00	2,22
Morocco	yes	no	13	0,68	0,13	no	13	0,10	0,26
Morocco	no		42	0,68	0,18		42	0,10	0,37
Mozambique	yes	no	13	0,25	0,29	yes	13	0,52	0,31
Mozambique	no		131	0,28	0,47		131	0,47	0,39
Nigeria	yes	yes	2	0,83	0,25	no	2	0,04	0,77
Nigeria	no		35	0,79	0,26		35	0,06	0,77
Rwanda	yes	yes	1	0,51	-	no	1	0,33	-
Rwanda	no		29	0,50	0,15		29	0,36	0,27
Senegal	yes	no	3	0,34	0,29	yes	3	0,37	0,51
Senegal	no		31	0,45	0,38		31	0,27	0,37
Sierra Leone	yes	no	11	0,27	0,25	yes	11	0,53	0,31
Sierra Leone	no		96	0,37	0,44		96	0,45	0,43
South Africa	yes	yes	60	0,92	0,06	no	60	0,02	0,62
South Africa	no		156	0,90	0,08		156	0,04	0,63
South Sudan	no	-	72	0,14	0,80	-	70	0,71	0,27
Sudan	yes	yes	13	0,37	0,79	no	13	0,39	0,62
Sudan	no		116	0,27	0,77		116	0,40	0,49
Tanzania	yes	no	25	0,78	0,12	yes	25	0,14	0,36
Tanzania	no		88	0,88	0,13		88	0,08	0,71
Togo	yes	yes	2	0,59	0,01	no	2	0,35	0,13
Togo	no		35	0,49	0,31		35	0,37	0,32
Uganda	yes	yes	2	0,72	0,11	no	2	0,21	0,40
Uganda	no		159	0,66	0,20		159	0,21	0,41
Zambia	yes	yes	15	0,67	0,17	no	15	0,25	0,45
Zambia	no		57	0,59	0,21		57	0,33	0,31
Zimbabwe	yes	no	20	0,97	0,07	yes	20	0,07	0,41
Zimbabwe	no		68	1,01	0,11		68	0,05	1,02
Total	yes	12	331	0,60	0,51	17	331	0,23	0,87
Total	no	16	2554	0,56	0,52	11	2553	0,26	0,86
Total All	-	28	2885	0,56	0,52	28	2884	0,26	0,86

Notes: This table shows the average conditional district-level educational IM by country and district with or without mineral discovery. Columns (1) gives the country name. Columns (2) is "yes" for districts with discovery, and "No" otherwise. Columns (3) and (7) is "yes" if upward and downward IM is higher in districts with discovery than without discovery, respectively. Columns (4)-(8), (5)-(9), and (6)-(10) give the number of districts, the average educational IM, and the coefficient of variation of education IM, respectively.

Table C.9: District-Level Secondary and tertiary IM by country and discovery

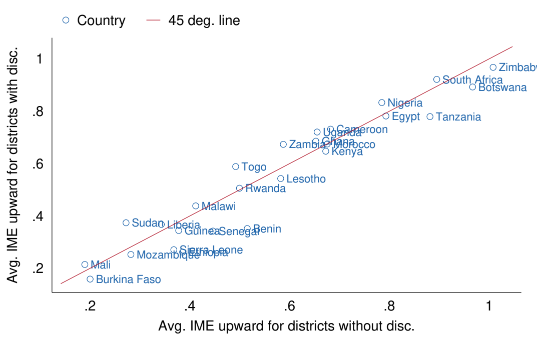
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Panel (A): Upward				Panel (B): Downward			
Country	discovery	disc. high	# districts	mean	cv	disc. high	# districts	mean	cv
Benin	yes	no	3	0,36	0,13	yes	2	0,87	0,39
Benin	no		74	0,39	0,15		57	0,64	0,40
Botswana	yes	no	12	0,40	0,07	yes	9	0,21	1,66
Botswana	no		9	0,40	0,16		5	0,16	1,23
Burkina Faso	yes	no	28	0,16	0,13	yes	16	0,76	0,46
Burkina Faso	no		17	0,18	0,25		11	0,67	0,62
Cameroon	yes	no	13	0,21	0,21	no	12	0,56	0,61
Cameroon	no		216	0,23	0,34		160	0,56	0,53
Egypt	yes	no	3	0,74	0,06	yes	3	0,06	0,02
Egypt	no		233	0,75	0,17		233	0,05	1,32
Ethiopia	yes	no	9	0,25	0,07	yes	7	0,56	0,77
Ethiopia	no		88	0,33	0,49		69	0,38	0,84
Ghana	yes	no	22	0,30	0,12	yes	22	0,54	0,20
Ghana	no		88	0,31	0,22		88	0,49	0,22
Guinea	yes	no	21	0,28	0,12	yes	20	0,69	0,18
Guinea	no		13	0,30	0,25		12	0,67	0,43
Kenya	yes	no	8	0,33	0,13	yes	8	0,39	0,22
Kenya	no		165	0,40	0,30		161	0,34	0,56
Lesotho	yes	no	2	0,29	0,13	yes	2	0,48	0,41
Lesotho	no		8	0,31	0,12		8	0,36	0,38
Liberia	yes	yes	6	0,22	0,19	yes	6	0,81	0,15
Liberia	no		41	0,22	0,32		41	0,65	0,33
Malawi	yes	no	5	0,27	0,13	yes	5	0,58	0,22
Malawi	no		222	0,31	0,42		198	0,43	0,68
Mali	yes	yes	19	0,20	0,11	yes	13	0,75	0,41
Mali	no		223	0,20	0,12		115	0,67	0,52
Mauritius	no	-	44	0,36	0,28	-	41	0,16	0,62
Morocco	yes	no	13	0,39	0,18	no	13	0,41	0,26
Morocco	no		42	0,39	0,22		42	0,41	0,25
Mozambique	yes	no	13	0,25	0,04	no	6	0,65	0,63
Mozambique	no		131	0,26	0,20		75	0,66	0,46
Nigeria	yes	yes	2	0,80	0,21	no	2	0,10	0,76
Nigeria	no		35	0,69	0,26		35	0,12	0,58
Rwanda	yes	no	1	0,36	.	no	1	0,24	.
Rwanda	no		29	0,39	0,19		29	0,32	0,45
Senegal	yes	no	3	0,31	0,06	yes	3	0,90	0,19
Senegal	no		31	0,35	0,14		30	0,74	0,16
Sierra Leone	yes	no	11	0,13	0,09	yes	6	0,92	0,13
Sierra Leone	no		96	0,14	0,20		58	0,80	0,28
South Africa	yes	yes	60	0,46	0,16	no	60	0,25	0,24
South Africa	no		156	0,43	0,17		156	0,26	0,35
South Sudan	no	-	72	0,16	0,26	-	45	0,75	0,41
Sudan	yes	yes	13	0,23	0,46	yes	12	0,72	0,31
Sudan	no		116	0,20	0,43		94	0,57	0,45
Tanzania	yes	no	25	0,35	0,07	yes	25	0,58	0,16
Tanzania	no		88	0,40	0,18		88	0,49	0,27
Togo	yes	yes	2	0,21	0,06	yes	2	1,02	0,02
Togo	no		35	0,20	0,22		27	0,86	0,30
Uganda	yes	no	2	0,37	0,01	no	2	0,53	0,25
Uganda	no		159	0,38	0,18		159	0,55	0,28
Zambia	yes	yes	15	0,34	0,18	no	15	0,42	0,39
Zambia	no		57	0,30	0,15		53	0,54	0,35
Zimbabwe	yes	no	20	0,30	0,11	no	16	0,46	0,68
Zimbabwe	no		68	0,39	0,32		58	0,55	0,53
Total	yes	7	331	0,31	0,39	19	288	0,51	0,56
Total	no	21	2556	0,35	0,53	9	2148	0,45	0,67
Total All	-	28	2887	0,34	0,52	28	2436	0,46	0,66

Notes: This table shows the average conditional district-level educational IM by country and district with or without mineral discovery. Columns (1) gives the country name. Columns (2) is "yes" for districts with discovery, and "No" otherwise. Columns (3) and (7) is "yes" if upward and downward IM is higher in districts with discovery than without discovery, respectively. Columns (4)-(8), (5)-(9), and (6)-(10) give the number of districts, the average educational IM, and the coefficient of variation of education IM, respectively.

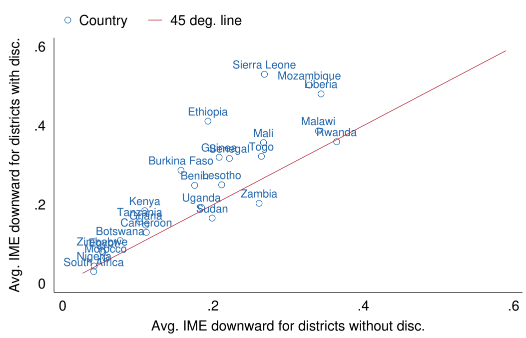
C.5.2 Gaps of IM by districts with and without discoveries for each country

Figure C.10: District-level educational IM

(A) Upward primary



(B) Downward primary



(C) Upward secondary and tertiary

(D) Downward secondary and tertiary

(A) Upward – Secondary and tertiary

(B) Downward – Secondary and tertiary

C.6 Baseline results with control variables

C.6.1 Primary educational IM

Table C.10: Baseline results with control variables, primary education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Upward mobility				Downward mobility			
	Disc-B/A	Disc-5	Prod-B/A	Prod-5	Disc-B/A	Disc-5	Prod-B/A	Prod-5
Mining	0.028***	0.027***	0.070***	0.059***	-0.013***	-0.007***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.037***	-0.037***	-0.038***	-0.038***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HH head female	0.038***	0.038***	0.037***	0.037***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Low skilled occupation	-0.046***	-0.046***	-0.045***	-0.045***	0.040***	0.040***	0.040***	0.040***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Medium skilled occupation	0.050***	0.050***	0.050***	0.050***	-0.005***	-0.005***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
High skilled occupation	0.151***	0.151***	0.150***	0.150***	-0.039***	-0.039***	-0.039***	-0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Mother/stepmother	0.001	0.001	0.002**	0.002**	-0.030***	-0.030***	-0.030***	-0.030***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Both father/stepfather and mother/stepmother	0.038***	0.038***	0.038***	0.038***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household size	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban	0.152***	0.152***	0.152***	0.152***	-0.060***	-0.060***	-0.060***	-0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8306024	8306024	8537407	8537407	4374423	4374423	4478390	4478390
R-squared	0.269	0.269	0.270	0.270	0.134	0.134	0.133	0.133
# Treated	148633	192236	53986	67663	98793	123151	36768	49337
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

C.6.2 Secondary and Tertiary educational IM

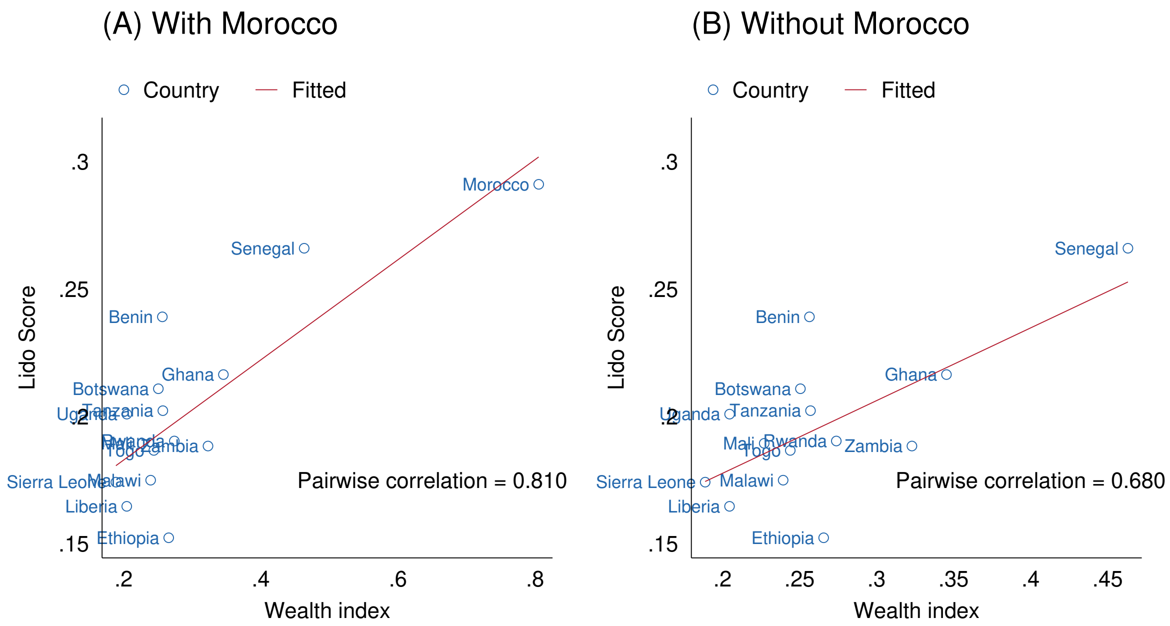
Table C.11: Baseline results with control variables, secondary and tertiary education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Upward mobility				Downward mobility			
	Disc-B/A	Disc-5	Prod-B/A	Prod-5	Disc-B/A	Disc-5	Prod-B/A	Prod-5
Mining	-0.007	-0.000	0.016	0.007	0.037**	0.015	-0.010	0.007
	(0.013)	(0.011)	(0.021)	(0.020)	(0.019)	(0.018)	(0.024)	(0.022)
Female	-0.021***	-0.021***	-0.021***	-0.021***	0.002	0.002	0.001	0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
HH head female	0.003	0.003	0.003	0.003	0.055***	0.055***	0.054***	0.054***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Low skilled occupation	-0.050***	-0.050***	-0.049***	-0.049***	0.093***	0.093***	0.091***	0.091***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Medium skilled occupation	-0.001	-0.001	0.000	0.000	0.050***	0.050***	0.050***	0.050***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
High skilled occupation	0.223***	0.223***	0.222***	0.222***	-0.027***	-0.027***	-0.027***	-0.027***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Mother/stepmother	0.006**	0.006**	0.005**	0.005**	-0.104***	-0.104***	-0.104***	-0.104***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Both father/stepfather and mother/stepmother	0.050***	0.050***	0.049***	0.049***	-0.061***	-0.061***	-0.062***	-0.062***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Household size	-0.004***	-0.004***	-0.004***	-0.004***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Urban	0.107***	0.107***	0.108***	0.108***	-0.087***	-0.087***	-0.090***	-0.090***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	3335415	3335415	3461167	3461167	323998	323998	331618	331618
R-squared	0.217	0.217	0.217	0.217	0.169	0.169	0.169	0.169
# Treated	67525	89986	38002	43715	6197	7491	2813	3380
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

C.7 Validation of LIDO score and Wealth index

Figure C.11: Correlations between LIDO score and Wealth index

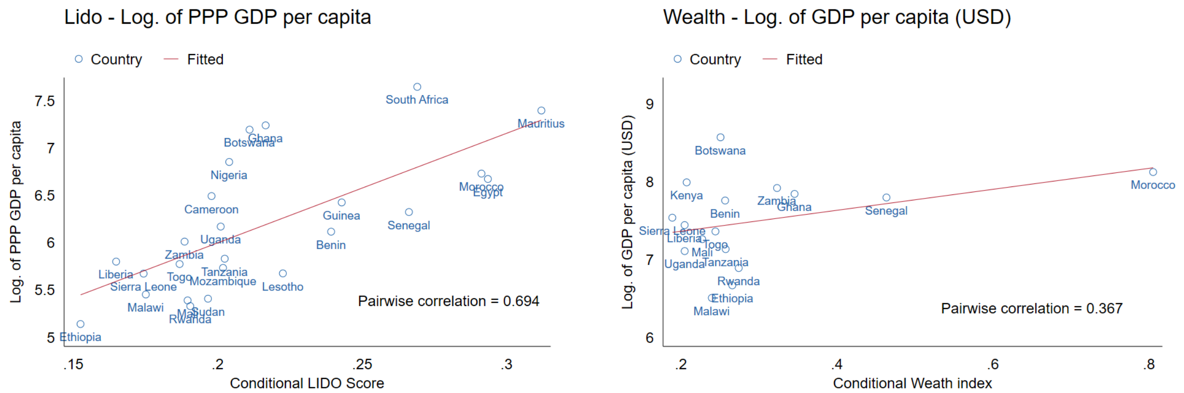


Source: Authors' calculations based on the Demographic and Health Survey wealth index (Rutstein and Staveteig 2014), LIDO score (Saavedra and Twinam 2020)

Figure C.12: Correlations between LIDO score, Wealth index and PPP GDP per capita

(A) LIDO score

(B) Wealth index



Source: Authors' calculations based on the Demographic and Health Survey wealth index (Rutstein and Staveteig 2014), LIDO score (Saavedra and Twinam 2020)

CHAPTER 5

Intergenerational occupational mobility and mineral discoveries in African countries

This chapter is joint work with Jean-Marc B. Atsebi (IMF) and Rasmane Ouedraogo (IMF).

Abstract

In this paper, we explore the effects of mineral discoveries and productions on intergenerational occupational mobility for around 1.5 million individuals across 2,690 districts from 27 African countries, linking children's occupation to that of their parents. We find that mineral discoveries and productions positively affect occupational mobility for both blue- and white-collar jobs in Africa for individuals exposed to the mineral sites and living in districts with discoveries. Specifically, the probability of upward blue-collar mobility increases by up to to 2.3 pp. following mineral activities. Downward blue-collar mobility decreases by around 4 pp. Likewise, the likelihood of upward white-collar mobility increases by up to 1.6 pp. following mining activities. Downward mobility decreases by up to 13.3 pp. These positive effects are also found for individuals aged 16–20 years old entering the labor market at the time of discovery or production, but interestingly, these effects are higher for those born after discoveries and productions. Moreover, our results show some heterogeneous effects depending on the African region's location, the mineral discovery's size, gender, and the urban-rural divide. In addition, we explore the demand for skilled workers channel (demand-side factor) and the educational channel (supply-side factor) through which mineral discoveries and productions affect occupational mobility. In terms of recommendation policies, this paper suggests to governments to enact reforms to facilitate the creation of jobs to boost education infrastructures and quality to allow children to access better occupational positions; implement targeted policies to ease access to female job opportunities and address urban-rural inequalities.

Keywords: Africa; Occupational Intergenerational Mobility; Mineral discoveries and productions; Generalized Difference-in-differences; Natural experiment
JEL Codes: C55; J62; N9; O10; O55; Q32; Q33

5.1 Introduction

In a society, the degree to which children's occupation is determined by their parents' occupation is an important indication of the amount of equality of job opportunities. According to the International Labour Organization, the share of African workers in agricultural, forestry and fishery as well as elementary occupations has declined but remain significantly large. It is projected to account for 57 percent of employment in 2023, unchanged from a decade earlier but down from 63 percent in 2000.[1]

Against this labor market development in Africa, our paper addresses an important and largely

[1] https://ilostat.ilo.org/africas-changing-employment-landscape/

unexplored question: what is the contribution of mineral discoveries and productions in delinking children's occupations to that of their parents in Africa? In other words, how do mineral discoveries and productions affect intergenerational occupational mobility in Africa? This is of particular interest because Africa is home to an abundance of mineral resources. It hosts 30 percent of the world's mineral reserves, 40 percent of the world's gold and up to 90 percent of some minerals like chromium and platinum.[2] According to Minex Consulting database (2019), 969 normal to super-giant mineral discoveries occurred in Africa between 1950 and 2019, and 396 of them (40 percent) since 2000. This paper provides a detailed analysis of occupational mobility following mineral discoveries and productions and how they affect labor market conditions using a sample of around 1.5 million individuals across 2,690 districts from 27 African countries.

The literature on occupational mobility has been fairly silent on the role of natural resources, especially in developing countries. So far, only Cilliers and Fourie (2018) for South Africa has investigated the effects of mineral resources on occupational mobility in Africa. Their study shows that absolute and relative occupational mobility have significantly increased for sons born after the start of the mineral revolution in 1868, particularly for sons of semi-skilled workers, whereas no improved mobility for sons of farmers was found. In particular, they find that sons in the immediate vicinity of the diamond mines seemed to benefit the most in terms of increased mobility, while those further afield appeared to be largely unaffected. They conclude that mineral discoveries marked the beginning of the industrialization of South Africa's agrarian economy. Outside of Africa, Bütikofer et al. (2018) focus on intergenerational earnings mobility and oil discoveries in Norway. They find that the Norwegian oil boom in the 1970s increased intergenerational earnings mobility for cohorts entering the labor market at the beginning of the oil boom in those labor markets most affected by the growing oil industry, which is more pronounced for individuals born to poor families in oil-affected regions. In other words, sons born in high-oil regions experienced more intergenerational earnings mobility than sons born in low-oil regions.

There are several mechanisms through which natural resources affect intergenerational mobility. This paper focuses on two channels, including i) the demand for skilled workers channel (demand side factor) and ii) the educational channel (supply-side factor). Indeed, mineral discoveries and productions could break the links between children and parent's occupation that have been identified by the theory to explain the persistence of occupational mobility: i) the biological transfers and heritage and ii) human capital development (Juárez et al. 2011; Twu-

[2] https://www.unep.org/regions/africa/our-work-africa

masi Baffour et al. 2021).[3] They can reduce the barriers to mobility through an expansion of the educational system offering new job opportunities to the less affluent persons, the diminishing importance of social networks, the structural transformation of the economy with a creation of job opportunities in higher skilled sectors, or the growing importance of achievement over ascription by birth (Cilliers and Fourie 2018; Atsebi et al. 2022). Specifically, Bütikofer et al. (2018) show that their findings are mainly explained by the returns to education. They find that average earnings are higher for individuals with an academic education compared with those with a vocational high school degree or without a high school degree. Atsebi et al. (2022) focus on educational mobility in Africa. They reveal that mineral discoveries and productions contributed to the increase in intergenerational educational mobility for primary level in Africa, explained by an income channel and returns to education channel. In more details, they find that mineral activities in Africa create new job and income opportunities for parents, allowing them to invest in their children's education. Moreover, the economic dynamism and the creation of jobs following the mineral discoveries and productions lead to an increase in the demand for skilled workers, and thereby boosting the returns to education with children prolonging their education to earn more or have a better socioeconomic status. Thus, by increasing their education and having a higher educational mobility than that of their parents, they will also have a higher likelihood of occupational mobility as shown by the well established positive relationship in the literature between educational and occupational mobility (see, e.g., Ouedraogo and Syrichas 2021).

The empirical analysis relies on a large dataset combining microeconomic and demographic data on individuals from IPUMS and mineral discoveries and productions from the Minex Consulting Dataset, covering around 1.5 million individuals across 2,690 districts from 27 African countries. We follow Ouedraogo and Syrichas (2021) and Atsebi et al. (2022) to define our measures of occupational mobility and design our empirical strategy, respectively. First, we classify the occupational categories into three groups of jobs from high to low skills: i) white-collar jobs, ii) blue-collar jobs, and iii) agricultural and elementary jobs. Second, we rely on absolute mobility measures to define upward and downward intergenerational occupational mobility for both blue- and white-collar jobs. More specifically, upward blue-collar occupational mobility is defined as the probability for a child born from parents working in agricultural and elementary jobs to work in either blue-collar or white-collar jobs. Downward blue-collar

[3] According to Becker and Tomes (1986) and Lam and Schoeni (1993), children will inherit the innate abilities, network, and productive endowments of their parents, leading to increased intergenerational persistence. Moreover, Becker and Tomes (1986) and Banerjee and Newman (1993) show that children's occupation or economic outcomes may be strongly linked to that of their parents because capital market imperfections prevent poorer families to invest in their children's human capital while richer families have the resource needed to invest in their children's human capital. According to them, this is one of the main sources of the transmission of inequality and poverty.

occupational mobility is defined as the probability for a child born from parents working in either blue-collar or white-collar jobs to work in agricultural or elementary jobs. Likewise, upward white-collar occupational mobility is defined as the probability for a child born from parents working in either agricultural and elementary jobs or blue-collar jobs to work in white-collar jobs. Downward white-collar occupational mobility is defined as the probability for a child born from parents working in white-collar jobs to work in either agricultural and elementary jobs or blue-collar jobs. Second, we employ a generalized difference-in-differences method in a quasi-natural experiment. Our quasi-natural experiment relies on the plausible exogeneity of mineral discoveries that revert specific characteristics, specifically the unpredicted time of discoveries, the unpredicted geographical location, and the lag between the natural resource discoveries and the beginning of production (Horn 2011; Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019).

The results show that mineral discoveries and productions increase both blue- and white-collar occupational mobility, thus contributing to an improvement of the labor market conditions in Africa. The likelihood for individuals who are born from parents working in agricultural or elementary jobs to have better chances of working in at least blue-collar jobs if exposed to mining activities increases by up to 2.3 percentage points (pp.). Also, the likelihood for individuals who are born from parents working in either blue-collar or white-collar jobs to perform less than their parents and work in agricultural and elementary jobs if exposed to mining activities decreases by around 4 pp. Likewise for white-collar mobility, the likelihood of upward mobility increases by up to 1.6 pp., while the likelihood of downward mobility declines by up to 13.3 pp. if exposed to mining activities. In addition, we find that the positive effects of mineral discoveries and productions also apply to individuals aged 16-20 years old entering in the labor market at the time of discovery and production, but interestingly, these effects are higher for those born after the discovery or production. This higher probability for those born later after the discovery or production could be explained by the fact that it takes time for mining activities to have an impact on the local communities, particularly in terms of education outcomes, provision of infrastructures and public goods, and the structure of the labor market.

To put our findings into perspective and extrapolate them to Africa, we show, for blue-collar mobility, that the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in agricultural or elementary jobs, who work in either blue- or white-collar jobs increases by up to 948 thousand in Africa. Also, the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in either blue-collar or white-collar jobs, who work in agricultural or elementary jobs decreases by up to 2.3 million. Similarly, for white-collar mobility, we find that the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in agricultural, elementary or blue-collar jobs, who work in white-collar jobs increases by up to 795 thousand in Africa. Also, the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in white-collar jobs, who work in agricultural, elementary or blue-collar jobs decreases by up to 3.8 million.

Furthermore, we provide evidence that the positive effects of mineral discoveries and productions on blue-collar and white-collar mobility operate through the demand for skilled workers channel and the educational channel. First, the results suggest that mineral discoveries and productions lead to the change in demand for skilled workers, with individuals moving from low-skill to medium-skill and high-skill industries. Specifically, mineral discoveries and productions reduce the likelihood to work in low-skill industries by up to 4.9 pp., while they increase the likelihood to work in medium-skill and high-industry by up to 2.6 pp and 2.4 pp., respectively. Second, they show that the effects of mineral discoveries and productions on occupational mobility operate through an improvement on educational mobility, emphasizing the strong link between employment and education. Specifically, mineral discoveries and productions significantly increase the likelihood of upward mobility for both blue- and white-collar jobs (also of higher magnitude compared to the baseline results) only for individuals with upward primary educational mobility. Similarly, they reduce the likelihood of downward mobility for both blue- and white-collar jobs (also of higher magnitude compared to the baseline results) only for individuals with no downward educational mobility.

Our baseline results are robust to several robustness checks. We also analyze the sensitivity of our findings across African regions, size of mineral discoveries, gender, and urban-rural living area. The results show that the effects of mining activities are different by African regions and the size of the discoveries. Also, we find evidence of unequal effects of mineral discoveries and productions on occupational mobility for females and males, generally in favor of females when considering blue-collar jobs, and in favor of males when considering white-collar jobs. With regards to residency, our results reveal that mineral discoveries lead to a higher likelihood to experience upward blue- and white-collar mobility for individuals living in rural than in urban areas, and both mineral discoveries and productions reduce more the likelihood to experience a downward blue- and white-collar mobility for individuals in rural than in urban areas.

Our paper is related to two strands of literature. First, we contribute to the limited literature on the determinants of occupational mobility in Africa. Bossuroy and Cogneau (2013) find that educational mobility and the geographic segregation of farm and non-farm jobs inherited from the colonial administrations are the main drivers of occupational mobility in five African countries. Lambert et al. (2014) show in Senegal that inheritance of non-land assets, parents' education and occupation, particularly of the mothers, and parents' choice about children's education matter more for an adult welfare than property inheritance. Likewise, Haile (2016), Fontep and Sen (2020), Asiedu et al. (2021), Twumasi Baffour et al. (2021) confirm that mothers' occupation and education are more critical for the increased earnings or occupational mobility of their children, particularly their daughters, in Ethiopia, Cameroon, Nigeria, and Ghana, respectively. There is also a gender inequality in terms of job opportunities, with males more likely to have a higher degree of mobility than females. Finally, Ouedraogo and Syrichas (2021) cover 28 African countries and reveal that educational mobility, quality of institutions, sound social policies, and public spending are the drivers of the evolution of occupational mobility in Africa.

Second, we contribute to the vast but inconclusive literature regarding the effects of natural resource discoveries and productions in Africa. At the macroeconomic level, natural resources are generally a curse rather than a blessing (see, e.g., Corden and Neary 1982; Sachs and Warner 1995, 2001; Kretzmann and Nooruddin 2005). Contrarily, other studies found positive effects on foreign direct investments in non-resource sectors (Toews and Vezina 2017) or ambiguous effects on macroeconomic activity and financial conditions (Arezki et al. 2017; Seri 2021). At the local level, a positive effect of natural resources on local economic development, governance, conflicts, provisions of public goods, and welfare has emerged in recent analyses focusing on African countries or other developing countries. Cavalcanti et al. (2019) find a positive impact of oil and gas discoveries on local development and urbanization in Brazil. Cust and Mensah (2020) reveal that oil, gas, and mineral discoveries positively impact the citizen's expectations, which is materialized by a decrease in outward migration and an increase in fertility in the short term. Bhattacharyya and Mamo (2021) show that oil and mineral discoveries reduce the likelihood of conflict in 48 African countries, mainly driven by an improvement in economic development and efficient political distribution patronage in districts with discoveries. Recently, Atsebi et al. (2022) focus on 28 African countries and show evidence that mineral discoveries and productions contributed to an increased educational mobility for primary levels but not for secondary and tertiary education.

The rest of the paper is organized as follows. Section 5.2 discusses the data, explains the construction of the occupational mobility, and discusses the cohabitation issues. Section 5.3 describes the methodology. Section 5.4 presents our main findings. Section 5.5 explains the transmission channels. Section 5.6 and Section 5.7 discuss our findings' robustness checks and sensitivity, respectively. Finally, Section 5.8 concludes and discusses potential policy implications.

5.2 Data sources and construction of the IM index

5.2.1 Data sources

We use two main data sources following closely Atsebi et al. (2022).[4] The data on occupation status and individual characteristics are from Integrated Public Use Microdata Series (IPUMS)[5] and the data on mineral discoveries and production are from Minex Consulting Dataset (2019).

5.2.1.1 IPUMS data

Our final data from the Integrated Public Use Microdata Series (IPUMS) database covers 51 national censuses surveys from 1976 to 2014 for 27 African countries: Benin, Botswana, Cameroon, Egypt, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Liberia, Malawi, Mali, Mauritius, Morocco, Mozambique, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, South Sudan, Sudan, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.[6] Regarding the data on occupation, we use two main information for both children and parents, including i) the primary occupation, coded according to the major categories of the International Standard Classification of Occupations (ISCO–08) proposed by the International Labour Organization (ILO), and ii) the industrial classifications of the various jobs into twelve groups, coded following the International Standard Industrial Classification (ISIC). Our sample is based on the availability of information at the district level and on the residency, occupation and individuals characteristics (gender, age) as well as whether individuals co-reside with their biological/step parents or immediate older generation. It also consists of individuals at working-age between 20 and 50, and born between 1950 and 2000. The minimum age of 20 years old corresponds to the average years of schooling to complete secondary education in most African countries and is a legal age to enter the labor market. The maximum age of 50 years old is to account for the cohabitation issue as the likelihood to not observe the occupation of the parents is higher for aged individuals as the parents may be deceased or retired. The final sample covers close to 1.5 million individuals across 2,690 districts. Table D.1 and Table D.2 describe the data for each census and country. We have harmonized the boundaries of districts following Atsebi et al. (2022) to deal with

[4] See Atsebi et al. (2022) for detailed description of the data.

[5] https://www.ipums.org/

[6] The population of the 27 countries covered in our analysis represents around 75 percent of the total population in Africa. As such our results can be extrapolated to the continent.

administrative boundaries changes.[7]

5.2.1.2 Mineral discoveries data

The data on mineral discoveries and productions in Africa come from Minex Consulting Dataset (2019). This dataset provides geolocalized information on discoveries, their size (moderate, major, giant, super-giant), the status of the mine (closed, feasibility study, operating, under-developed), and the type of minerals.[8] After merging this dataset with the IPUMS data, we identify 296 districts out of the total of 2,690 in which mineral sites were discovered or entered in production. Please refer to Atsebi et al. (2022) for a comprehensive description of the evolution, localization, type, and size of discoveries in Africa.

5.2.2 Construction of the occupational IM

We rely on the occupational categories for both children and parents to define our absolute measures of occupation mobility. IPUMS classifies occupation into 11 occupational types. A key challenge in quantifying occupational intergenerational mobility - as compared to educational intergenerational mobility - is to rank (or group) the occupational categories so that we can qualify both upward and downward occupational mobility. To do so, we drop the armed forces and other unspecified occupation categories as these categories are difficult to rank or classify. Next, we follow Ouedraogo and Syrichas (2021) to classify the occupational categories into three groups of jobs from high to low skills: i) white-collar jobs, ii) blue-collar jobs, and iii) agricultural and elementary jobs. Table 5.1 shows the classification and structure of the African labor force across the occupations and related groupings. More than 65 percent of working people aged 20 to 50 are employed in low-skilled agricultural (53.6 percent) and elementary jobs (12 percent). One-quarter of workers operated in medium-skilled blue-collar jobs, with the majority of them in crafts and related trades (12.2 percent), and service, shop, and market sales (8.7 percent). Very few (8 percent) are employed in white-collar jobs such as legislators, senior officials and managers, professionals, and technicians and associate professionals.

[7] We drop Kenya (1979), Liberia (1974), Togo (1960, 1970) since they do not cover all local regions or do not have any identifier to match children to parents. Moreover, we have harmonized the countries boundaries and district names for countries such as Botswana, Ethiopia, Ghana, Guinea, Lesotho, Malawi, Mauritius, Morocco, Nigeria, South Africa, and Uganda. For Nigeria, data come from households' survey rather than census surveys, therefore the number of observations is small as compared to other countries.

[8] According to Bhattacharyya and Mamo (2021), mineral discoveries are defined as giant if they generate an amount of at least US$500 million of revenue per annum for 20 years or more. They are qualified as major if they generate an annual revenue stream superior or equal to US$50 million over a shorter lifetime than in the case of giant discoveries.

Table 5.1: Classification of occupational categories

	Occupation, ISCO general	**Freq.**	**Percent**
White-collar	Legislators, senior officials and managers	66,233	1.9
	Professionals	125,776	3.6
	Technicians and associate professionals	87,330	2.5
Blue-collar	Clerks	85,231	2.4
	Service workers and shop and market sales	303,647	8.7
	Crafts and related trades workers	426,677	12.2
	Plant and machine operators and assemblers	103,955	3.0
Agri/ Elem	Skilled agricultural and fishery workers	1,870,081	53.6
	Elementary occupations	418,219	12.0
	Total	3,487,149	100

Note: This table presents the grouping and ranking of the nine broad ISCO-08 occupational categories into white-collar, blue-collar, and agricultural and elementary jobs. Military and other unclassified professions are excluded.

In the robustness, we draw upon Ahsan and Chatterjee (2017) and Mitra et al. (2022) and construct three indicators to rank the occupational categories at the country level: i) the occupational income ranking lasso-adjusted industry, demographic, and occupational (LIDO) score computed using actual data of labor market for the United States in 1950 by Saavedra and Twinam (2020), ii) educational levels proxied by the years of schooling, and iii) an index averaging the first two indicators.

We define both absolute upward and downward intergenerational occupational mobility for both the blue- and white-collar jobs. First, upward blue-collar occupational mobility is defined as the probability for a child born from parents working in agricultural and elementary jobs to work in either a blue-collar or white-collar jobs. Downward blue-collar occupational mobility is defined as the probability for a child born from parents working in either blue-collar or white-collar jobs to work in agricultural or elementary jobs. Second, upward white-collar occupational mobility is defined as the probability for a child born from parents working in either agricultural and elementary jobs or blue-collar jobs to work in a white-collar job. Downward white-collar occupational mobility is defined as the probability for a child born from parents working in white-collar jobs to work in either agricultural and elementary jobs or blue-collar jobs. To identify the old generation benchmark for each child, we use the average of occupational groups for their biological/step parents, rounded to the nearest integer. In the robustness section, we use the minimum or maximum of the education levels of the biological/step parents as benchmark. We also consider the immediate older generation and broaden the definition of parental authority to include uncles/aunts (in law), parents-in-law, grand-parents, and grand-uncles/aunts in the reference group, to take into account fostered, abandoned, or orphan children.

Practically, first, for each individual (parents and children), we compute two occupational variables B_{jith} and W_{jith} for blue-collar and white-collar jobs, respectively. B_{jith} takes that value of one if the individual j born in district i and year h, and surveyed in year t works in a blue-collar or white-collar job, and zero otherwise. Similarly, W_{jith} takes that value of one if the individual j born in district i and year h, and surveyed in year t works in a white-collar job only. Second, for each child j, we computed two averaged measures of parents' occupational levels, PB_{jith} and PW_{jith} as the average of B_{jith} and W_{jith} rounded to the nearest integer, respectively, for the biological/step parents if both cohabit with the child, or for only the father/step-father or mother/step-mother if the child lives with only one of its parents. Third, we compare the occupation level for each child j cohabiting with at least one parent to the average occupation levels of its parents and obtain our absolute measures of intergenerational occupational mobility as follows:[9]

i) Upward blue-collar IM: $$IMUB_{jith} = \begin{cases} 1 \text{ if } B_{jith} = 1 \text{ and } PB_{jith} = 0 \\ 0 \text{ if } B_{jith} = 0 \text{ and } PB_{jith} = 0 \end{cases}$$

ii) Downward blue-collar IM: $$IMDB_{jith} = \begin{cases} 1 \text{ if } B_{jith} = 0 \text{ and } PB_{jith} = 1 \\ 0 \text{ if } B_{jith} = 1 \text{ and } PB_{jith} = 1 \end{cases}$$

iii) Upward white-collar IM: $$IMUW_{jith} = \begin{cases} 1 \text{ if } W_{jith} = 1 \text{ and } PW_{jith} = 0 \\ 0 \text{ if } W_{jith} = 0 \text{ and } PW_{jith} = 0 \end{cases}$$

iv) Downward white-collar IM: $$IMDW_{jith} = \begin{cases} 1 \text{ if } W_{jith} = 0 \text{ and } PW_{jith} = 1 \\ 0 \text{ if } W_{jith} = 1 \text{ and } PW_{jith} = 1 \end{cases}$$

We present in Section 5.8 some stylized facts on occupational mobility in Africa. Figure D.2, Figure D.2, and Figure D.3 show the trends by cohorts, the cross-country differences, and the mapping at the district level of upward and downward occupational mobility for both blue- and white-collar jobs, respectively.

5.2.3 Cohabitation-selection issues

The cohabitation-selection issues have been extensively discussed in Atsebi et al. (2022). The only difference is that this paper does not include Burkina-Faso due to missing values in the control variables (representing 2.58 percent of total population in Atsebi et al. (2022). It is very unlikely that not accounting for this country would change the patterns of the cohabitation issues. Indeed, Atsebi et al. (2022) show that the cohabitation selection is independent from the discoveries of natural resources. Both districts with and without discoveries exhibit the same

[9]By replacing biological/step parents in the last sentences with immediate older generation, we obtain our alternative measures of absolute occupational IM including other relatives on top of the biological/step parents. We will use these alternative definitions of IM in the robustness section.

patterns of cohabitation by age and gender, therefore the cohabitation selection issues might have limited impact on our analysis.[10]

Next, we further investigate the potential direction of the cohabitation selection bias. To do so, we compare in Table 5.2 the occupational levels for both individuals co-residing with their biological/step parents (selected individuals) and those that do not, both in districts with and without discoveries, separately. We test the significance of the differences between those two groups of individuals through a Khi-2 test. We show that the unconditional likelihood to work in agricultural and elementary jobs is higher for individuals not co-residing with their biological/step parents than those who do both in districts with and without discoveries. However, this difference is more accentuated in districts without discoveries than districts with discoveries. Also, the unconditional likelihood to work in blue-collar jobs is lower for those not co-residing with their parents than those who do not, which is also more pronounced in districts without discoveries. Finally, the unconditional likelihood to work in white-collar jobs is lower (higher) for individuals not co-residing with their parents and living in districts without (with) discoveries. These differences are significant as indicated by the Khi-2 tests. Therefore, given that the gap in occupational levels in favor of those co-residing with their biological/step parents is higher in districts without discoveries, we believe that if the cohabitation selection creates any biases, our estimates of the effects of discoveries on upward (downward) occupational mobility would be downward (upward) bias. Indeed, if we would have consider individuals not co-residing with their parents, the upward (downward) mobility would have been much lower (higher) in districts with and without discoveries than the one in our baseline. This decline (increase) would have been more pronounced in districts without discoveries, resulting in a higher (lower) estimate of the effect of mineral discoveries on upward (downward) mobility than the one we capture in our baseline findings. In other words, as we expect discoveries to have a positive effect on occupational mobility (i.e., increase upward mobility and decrease downward mobility), our estimates discussed in the Section 5.4 may be considered as a lower bound.

Table 5.2: Differences in educational attainment between individuals living with biological parents or step-parents or not

	(A) With discoveries			(B) Without discoveries		
	(1) Without relatives	(2) With relatives	(3) Differences	(4) Without relatives	(5) With relatives	(6) Differences
Agriculture and elementary jobs	69,21	65,76	3,45	59,56	54,2	5,36
Blue-collar jobs	22,35	27,03	-4,68	28,45	33,74	-5,29
White-collar jobs	8,44	7,22	1,22	11,98	12,06	-0,08
Total	100	100		100	100	
Khi-2 tests p-value	0.000			0.000		

Note: This table tests the differences in occupational levels between individuals co-residing with their parents and those that do not, both in districts with discoveries and districts without discoveries.

[10] We also verify that cohabitation rates are similar between rural and urban areas, across ages and districts with and without discoveries (available upon request).

5.3 Empirical methodology

The main interest of this analysis is to understand how mineral discoveries and productions affect intergenerational occupational mobility. To do so, we follow closely Atsebi et al. (2022) and adopt an experimental approach and exploit the exogeneity of natural resource discoveries to capture a causal effect of mineral discoveries and productions on occupational mobility in African countries. First, the timing and exact location of mineral resource discoveries is plausibly exogenous due to the uncertainty related to the timing of the discovery and exploration success, and as it depends on random geographical factors of the area (Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019; Seri 2021; Atsebi et al. 2022). Second, mineral discoveries provide a significant source of revenues and represent a major economic shock that can affect the trajectory of the development in countries and districts where they are found. They can also change the habit of individuals and impact the local labor markets. Third, as shown by Horn (2011) and Arezki et al. (2017), there is a significant lag between the discoveries of natural resources and the beginning of their production, around five to six years. This allows us to study the effects of both mineral discoveries and productions on occupational mobility, separately.

Throughout the paper, we analyze both the effects of the first discoveries and productions on upward and downward occupational mobility, and later in the robustness section, of multiple and successive discoveries and productions.

We employ a generalized difference-in-differences (GDID) strategy in a quasi-natural experiment and estimate treatment effects by comparing the changes in occupational mobility between a treatment group (people with exposure to the mineral discoveries and productions) and a control group, across pre-discovery/production and post-discovery/production. By doing so, our goal is to identify how occupational mobility for a group of people with exposition to mineral discoveries or productions compared to a group of people born in the same district but not exposed to it, while controlling for the dynamics of occupational mobility in other districts without any discovery/production.

We focus on four treated groups defined along with the distance between individuals' year of birth and the year of mineral discovery and start of production, with the objective to capture also individuals entering the labor market at the time of discovery or production because excluding them may bias our findings. As such, we also focus on four control groups. Our treated groups include: i) individuals born after the discovery or production, ii) individuals born from 10 years before the discovery or production to after, ii) individuals born from 16 years before the discovery or production to after, and iv) individuals born from 20 years before the discovery or production to after. Our control group for each treated group above including: i) individuals born before the discovery or production and those born in districts without discovery or production, ii) individuals born 11 years before the discovery or production and those born in districts without discovery or production, iii) individuals born 17 years before the discovery or production and those born in districts without discovery or production, and iv) individuals born 21 years before the discovery or production and those born in districts without discovery or production, respectively. The model is estimated using a linear probability specification and obtained as follows

$$IM_{jith} = \alpha_i + \gamma_t + \delta_t + \beta d_h + X_{jit}\theta + \varepsilon_{jit} \quad (5.1)$$

Where IM_{jith} is our measure of upward (and downward) occupational mobility for blue-collar and white-collar jobs categories as defined in Section 5.2.2. d_h is a dummy that takes the value of one if the individual is in the treated group and zero if the individual is in the control group. β is the coefficient of interest. It captures the treatment effect of mineral discovery/production on upward and downward occupational mobility by comparing occupational mobility in the treated and control groups. X_{it} is a set of control variables in line with the existing literature, including the gender of individuals and of their household head, age and age squared, marital status, level of education (less than primary, primary, secondary, or tertiary), average level of education of biological/step parents, household size, urban/rural residency, and the dummies of cohabitation with biological/step-parents (i.e, with only biological/step-father, only biological/step-mother, or both biological/step-father and mother). Lastly, α_i are district fixed effects, γ_t are cohort fixed-effects, δ_t are census-year fixed-effects. These sets of fixed effects allow to filter out all rigid characteristics specific to districts, cohorts or year of birth, and census year found to be critical. ε_{jit} is the idiosyncratic term.

Our model requires the parallel trends assumption to hold, i.e., in the absence of the discovery or production, the change of occupational mobility would have been the same in both the treated and control groups. This assumption is violated when there are unobserved factors that are correlated with both the exposition to the discovery or production and the timing of the discovery or production. As discussed above, we have good reasons to believe that the timing of mineral discoveries is exogenous. Moreover, our structure of fixed effects allows us to limit the risks that other shocks or interventions polluted our findings by focusing on individuals with some similarities (born in the same districts, interviewed in the same survey, and from the same cohort or year birth). However, since we cannot test for the parallel trends' assumption in our GDID, we apply the following strategy to test the robustness of our findings and implicitly verified whether this assumption holds. First, we analyze the dynamic effects and conduct a standard leads-and-lags test following the literature (see e.g., Angrist and Pischke 2009; Maurer 2019; Atsebi et al. 2022). This allows to test how the effects of mineral discoveries and productions vary for different population, and if there are weak for population less exposed. Second, we cross validate our findings by using different control groups while dropping from the control group all individuals in (i) countries without mineral discoveries (Mauritius and South Sudan) and (ii) in districts without mineral discoveries. This reduces the heterogeneity and differences in characteristics between our treated and control groups.

5.4 Results

This section exposes our main results. We first discuss our main findings for the blue-collar and white-collar upward and downward mobility and later present the dynamic effects of mineral discoveries and productions on occupational mobility. In the next section on the channels, we provide some explanations by testing two mechanisms through which mineral discoveries and productions affect occupational mobility.

5.4.1 Baseline results

5.4.1.1 Blue-collar mobility

Table 5.3 reports the baseline results for the various samples treated groups for both blue-collar upward (Panel A) occupational mobility and downward mobility (Panel B). The results show that the coefficients associated with mineral discoveries and productions are generally positive and significant for upward mobility and negative and significant for downward mobility, except in columns (1) and (5). In terms of magnitude, the probability of experiencing an upward blue-collar mobility is higher for an individual exposed to the discovery of a mining site compared to an individual not exposed to by 0.9 to 1.7 percentage points (pp.) for discoveries, and 1.7 to 2.3 pp. for productions. In other words, individuals who are born from parents working in agricultural or elementary jobs have better chances of getting a blue-collar job if exposed to and living in a district with a mining site. Similarly, the likelihood of experiencing a downward blue-collar mobility is lower for an individual exposed to mining activities compared to an individual not exposed to by around 4 pp. That said, individuals who are born from parents working in either blue-collar or white-collar jobs are less likely to work in agricultural and elementary jobs if exposed and living in a district with a mining site.

However, the effects are generally non-significant in columns (1) and (5) where we consider only individuals born after the discovery or production in the treated group. Mineral discoveries and productions also matter for individuals entering the labor market aged 16 or 20 years old at the time of discovery or production as the coefficients become significant when including them in the treated group in columns (2-4) and (6-8). As such, including them in the control group may cancel out the positive effect of mineral discoveries on upward (increase) and downward (reduce) mobility. Therefore, our preferred treated groups include individuals aged 16-20 years, entering the labor market at the time of discovery or production.

Table 5.3: Baseline results, Blue-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Discoveries				Productions			
Panel (A) Upward Mobility								
	Disc-B/A	Disc-10	Disc-16	Disc-20	Prod-B/A	Prod-10	Prod-16	Prod-20
Mining	0.013	0.009***	0.014***	0.017***	0.021	0.017**	0.014***	0.023***
	(0.011)	(0.003)	(0.003)	(0.003)	(0.016)	(0.007)	(0.005)	(0.005)
Observations	1428725	1428725	1428725	1428725	1428725	1428725	1428725	1428725
R-squared	0.307	0.307	0.307	0.307	0.307	0.307	0.307	0.307
# Treated	44135	65016	80751	93116	14236	18746	23602	26912
Panel (B) Downward Mobility								
Mining	-0.019	-0.008	-0.037***	-0.042***	-0.012	-0.034**	-0.042***	-0.035***
	(0.018)	(0.009)	(0.008)	(0.008)	(0.022)	(0.014)	(0.012)	(0.013)
Observations	771244	771244	771244	771244	771244	771244	771244	771244
R-squared	0.195	0.195	0.195	0.195	0.195	0.195	0.195	0.195
# Treated	17692	23452	27587	30765	7820	10203	11696	12815
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the baseline results for the effects of first mineral discoveries (Columns 1-4) and first productions (Columns 5-8) on the probability of upward (Panel A) and downward (Panel B) blue-collar occupational mobility. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group includes individuals born after the discovery (production) and the control group those born before the discovery (production) or in districts without discovery; Disc-10 (Prod-10) means that the treatment group includes individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production) or in districts without discovery; Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.4.1.2 White-collar mobility

Next, we employ a more stringent definition of occupational mobility and focus on white-collar mobility. The results are reported in Table 5.4. We find that the coefficients associated with mineral discoveries and productions are statistically significant for almost all specifications, except in columns (1) and (5) in line with the findings for blue-collar mobility. More specifically, the effects of mineral discoveries and productions are positive on white-collar mobility as they increase the likelihood of upward mobility and reduce the likelihood of downward mobility. As compared to blue-collar mobility, the magnitude of the effects is lower for upward mobility following productions, and higher for downward mobility following both discoveries and productions.

Quantitatively, the results show that the probability of experiencing an upward white-collar mobility is higher for an individual exposed to mining activities compared to an individual not exposed to by 1.6 pp. for discoveries (columns 2-4), and 0.6 to 1.3 pp. for productions (columns 6-8). In other words, individuals who are born from parents working in agricultural or elementary or blue-collar jobs have better chances of working in white-collar jobs if exposed to mining activities. Also, the likelihood of experiencing a downward white-collar mobility is lower for an individual exposed to mining activities compared to an individual not exposed to by around 5.8 to 10.4 pp. for discoveries, and 9.1 to 13.3 pp. for productions. That said, individuals who are born from parents working in white-collar jobs are less likely to perform less than their parents and work in agricultural and elementary or blue-collar jobs if exposed to mining activities.

Table 5.4: Baseline results, White-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Discoveries				Productions			
Panel (A) Upward Mobility								
	Disc-B/A	Disc-10	Disc-16	Disc-20	Prod-B/A	Prod-10	Prod-16	Prod-20
Mining	0.015***	0.016***	0.014***	0.016***	0.007	0.010***	0.006**	0.013***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.005)	(0.003)	(0.003)	(0.003)
Observations	1987149	1987149	1987149	1987149	1987149	1987149	1987149	1987149
R-squared	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269
# Treated	57339	82336	100856	115358	20167	26550	32414	36513
Panel (B) Downward Mobility								
Mining	-0.070	-0.104***	-0.087***	-0.058***	-0.041	-0.091***	-0.133***	-0.098***
	(0.049)	(0.018)	(0.015)	(0.015)	(0.048)	(0.031)	(0.024)	(0.024)
Observations	212820	212820	212820	212820	212820	212820	212820	212820
R-squared	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
# Treated	4488	6132	7482	8523	1889	2399	2884	3214
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the baseline results for the effects of first mineral discoveries (Columns 1-4) and first productions (Columns 5-8) on the probability of upward (Panel A) and downward (Panel B) white-collar occupational mobility. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group includes individuals born after the discovery (production) and the control group those born before the discovery (production) or in districts without discovery; Disc-10 (Prod-10) means that the treatment group includes individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production) or in districts without discovery; Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

To put our findings into perspective and extrapolate them to Africa, we show, for blue-collar mobility, that the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in agricultural or elementary jobs, who work in either blue- or white-collar jobs increases by up to 948 thousand in Africa. Also, the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in either blue-collar or white-collar jobs, who work in agricultural or elementary jobs decreases by up to 2.3 million. Similarly, for white-collar mobility, we find that the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in agricultural, elementary or blue-collar jobs, who work in white-collar jobs increases by up to 795 thousand in Africa. Also, the number of individuals aged 15 and above, exposed to mineral activities and born from parents working in white-collar jobs, who work in agricultural, elementary or blue-collar jobs decreases by up to 3.8 million.

5.4.1.3 Effects of control variables

We present in Table D.3 to Table D.6, the full set of results, including the estimates of control variables. First, looking at individuals' characteristics, we find that females are more (less) likely to experience an upward (downward) occupational mobility for both blue- and white-collar jobs than males. Also, individuals living in urban areas are more (less) likely to experience an upward (downward) occupational mobility for both blue- and white-collar jobs than those living in rural areas, highlighting unequal opportunities in favor of richer regions. There is a U-inverted relationship between age and upward occupational mobility and a U relationship between age and downward mobility. In other words, the likelihood to experience upward (downward) mobility for both blue- and white-collar jobs increase (decrease) with age until a certain point beyond which it starts decreasing (increasing). Also, individuals' education and marital status matter. We find that higher is the level of education achieved, higher (lower) is your likelihood to experience upward (downward) occupational mobility for both blue- and white-collar jobs. Singles have a higher (lower) likelihood of upward (downward) occupational mobility than other categories of marital status, especially separated or divorced and widowed. Second, turning to household characteristics, our results show that the gender of the household head and household size also affect individuals' occupational mobility. Having a female household head increases the likelihood to experience upward occupational mobility for blue-collar jobs and decreases the likelihood to experience downward occupational mobility for both blue- and white-collar jobs. Living in a larger household increases the likelihood to experience upward mobility for blue-collar jobs and downward mobility for white-collar jobs. Third, looking at parents' education and cohabitation, we find that higher level of parents' education led to a higher (lower) likelihood to experience upward (downward) occupational mobility for both blue- and white-collar jobs, with some exceptions for tertiary education. Living with mother or stepmother only increases the likelihood to experience upward mobility for both blue- and white-collar jobs, while living with father or stepfather only decreases the likelihood to experience downward mobility for blue-collar jobs and living with both parents decreases the likelihood to experience downward mobility for white-collar jobs.

5.4.2 The Dynamic effects of mineral discoveries and productions on educational IM

In this subsection, we explore the dynamic effects of mining activities based on the time distance between the years of discoveries or productions and the birth years of individuals. As explained previously, we conduct a leads-and-lags test following the literature (Angrist and Pischke 2009;

Maurer 2019; Atsebi et al. 2022) to analyze whether the effects of mineral discoveries on occupational mobility tend to intensify for the individuals entering the labor market and those born after the discovery and production. To do so, we estimate the likelihood of upward and downward occupational mobility for the specific treated groups, including individuals born 20-16, 15-10, and 9-0 years before the discoveries or the beginning of mining production, and those born 1-10 and 11-20 years after the discoveries or the start of mining production. The reference group is given by individuals born 30-21 years before the discoveries or the start of mining productions. The results are reported in Table 5.5 for blue-collar (columns 1-4) and white-collar mobility (columns 5-8), and upward (columns 1-2, and 5-6) and downward mobility (columns 3-4, and 7-8).

Table 5.5: Dynamic Effects of Mining Activities on Occupational IM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Blue-Collar				**White-Collar**			
	Upward Mobility		Downward Mobility		Upward Mobility		Downward Mobility	
	Discovery	Production	Discovery	Production	Discovery	Production	Discovery	Production
20-16 years before	0.010***	0.016**	-0.034***	-0.013	0.009***	0.015***	-0.050***	-0.050*
	(0.004)	(0.007)	(0.008)	(0.013)	(0.002)	(0.004)	(0.017)	(0.027)
15-10 years before	0.017***	0.015**	-0.059***	-0.041***	0.012***	0.008*	-0.095***	-0.152***
	(0.004)	(0.007)	(0.009)	(0.013)	(0.002)	(0.004)	(0.019)	(0.027)
9-0 years before	0.018***	0.028***	-0.056***	-0.061***	0.022***	0.010*	-0.204***	-0.200***
	(0.004)	(0.010)	(0.010)	(0.016)	(0.003)	(0.005)	(0.021)	(0.038)
1-10 years after	0.028***	0.044***	-0.067***	-0.055***	0.033***	0.017***	-0.203***	-0.201***
	(0.006)	(0.011)	(0.012)	(0.019)	(0.003)	(0.006)	(0.029)	(0.049)
11-20 years after	0.037***	0.065***	-0.060***	-0.052**	0.036***	0.019**	-0.235***	-0.202***
	(0.007)	(0.014)	(0.016)	(0.022)	(0.004)	(0.007)	(0.037)	(0.054)
Observations	1386363	1412072	753434	759696	1932795	1963261	207002	208507
R-squared	0.309	0.308	0.195	0.195	0.270	0.270	0.289	0.289
# Treated, born 30-21 years before Disc/Prod	26242	9219	8131	3337	31100	11624	3273	932
# Treated, born 20-16 years before Disc/Prod	15770	4365	4093	1419	18534	5340	1329	444
# Treated, born 15-10 years before Disc/Prod	15313	5462	3750	2300	17830	7176	1233	586
# Treated, born 9-0 years before Disc/Prod	19378	3639	5626	1848	23406	5119	1598	368
# Treated, born 1-10 years after Disc/Prod	15569	4280	4904	2308	19461	6134	1012	454
# Treated, born 11-20 years after Disc/Prod	9517	4029	3522	3010	12001	6178	1038	861
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the dynamic effects of mineral discoveries and productions on blue-collar (columns 1–4) and white-collar (columns 5–8) occupational mobility. Robust standard errors are in parentheses. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

The results generally confirm our main results presented in the previous section. We find that mining activities affect the likelihood of both blue-collar and white-collar upward and downward occupational mobility for all age groups. In fact, the results show that the coefficients associated with mineral discoveries and productions are positive and significant in columns 1-2 and 5-6, suggesting that mining activities tend to increase the likelihood of upward blue-collar and white-collar mobility for all age groups of individuals. Similarly, the coefficients associated with mineral discoveries and productions are negative and significant in columns 3-4 and 7-8, meaning that mining activities are correlated with lower likelihood of downward blue-collar and white-collar occupational mobility for all age groups.

More importantly, we find that the effects are increasing and more positive for those born after the discovery or production.

For instance, the probability of upward blue-collar occupational mobility is 6.5 pp. higher for individuals born 11-20 years after the start of mining production against only 1.6 pp. higher for those born 20-16 years before the start of mining production (column 2). Also, the probability of downward white-collar occupational mobility is 23.5 pp. lower for individuals born 11-20 years after discovery against only 0.5 pp. higher for those born 20-16 years before discovery (column 7). This higher probability could be explained by the fact that it takes time for mining activities to have an impact on the local communities, particularly in terms of education levels, provision of infrastructures and public goods, and the structure of the labor market. It also supports that the parallel trend assumption might be verified, and therefore the effects we are capturing could be attributed to mineral discoveries and start of productions.

5.5 Transmission channels

The results thus far suggest that children in districts with mineral discoveries or productions are more likely (less likely) to be in occupations that are higher (lower) ranked than that of their parents. In this section, we explore two potential channels through which mining activities affect the likelihood of occupational mobility, including i) the demand for skilled workers channel (demand-side factor), and ii) the educational channel (supply-side factor).

First, mineral discoveries and productions could lead to an increase of the demand for skilled workers in districts with mining activities. In these districts, we expect an increase of the share of people working in high-skilled industries, and a decrease of the share of people working in low-skilled industries. For instance Cavalcanti et al. (2019) show that mineral activities induce a structural transformation or job creation in the districts with natural resources, creating new opportunities that will increase households' income (Becker and Tomes 1979; Weber-Fahr 2002; Loayza et al. 2013).

Second, under the educational channel, we hypothesize that the mining activities will generate new and higher income for parents (Becker and Tomes 1979; Loayza et al. 2013), thus allowing them to invest in their children's education. Education attainment is therefore expected to be higher for children exposed to mining activities. As such by increasing their education and having a higher educational mobility than that of their parents, they will also have a higher likelihood of occupational mobility as shown by the well established positive relationship in the literature between educational and occupational mobility (see, e.g., Ouedraogo and Syrichas 2021).

5.5.1 The demand for skilled workers channel

To test this channel, we need to first rank industries by the intensity of skilled workers and group them in three categories: i) high-skill, ii) medium-skill, and iii) low-skill industries. Second, we examine the impact of mineral discoveries and productions on the likelihood to be employed in high-skill, medium-skill and low-skill industries for individuals in districts with mining discoveries and productions as compared to districts without mining activities. We create an income and education-based index to rank the different industries. This index is computed as the average of two variables: i) the lasso-adjusted industry, demographic, and occupational (LIDO) score, and ii) the years of schooling. Our income and education-based index vary between zero and one, with one meaning that the individuals have the highest level of LIDO score and education in our sample. The LIDO score is an occupational income ranking score computed using actual data of labor market for the United States in 1950 by Saavedra and Twinam (2020). It is used as an alternative measure of income, socioeconomic status, and labor market outcome. It depends on (i) the fine categories of sectors of employment based on the industry classification (e.g., agriculture, mining and extraction, manufacturing, construction, hotels and restaurants, etc.), and (ii) the occupation within employment based on the occupation classification (e.g., legislators, senior officials and managers, technicians and associate professionals, service works and market sales, elementary occupations). When applied to workers in Africa, the cross-individual, district and country differences at each period and over time would only come from the differences in the labor market conditions (sectors of activities, and occupation within employment).

To rank the 15 industries in our data, we compute the average of the income and education-based index for each industry as shown in Table 5.6. This table shows that 57 percent of individuals work in low-skill industries, while few of them work in medium-skill and high-skill industries (29.6 and 13.3 percent, respectively). Next, we estimate similar specifications as in Equation (5.1) by using the dummies for working in high-skill, medium-skill, and low-skill industries as dependent variables.

Table 5.6: Classification of industries based on the income and education based index

	Industries	Code	Lido and Years of Schooling Index		
			Obs	Share (%)	Mean
High	Public administration and defense	100	56,923	2.57	0.60
	Financial services and insurance	90	17,408	0.79	0.59
	Electricity, gas, water and waste manag	40	10,238	0.46	0.56
	Mining and extraction	20	14,958	0.68	0.54
	Manufacturing	30	195,055	8.81	0.54
Medium	Transportation, storage, and communica	80	78,760	3.56	0.53
	Education	112	75,917	3.43	0.52
	Business services and real estate	111	39,382	1.78	0.51
	Construction	50	126,369	5.71	0.44
	Wholesale and retail trade	60	219,487	9.92	0.41
	Health and social work	113	31,069	1.40	0.38
	Other services	114	86,027	3.89	0.32
Low	Hotels and restaurants	70	40,393	1.83	0.25
	Agriculture, fishing, and forestry	10	1,196,008	54.04	0.19
	Private household services	120	24995	1.13	0.10
	Total	-	2212989	100	0.31

Notes: This table presents the classification of the industries using the income and education-based index. It classifies industries into three groups: i) high-skill, ii) medium-skill, and iii) low-skill industries.

The results are displayed in Table 5.7, with the estimates about mineral discoveries in columns 1-2, and productions in columns 3-4. We present the effects of mineral discoveries and productions on the likelihood of working in high-skill (Panel A), medium-skill (Panel B), and low-skilled (Panel C) industries. The results suggest that mineral discoveries and productions lead to change in demand for skill workers with individuals moving from low-skill to medium-skill and high-skill industries. More specifically, mineral discoveries and productions reduce the likelihood to work in low-skill industries by 3.8 to 4.9 pp., while increase the likelihood to work in medium-skill and high-industry by 2.1 to 2.6 pp, and 1.5 to 2.4 pp., respectively. That being said, individuals are moving out of the low-skilled sectors to high-skilled sectors, therefore raising (reducing) the likelihood of upward (downward) occupational mobility. The structural change that occurs in districts with mining activities is a channel through which mining activities lead to a positive effect on occupation mobility

Table 5.7: The demand for skilled workers channel

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (A) High-Skill Industries				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.015***	0.017***	0.024***	0.023***
	(0.002)	(0.002)	(0.004)	(0.004)
Observations	2098094	2098094	2098094	2098094
R-squared	0.133	0.133	0.133	0.133
# Treated	99693	114862	32955	37127
Panel (B) Medium-Skill Industries				
Mining	0.026***	0.021***	0.022***	0.026***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	2098094	2098094	2098094	2098094
R-squared	0.263	0.263	0.263	0.263
# Treated	99693	114862	32955	37127
Panel (C) Low-Skill Industries				
Mining	-0.041***	-0.038***	-0.046***	-0.049***
	(0.003)	(0.003)	(0.006)	(0.005)
Observations	2098094	2098094	2098094	2098094
R-squared	0.463	0.463	0.463	0.463
# Treated	99693	114862	32955	37127
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of working in high-skill (Panel A), medium-skill (Panel B), and low-skill (Panel C) industries. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts with discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.5.2 The educational channel: intergenerational mobility in education

We test the educational channel by checking whether the positive effects of mining activities on occupational mobility are conditional to higher intergenerational mobility in education and whether there is any difference based on the strength of intergenerational educational mobility. Higher investments in education following mining discoveries and productions can be driven by higher returns to education as shown by Atsebi et al. (2022). Thus, all else equal, well-educated children will be able to work in higher ranked-occupations than their parents as shown by Ouedraogo and Syrichas (2021). To test this channel, we split our sample between i) individuals born from uneducated parents or parents with less than primary education attainment that complete at least primary education (with upward primary educational mobility) and those that do not complete primary education (no upward primary educational mobility) when analyzing upward occupational mobility, and ii) individuals born from parents with at least primary education attainment that complete at least primary education (no downward primary educational mobility) and those that are uneducated or have less than primary education attainment (downward primary educational mobility) when analyzing downward occupational mobility. We estimate Equation (5.1) on the different sub-groups and focus on primary education as it allows to have sufficient observations in each sub-group for the analysis.

The results are presented in Table 5.8 and Table 5.9 for blue-collar and white collar occupational mobility, respectively. They show that for individuals with upward primary educational mobility (Panel I.A), the effects of mineral discoveries and productions on both blue-collar and white-collar occupational mobility are positive and significant, meaning that they increase the likelihood for children to work in higher ranked occupations thaN their parents. Moreover, the magnitude of the effects are much higher as compared to the baseline results. On the contrary, for individuals with no upward primary educational mobility (Panel I.B), these effects are generally not significant and of lower magnitude. As such, having an upward primary educational mobility is a prerequisite for a positive effect of mineral discoveries and productions on occupational blue-collar and white-collar occupational mobility. We also confirm these findings for downward occupational mobility. Indeed, for individuals with no downward primary educational mobility (Panel II.A), the effects of mineral discoveries and productions on both blue-collar and white-collar occupational mobility are negative and significant, meaning that mining activities reduce the likelihood for children to work in lower ranked occupations than their parents. Moreover, the magnitude of the effects are much higher as compared to the baseline results. On the contrary, for individuals with downward primary educational mobility (Panel II.B), these effects are generally not significant. Thus, the effects of mineral discoveries and productions on occupational mobility operate through an improvement on educational mobility, emphasizing the strong link between employment and education.

Table 5.8: The educational channel for blue-collar occupational mobility

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Upward Occupational Mobility				
Panel (A) Only Individuals with Upward Primary Mobility in Education				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.045***	0.047***	0.047***	0.055***
	(0.005)	(0.005)	(0.009)	(0.009)
Observations	418945	418945	418945	418945
R-squared	0.281	0.281	0.281	0.281
# Treated	24416	28245	8905	9936
Panel (B) Only Individuals with NO Upward Primary Mobility in Education				
Mining	0.007	0.010	0.019	0.021
	(0.011)	(0.010)	(0.015)	(0.014)
Observations	790412	790412	790412	790412
R-squared	0.180	0.180	0.180	0.180
# Treated	37037	42289	8177	9467
Panel (II) : Downward Occupational Mobility				
Panel (A) Only Individuals with NO Downward Primary Mobility in Education				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	-0.067***	-0.069***	-0.071***	-0.046***
	(0.013)	(0.013)	(0.017)	(0.017)
Observations	323212	323212	323212	323212
R-squared	0.150	0.150	0.149	0.149
# Treated	10951	12234	5215	5728
Panel (B) Only Individuals with Downward Primary Mobility in Education				
Mining	-0.060	-0.050	-0.101**	-0.018
	(0.037)	(0.034)	(0.047)	(0.079)
Observations	33431	33431	33431	33431
R-squared	0.293	0.293	0.293	0.292
# Treated	1371	1611	398	458
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of working in high-skill (Panel A), medium-skill (Panel B), and low-skill (Panel C) industries. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts with discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.9: The educational channel for white-collar occupational mobility

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Upward Occupational Mobility				
Panel (A) Only Individuals with Upward Primary Mobility in Education				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.047***	0.057***	0.032***	0.046***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	616829	616829	616829	616829
R-squared	0.140	0.140	0.140	0.140
# Treated	31369	35840	12512	13791
Panel (B) Only Individuals with NO Upward Primary Mobility in Education				
Mining	0.004**	0.003*	0.001	0.002
	(0.002)	(0.002)	(0.004)	(0.003)
Observations	954202	954202	954202	954202
R-squared	0.0723	0.0723	0.0723	0.0723
# Treated	43134	49090	10151	11642
Panel (II) : Downward Occupational Mobility				
Panel (A) Only Individuals with NO Downward Primary Mobility in Education				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	-0.115***	-0.116***	-0.163***	-0.108***
	(0.020)	(0.020)	(0.032)	(0.031)
Observations	148594	148594	148594	148594
R-squared	0.150	0.150	0.150	0.150
# Treated	4787	5435	2258	2475
Panel (B) Only Individuals with Downward Primary Mobility in Education				
Mining	-0.066	0.013	-0.163**	-0.040
	(0.040)	(0.054)	(0.077)	(0.103)
Observations	11299	11299	11299	11299
R-squared	0.550	0.550	0.551	0.550
# Treated	480	564	124	140
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) white-collar occupational mobility for different groups based in educational mobility. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.6 Robustness checks

In this section, we undertake various robustness tests to check the validity of our baseline results to alternative samples and specifications.

5.6.1 Use of alternative control groups (only countries/districts with discoveries)

We start by using an alternative definition of the control groups. In the baseline, our sample includes individuals in countries with and without discoveries, and districts with and without discoveries. Indeed, individuals in countries and districts without discoveries can have different characteristics as compared to those living in countries and districts with discoveries. In this robustness check, we restrict the control group to individuals living in countries or districts where mining sites are discovered or with production activities. The results are reported in Table 5.10 and Table 5.11 for blue-collar and white-collar jobs, respectively. In Panel (I), we focus on individuals living in the countries with mineral discoveries only, and in Panel (II), we rather focus on individuals living in districts with discoveries. We find that our main baseline results hold after restricting the sample to only individuals living in countries and districts with discoveries. Our results remain unchanged and are robust to the change of control groups and samples.

Table 5.10: Robustness check: using different control groups, blue-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Only Countries with Mining Activities				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.016***	0.019***	0.016***	0.025***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	1374837	1374837	1374837	1374837
R-squared	0.276	0.276	0.276	0.276
# Treated	80751	93116	23602	26912
Panel (B) Downward Mobility				
Mining	-0.038***	-0.043***	-0.043***	-0.035***
	(0.008)	(0.008)	(0.012)	(0.013)
Observations	714653	714653	714653	714653
R-squared	0.194	0.194	0.194	0.194
# Treated	27587	30765	11696	12815
Panel (II) : Only Districts with Mining Activities				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.006*	0.007**	0.009*	0.016***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	146083	146083	146083	146083
R-squared	0.243	0.243	0.243	0.243
# Treated	80751	93116	23602	26912
Panel (B) Downward Mobility				
Mining	-0.032***	-0.039***	-0.030**	-0.023*
	(0.009)	(0.009)	(0.013)	(0.013)
Observations	48206	48206	48206	48206
R-squared	0.152	0.153	0.152	0.152
# Treated	27587	30765	11696	12815
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) white-collar occupational mobility for different groups based on the residency in countries (Panel I) or districts (Panel II) with discoveries. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.11: Robustness check: using different control groups, white-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Only Countries with Mining Activities				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.016***	0.018***	0.008***	0.015***
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	1889913	1889913	1889913	1889913
R-squared	0.271	0.271	0.271	0.271
# Treated	100856	115358	32414	36513
Panel (B) Downward Mobility				
Mining	-0.087***	-0.057***	-0.134***	-0.099***
	(0.015)	(0.015)	(0.024)	(0.024)
Observations	199577	199577	199577	199577
R-squared	0.287	0.287	0.287	0.287
# Treated	7482	8523	2884	3214
Panel (II) : Only Districts with Mining Activities				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.002	0.002	-0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
Observations	178870	178870	178870	178870
R-squared	0.178	0.178	0.178	0.178
# Treated	100856	115358	32414	36513
Panel (B) Downward Mobility				
Mining	-0.040**	-0.001	-0.079***	-0.038
	(0.017)	(0.017)	(0.025)	(0.025)
Observations	15419	15419	15419	15419
R-squared	0.205	0.205	0.205	0.205
# Treated	7482	8523	2884	3214
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) white-collar occupational mobility for different groups based on the residency in countries (Panel I) or districts (Panel II) with discoveries. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.6.2 Use of alternative structures of fixed effects and time variable

Next, we check the robustness of our findings to the addition of time-trend in the specifications and the use of different structure of the fixed effects. The results are displayed in Table 5.12 and Table 5.13 for blue-collar and white-collar jobs, respectively. In Panel (I), we add a common time trend to the specification to capture the dynamic of occupational mobility over time and ensure that our identification strategy does not capture the effects of pre-existing trends. In Panel (II), we replace cohort fixed-effects in our baseline by year birth fixed-effects. As such, we compare individuals born in the same year rather than in the same cohort of 10 years, and therefore reduce the risks that they have experienced different shocks. Our findings show that our main findings remain unchanged even after accounting for time trend and birth year fixed effects.

Table 5.12: Robustness check: inclusion of time trend of birth year fixed effects, blue-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Common Time Trend Added				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.011***	0.014***	0.011**	0.020***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	1428725	1428725	1428725	1428725
R-squared	0.307	0.307	0.307	0.307
# Treated	80751	93116	23602	26912
Panel (B) Downward Mobility				
Mining	-0.034***	-0.039***	-0.038***	-0.033**
	(0.008)	(0.008)	(0.012)	(0.013)
Observations	771244	771244	771244	771244
R-squared	0.195	0.195	0.195	0.195
# Treated	27587	30765	11696	12815
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes
Common Time-Trend	Yes	Yes	Yes	Yes
Birth Year FE	No	No	No	No
Panel (II) : Year Birth Fixed-Effects in Place of Cohort Fixed-Effects				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.009***	0.011***	0.007	0.017***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	1428725	1428725	1428725	1428725
R-squared	0.308	0.308	0.308	0.308
# Treated	80751	93116	23602	26912
Panel (B) Downward Mobility				
Mining	-0.032***	-0.037***	-0.034***	-0.032**
	(0.008)	(0.008)	(0.012)	(0.013)
Observations	771244	771244	771244	771244
R-squared	0.197	0.197	0.197	0.197
# Treated	27587	30765	11696	12815
District FE	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No
Census-Year FE	Yes	Yes	Yes	Yes
Common Time-Trend	No	No	No	No
Birth Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) blue-collar occupational mobility for specifications where we add time trend (Panel I) and replace cohort fixed-effects by year birth fixed-effects (Panel II). Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.13: Robustness check: inclusion of time trend of birth year fixed effects, white-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Common Time Trend Added				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.017***	0.018***	0.009***	0.016***
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	1987149	1987149	1987149	1987149
R-squared	0.269	0.269	0.269	0.269
# Treated	100856	115358	32414	36513
Panel (B) Downward Mobility				
Mining	-0.089***	-0.059***	-0.135***	-0.099***
	(0.015)	(0.015)	(0.024)	(0.024)
Observations	212820	212820	212820	212820
R-squared	0.286	0.286	0.286	0.286
# Treated	7482	8523	2884	3214
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes
Common Time-Trend	Yes	Yes	Yes	Yes
Birth Year FE	No	No	No	No
Panel (II) : Year Birth Fixed-Effects in Place of Cohort Fixed-Effects				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.014***	0.014***	0.003	0.010***
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	1987149	1987149	1987149	1987149
R-squared	0.270	0.270	0.270	0.270
# Treated	100856	115358	32414	36513
Panel (B) Downward Mobility				
Mining	-0.067***	-0.041***	-0.108***	-0.078***
	(0.015)	(0.015)	(0.024)	(0.024)
Observations	212820	212820	212820	212820
R-squared	0.289	0.289	0.289	0.289
# Treated	7482	8523	2884	3214
District FE	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No
Census-Year FE	Yes	Yes	Yes	Yes
Common Time-Trend	No	No	No	No
Birth Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) white-collar occupational mobility for specifications where we add time trend (Panel I) and replace cohort fixed-effects by year birth fixed-effects (Panel II). Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.6.3 Use of alternative IM definitions

We also check the robustness of our findings to the use of alternative definitions of occupational mobility. In the baseline, we considered children living with their biological/step parents and used the average values of parents' occupational levels to construct the intergenerational occupational mobility. In this section, we first use the minimum and the maximum of the parents' occupational levels instead of the average occupational levels to better capture potential parents' occupational inequalities as women tend to have lower level of occupation than men in

Africa. As such, by focusing on the minimum, we loosen the definition of occupational mobility as we are more likely to compare children with their mothers. On the contrary, by focusing on the maximum, we tighten the definition of occupational mobility as we are more likely to compare children with their fathers. The results of the estimates are displayed in Table 5.14 and Table 5.15 for blue-collar and white-collar jobs, and Panel (I) and (II) when using the minimum and maximum of parents' occupation, respectively. In line with our baseline results, we find that mineral discoveries and productions increase (decrease) the likelihood of upward (downward) blue-collar and white-collar occupational mobility.

Next, we broaden the definition of parental authority to include all other immediate relatives from older generations such as uncles/aunts (in law), parents-in-law, grand-parents, and grand-uncles/aunts to account for abandoned or orphan children sent to relatives, and biological parents deliberately sending their children to relatives or places where education conditions are better. The results are reported in Panel (III) of Table 5.14 and Table 5.15 for blue-collar and white-collar jobs, respectively. Here also, our findings are in line with those in the baseline, confirming the robustness of our findings to the use of a broader comparison groups for children.

Lastly, we significantly alter the definitions of occupational mobility and use indicators to construct a ranking of occupations rather than the ah-doc ranking and grouping used in the baseline results. First, we use the LIDO score and compute its mean for each occupational category for each country. This indicator provides an income-intensity of occupations. We therefore rank the occupational categories according to their average LIDO score, with a higher value meaning a higher ranking. Second, we use the years of schooling and compute the average years of schooling for each occupational category to rank them, with occupation with higher educational value in higher ranking. This indicator provides an education-intensity of occupations. Third, we define an index averaging the LIDO score and years of schooling. We also use this index to rank the occupations. Using these indexes, we define an upward (downward) occupational mobility if children work in occupation of a higher (lower) ranking than that of their parents' average occupational levels. The results are reported in Table 5.16. Our results generally hold when using the LIDO score (Panel I), years of schooling (Panel II), and the average of the LIDO score and years of schooling (Panel III) to rank the occupational categories.

Table 5.14: Robustness check: using alternative IM definitions, blue-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Minimum Parents' Occupation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.015***	0.019***	0.017***	0.024***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	1520179	1520179	1520179	1520179
R-squared	0.314	0.314	0.314	0.314
# Treated	85305	98457	24824	28342
Panel (B) Downward Mobility				
Mining	-0.029***	-0.033***	-0.030**	-0.039***
	(0.009)	(0.009)	(0.012)	(0.013)
Observations	679790	679790	679790	679790
R-squared	0.157	0.157	0.157	0.157
# Treated	23033	25424	10474	11385
Panel (II) : Maximum Parents' Occupation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.014***	0.017***	0.014***	0.023***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	1428725	1428725	1428725	1428725
R-squared	0.307	0.307	0.307	0.307
# Treated	80751	93116	23602	26912
Panel (B) Downward Mobility				
Mining	-0.037***	-0.042***	-0.042***	-0.035***
	(0.008)	(0.008)	(0.012)	(0.013)
Observations	771244	771244	771244	771244
R-squared	0.195	0.195	0.195	0.195
# Treated	27587	30765	11696	12815
Panel (III) : All immediate older generation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.013***	0.016***	0.015***	0.024***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	1428938	1428938	1428938	1428938
R-squared	0.306	0.306	0.306	0.306
# Treated	80755	93133	23579	26880
Panel (B) Downward Mobility				
Mining	-0.037***	-0.043***	-0.041***	-0.032**
	(0.008)	(0.008)	(0.012)	(0.013)
Observations	771770	771770	771770	771770
R-squared	0.192	0.192	0.192	0.192
# Treated	27616	30786	11720	12848
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of mineral discoveries (Columns 1-4) and productions (Columns 5-8) on the probability of upward (Panel A) and downward (Panel B) blue-collar occupational IM for specifications where we use the minimum of parents' occupations (Panel I), the maximum of parents' occupation (Panel II), and all immediate older generation (Panel III). Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group include individuals born the discovery (production) and the control group those born before the discovery (production); Disc-10 (Prod-10) means that the treatment group include individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production); Disc-16 (Prod-16) means that the treatment group include individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) ; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production). *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.15: Robustness check: using alternative IM definitions, white-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Minimum Parents' Occupation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.014***	0.015***	0.008***	0.014***
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	2031291	2031291	2031291	2031291
R-squared	0.279	0.279	0.279	0.279
# Treated	102877	117702	33145	37353
Panel (B) Downward Mobility				
Mining	-0.095***	-0.070***	-0.130***	-0.126***
	(0.018)	(0.019)	(0.028)	(0.029)
Observations	168678	168678	168678	168678
R-squared	0.293	0.293	0.293	0.293
# Treated	5461	6179	2153	2374
Panel (II) : Maximum Parents' Occupation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.014***	0.016***	0.006**	0.013***
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	1987149	1987149	1987149	1987149
R-squared	0.269	0.269	0.269	0.269
# Treated	100856	115358	32414	36513
Panel (B) Downward Mobility				
Mining	-0.087***	-0.058***	-0.133***	-0.098***
	(0.015)	(0.015)	(0.024)	(0.024)
Observations	212820	212820	212820	212820
R-squared	0.286	0.286	0.286	0.286
# Treated	7482	8523	2884	3214
Panel (III) : All immediate older generation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.014***	0.016***	0.006**	0.014***
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	1988760	1988760	1988760	1988760
R-squared	0.268	0.268	0.268	0.268
# Treated	100963	115496	32432	36532
Panel (B) Downward Mobility				
Mining	-0.087***	-0.059***	-0.131***	-0.095***
	(0.016)	(0.016)	(0.025)	(0.024)
Observations	211948	211948	211948	211948
R-squared	0.284	0.284	0.284	0.284
# Treated	7408	8423	2867	3196
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) blue-collar occupational mobility for specifications where we use the minimum of parents' occupations (Panel I), the maximum of parents' occupation (Panel II), and all immediate older generation (Panel III). Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group include individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.16: Robustness check: using alternative IM definitions based on LIDO score and years of schooling

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Lido Score Based Index Used for Ranking Occupation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.021***	0.027***	0.012**	0.022***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	2072089	2072089	2072089	2072089
R-squared	0.173	0.173	0.173	0.173
# Treated	99805	114748	32939	37070
Panel (B) Downward Mobility				
Mining	-0.015***	-0.012***	-0.009**	-0.013***
	(0.002)	(0.002)	(0.004)	(0.004)
Observations	2072089	2072089	2072089	2072089
R-squared	0.111	0.111	0.111	0.111
# Treated	99805	114748	32939	37070
Panel (II) : Years of Schooling Used for Ranking Occupation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.005*	0.012***	0.007	0.010*
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	1534747	1534747	1534747	1534747
R-squared	0.206	0.206	0.206	0.206
# Treated	103016	117557	34577	38867
Panel (B) Downward Mobility				
Mining	-0.010***	-0.006***	-0.008*	-0.007
	(0.002)	(0.002)	(0.004)	(0.004)
Observations	1534747	1534747	1534747	1534747
R-squared	0.113	0.113	0.113	0.113
# Treated	103016	117557	34577	38867
Panel (III) : Lido Score and Years of Schooling Based Index Used for Ranking Occupation				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.021***	0.029***	0.017***	0.025***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	2199969	2199969	2199969	2199969
R-squared	0.178	0.178	0.178	0.178
# Treated	108338	123881	35298	39727
Panel (B) Downward Mobility				
Mining	-0.016***	-0.013***	-0.014***	-0.016***
	(0.002)	(0.002)	(0.004)	(0.004)
Observations	2199969	2199969	2199969	2199969
R-squared	0.114	0.114	0.114	0.114
# Treated	108338	123881	35298	39727
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) blue-collar and white-collar occupational mobility for specifications where we use LIDO score (Panel I), years of schooling (Panel II), and both LIDO score and years of schooling (Panel III) to rank occupational categories. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group include individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.6.4 Use of all mineral discoveries and productions

Finally, we also test whether our findings are consistent with the use of all mineral discoveries and productions, instead of the first discoveries and productions in the baseline. Indeed, we focused on the first discoveries and productions to account for any potential anticipation and duplication effects as resource-rich districts are more likely to experience several discoveries or have many production sites, although the timing of the discoveries remains uncertain. The results are displayed in Table 5.17, Panel (I) for blue-collar jobs, and Panel (II) for white-collar jobs. Using all mineral discoveries and productions generally lead to similar results as in our baseline where we focus on the first discoveries and productions. This suggest that subsequent discoveries and productions do not change our key findings.

Table 5.17: Robustness check: using all mineral discoveries and productions

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (I) : Blue-collar jobs				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.016***	0.020***	0.010***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Observations	1491890	1491890	1491890	1491890
R-squared	0.305	0.305	0.305	0.305
# Treated	100187	118437	28351	33530
Panel (B) Downward Mobility				
Mining	-0.027***	-0.035***	-0.023***	-0.017***
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	793630	793630	793630	793630
R-squared	0.193	0.193	0.193	0.193
# Treated	37517	43632	13879	16818
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes
Panel (II) : White-collar jobs				
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Mining	0.011***	0.013***	0.002	0.006***
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	2067152	2067152	2067152	2067152
R-squared	0.267	0.267	0.267	0.267
# Treated	128212	150618	38813	46311
Panel (B) Downward Mobility				
Mining	-0.048***	-0.041***	-0.046***	-0.035***
	(0.010)	(0.010)	(0.012)	(0.012)
Observations	218368	218368	218368	218368
R-squared	0.282	0.282	0.282	0.282
# Treated	9492	11451	3417	4037
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of all mineral discoveries (Columns 1-2) and productions (Columns 5-8) on the probability of upward (Panel A) and downward (Panel B) blue-collar (Panel I) and white-collar (Panel II) occupational mobility. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.7 Sensitivity tests

In this section, we conduct several sensitivity tests to explore whether our findings vary across African regions, size of the mining sites, gender, and urban-rural residency.

5.7.1 Depending on the African regions

Our first interest is to check whether our findings vary across African regions. Thus, we split the African continent into four regions: Eastern Africa, Northern Africa, Southern Africa, and Western and Central Africa. We then estimate the effects of mining activities on the probability of upward/downward occupational mobility for each region. The results are reported in Table 5.18 and Table 5.19 for blue-collar and white-collar jobs, respectively. They reveal that there are some heterogeneities across regions. For blue-collar occupational mobility, we find that the positive effects of mineral discoveries on upward mobility are higher in Western and Central Africa, followed by Southern and Eastern Africa. However, they are non-significant for Northern Africa. Following mineral productions, these positive effects are higher in Eastern Africa, followed by Southern and Northern Africa, while they are non-significant in Western and Central Africa. For downward mobility, the positive effects are significant and higher in Southern Africa for both mineral discoveries and productions, and sometimes in Eastern Africa (following mineral discoveries), Western and Central Africa and Northern Africa (following mineral productions). For white-collar upward mobility, the positive effects of mineral discoveries are found in all regions, and they are higher in Western and Central Africa. For downward white-collar mobility, we find that the positive effects are generally confirmed in all regions, except in Western and Central Africa, following both mineral discoveries and productions.

Table 5.18: Sensitivity: African regions, blue-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Eastern Africa	0.014***	0.020***	0.021**	0.035***
	(0.003)	(0.003)	(0.009)	(0.010)
Northern Africa	-0.001	-0.007	0.010	0.016*
	(0.005)	(0.005)	(0.008)	(0.008)
Southern Africa	0.015**	0.018**	0.010	0.019**
	(0.007)	(0.007)	(0.008)	(0.008)
Western and Central Africa	0.169***	0.154***	0.073	0.047
	(0.027)	(0.024)	(0.061)	(0.073)
Observations	1428725	1428725	1428725	1428725
R-squared	0.307	0.307	0.307	0.307
# Treated; Eastern Africa	42480	49989	14557	15379
# Treated; Northern Africa	24089	27527	5071	6179
# Treated; Southern Africa	13360	14479	3675	5012
# Treated; Western and Central Africa	822	1121	299	342
Panel (B) Downward Mobility				
Eastern Africa	-0.045***	-0.055***	0.013	-0.005
	(0.011)	(0.010)	(0.019)	(0.018)
Northern Africa	0.011	0.010	-0.051**	-0.023
	(0.015)	(0.016)	(0.020)	(0.023)
Southern Africa	-0.153***	-0.125***	-0.109***	-0.104***
	(0.028)	(0.031)	(0.027)	(0.031)
Western and Central Africa	-0.079	-0.043	-0.118	-0.216**
	(0.066)	(0.087)	(0.076)	(0.102)
Observations	771244	771244	771244	771244
R-squared	0.195	0.195	0.195	0.195
# Treated; Eastern Africa	11504	13420	4897	5293
# Treated; Northern Africa	10147	11130	3279	3711
# Treated; Southern Africa	5343	5566	3134	3402
# Treated; Western and Central Africa	593	649	386	409
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) blue-collar occupational mobility across African regions. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.19: Sensitivity: African regions, white-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Eastern Africa	0.012***	0.015***	0.010*	0.014***
	(0.002)	(0.002)	(0.005)	(0.005)
Northern Africa	0.015***	0.013***	0.005	0.013***
	(0.003)	(0.003)	(0.004)	(0.004)
Southern Africa	0.014***	0.022***	0.002	0.008*
	(0.004)	(0.004)	(0.004)	(0.005)
Western and Central Africa	0.042***	0.037***	0.030	0.133***
	(0.007)	(0.006)	(0.035)	(0.032)
Observations	1987149	1987149	1987149	1987149
R-squared	0.269	0.269	0.269	0.269
# Treated; Eastern Africa	51317	60149	18556	19696
# Treated; Northern Africa	31964	36027	7646	9050
# Treated; Southern Africa	16347	17610	5654	7153
# Treated; Western and Central Africa	1228	1572	558	614
Panel (B) Downward Mobility				
Eastern Africa	-0.090***	-0.072***	-0.110**	-0.098**
	(0.021)	(0.020)	(0.044)	(0.041)
Northern Africa	-0.044*	-0.001	-0.119***	-0.052
	(0.026)	(0.027)	(0.040)	(0.037)
Southern Africa	-0.180***	-0.152***	-0.166***	-0.170***
	(0.047)	(0.051)	(0.045)	(0.051)
Western and Central Africa	-0.165	-0.154	-0.166	-0.127
	(0.136)	(0.179)	(0.136)	(0.171)
Observations	212820	212820	212820	212820
R-squared	0.286	0.286	0.286	0.286
# Treated; Eastern Africa	2667	3260	898	976
# Treated; Northern Africa	2272	2630	704	840
# Treated; Southern Africa	2356	2435	1155	1261
# Treated; Western and Central Africa	187	198	127	137
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) white-collar occupational mobility across African regions. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.7.2 Depending on the size of mineral discoveries

Next, we explore whether our results depend on the sizes of mineral discoveries or if the size of mineral discoveries matter for the effects of mineral activities on occupational mobility. The Minex Consulting Dataset (2019) provides information on four size categories of mineral discoveries: moderate, major, giant and super-giant mining. We merge the last two categories as there are not sufficient observations to run the estimates for each of them. The results are presented in Table 5.20 and Table 5.21 for blue-collar and white-collar respectively. Our results show that the size of mineral discoveries also matters. We find that the positive effects of mineral discoveries and productions are generally of a greater magnitude for giant and super-giant discoveries. Moderate discoveries also have a positive effect on both upward and downward blue-collar and white-collar mobility following discoveries and productions, with the exception for downward blue-collar mobility following productions. Similar results are found for major discoveries, with the exception for upward blue-collar mobility, and downward blue-collar mobility. Our baseline findings are generally consistent although they vary with the size of mineral discoveries.

Table 5.20: Sensitivity: size of mineral discoveries, blue-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Moderate Mining	0.014***	0.021***	0.021**	0.035***
	(0.003)	(0.003)	(0.009)	(0.010)
Major Mining	-0.001	-0.007	0.010	0.016*
	(0.005)	(0.005)	(0.008)	(0.008)
Giant and Super-Giant Mining	0.040***	0.046***	0.012	0.020**
	(0.007)	(0.008)	(0.008)	(0.008)
Observations	1428725	1428725	1428725	1428725
R-squared	0.307	0.307	0.307	0.307
# Treated; Moderate	42480	49989	14557	15379
# Treated; Major	24089	27527	5071	6179
# Treated; Giant and Super-Giant	14182	15600	3974	5354
Panel (B) Downward Mobility				
Moderate Mining	-0.045***	-0.055***	0.013	-0.005
	(0.011)	(0.010)	(0.019)	(0.018)
Major Mining	0.011	0.010	-0.051**	-0.023
	(0.015)	(0.016)	(0.020)	(0.023)
Giant and Super-Giant Mining	-0.142***	-0.116***	-0.110***	-0.113***
	(0.026)	(0.029)	(0.025)	(0.030)
Observations	771244	771244	771244	771244
R-squared	0.195	0.195	0.195	0.195
# Treated; Moderate	11504	13420	4897	5293
# Treated; Major	10147	11130	3279	3711
# Treated; Giant and Super-Giant	5936	6215	3520	3811
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2) and first productions (Columns 3-4) on the probability of upward (Panel A) and downward (Panel B) blue-collar occupational mobility across the size of mineral discoveries. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.21: Sensitivity: size of mineral discoveries, white-collar jobs

	(1)	(2)	(3)	(4)
	Discoveries		Productions	
Panel (A) Upward Mobility				
	Disc-16	Disc-20	Prod-16	Prod-20
Moderate Mining	0.012***	0.015***	0.010*	0.014***
	(0.002)	(0.002)	(0.005)	(0.005)
Major Mining	0.015***	0.013***	0.005	0.013***
	(0.003)	(0.003)	(0.004)	(0.004)
Giant and Super-Giant Mining	0.018***	0.025***	0.004	0.013***
	(0.004)	(0.004)	(0.005)	(0.005)
Observations	1987149	1987149	1987149	1987149
R-squared	0.269	0.269	0.269	0.269
# Treated; Moderate	51317	60149	18556	19696
# Treated; Major	31964	36027	7646	9050
# Treated; Giant and Super-Giant	17575	19182	6212	7767
Panel (B) Downward Mobility				
Moderate Mining	-0.090***	-0.072***	-0.110**	-0.098**
	(0.021)	(0.020)	(0.044)	(0.041)
Major Mining	-0.044*	-0.001	-0.119***	-0.052
	(0.026)	(0.027)	(0.040)	(0.037)
Giant and Super-Giant Mining	-0.179***	-0.152***	-0.166***	-0.167***
	(0.045)	(0.049)	(0.042)	(0.049)
Observations	212820	212820	212820	212820
R-squared	0.286	0.286	0.286	0.286
# Treated; Moderate	2667	3260	898	976
# Treated; Major	2272	2630	704	840
# Treated; Giant and Super-Giant	2543	2633	1282	1398
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of all mineral discoveries (Columns 1-4) and productions (Columns 5-8) on the probability of upward (Panel A) and downward (Panel B) white-collar occupational IM across the size of mineral discoveries. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group include individuals born the discovery (production) and the control group those born before the discovery (production); Disc-10 (Prod-10) means that the treatment group include individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production); Disc-16 (Prod-16) means that the treatment group include individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) ; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production). *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.7.3 Depending on the gender

We examine whether the effects of mineral discoveries or productions on occupational mobility vary with the gender status of individuals and create a gender inequality issue.[11] The models are separately estimated for males and females. The results are reported in Table 5.22 and Table 5.23 for blue-collar and white-collar jobs, respectively, and for both males (Panel A) and females (Panel B). Overall, we find evidence of unequal effects of mineral discoveries and productions on occupational mobility for females and males, generally in favor of females when considering blue-collar jobs, and in favor of males when considering white-collar jobs. For blue-collar mobility, our results show that mineral productions lead to a higher likelihood to experience

[11] In terms of individuals in the sample, the fraction of males and females is unbalanced, with the share of males at 70 percent.

upward mobility for females than males, and both mineral discoveries and productions reduce more the likelihood to experience a downward mobility for females than males. The opposite results hold for white-collar mobility, for which we find that mineral discoveries and productions lead to a higher likelihood to have an upward mobility for males than females and reduce more the likelihood to experience a downward mobility for males than females.

Table 5.22: Sensitivity: gender, blue-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (I) Upward Mobility				**Panel (II) Downward mobility**			
	Discoveries		Productions		Discoveries		Productions	
	Disc-16	Disc-20	Prod-16	Prod-20	Disc-16	Disc-20	Prod-16	Prod-20
Panel (A) Males								
Mining	0.016***	0.019***	0.009	0.017***	-0.037***	-0.036***	-0.032**	-0.026
	(0.003)	(0.003)	(0.006)	(0.006)	(0.010)	(0.010)	(0.016)	(0.017)
Observations	1022013	1022013	1022013	1022013	536080	536080	536080	536080
R-squared	0.303	0.303	0.303	0.303	0.207	0.207	0.207	0.207
# Treated	56062	64168	16676	18844	18281	20266	8075	8746
Panel (B) Females								
Mining	0.008*	0.006	0.020**	0.028***	-0.033**	-0.045***	-0.048***	-0.048**
	(0.004)	(0.004)	(0.009)	(0.009)	(0.013)	(0.013)	(0.018)	(0.019)
Observations	406712	406712	406712	406712	235164	235164	235164	235164
R-squared	0.369	0.369	0.369	0.369	0.241	0.241	0.241	0.241
# Treated	24689	28948	6926	8068	9306	10499	3621	4069
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of all mineral discoveries (Columns 1-4) and productions (Columns 5-8) on the probability of upward (Panel A) and downward (Panel B) blue-collar occupational IM by gender. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group include individuals born the discovery (production) and the control group those born before the discovery (production); Disc-10 (Prod-10) means that the treatment group include individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production); Disc-16 (Prod-16) means that the treatment group include individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) ; Disc-20 (Prod-20) means that the treatment group include individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production). *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table 5.23: Sensitivity: gender, white-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (I) Upward Mobility				**Panel (II) Downward mobility**			
	Discoveries		Productions		Discoveries		Productions	
	Disc-16	Disc-20	Prod-16	Prod-20	Disc-16	Disc-20	Prod-16	Prod-20
Panel (A) Males								
Mining	0.017***	0.020***	0.008**	0.012***	-0.099***	-0.058***	-0.162***	-0.114***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.020)	(0.020)	(0.033)	(0.034)
Observations	1420027	1420027	1420027	1420027	138066	138066	138066	138066
R-squared	0.266	0.266	0.266	0.266	0.301	0.301	0.301	0.301
# Treated	69914	79359	23054	25702	4429	5075	1697	1888
Panel (B) Females								
Mining	0.006**	0.006***	0.000	0.011**	-0.069***	-0.049**	-0.095***	-0.073**
	(0.002)	(0.002)	(0.005)	(0.005)	(0.024)	(0.024)	(0.037)	(0.035)
Observations	567122	567122	567122	567122	74754	74754	74754	74754
R-squared	0.303	0.303	0.303	0.303	0.293	0.293	0.293	0.293
# Treated	30942	35999	9360	10811	3053	3448	1187	1326
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2 and 5-6) and first productions (Columns 3-4 and 7-8) on the probability of upward (Panel I) and downward (Panel II) white-collar occupational mobility by males (Panel A) and females (Panel B). Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

5.7.4 Depending on the urban-rural living area

We also study the differentiated effects of mineral discoveries and productions in urban and rural areas. We estimate the models separately for urban and rural areas. The results are presented in Table 5.24 and Table 5.25 for blue-collar and white-collar jobs, respectively, and for both urban (Panel A) and rural (Panel B) areas. Overall, we find that the positive effects of mineral activities on both blue- and white-collar mobility is higher in rural than urban areas, with the exception for upward mobility following mineral productions. In other words, our results reveal that mineral discoveries lead to a higher likelihood to experience upward blue- and white-collar mobility for individuals living in rural than those in urban areas, and both mineral discoveries and productions reduce more the likelihood to experience a downward blue- and white-collar mobility for individuals living in rural than those in urban areas. These findings reveal that mineral activities (close to 80 percent of them occur in rural areas) are more likely to create new job opportunities and favor structural changes in rural than urban areas.

Table 5.24: Sensitivity: residency, blue-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (I) Upward Mobility				**Panel (II) Downward mobility**			
	Discoveries		Productions		Discoveries		Productions	
	Disc-16	Disc-20	Prod-16	Prod-20	Disc-16	Disc-20	Prod-16	Prod-20
Panel (A) Urban								
Mining	-0.008	0.000	0.038**	0.041**	-0.011	-0.021**	-0.003	-0.015
	(0.010)	(0.009)	(0.019)	(0.018)	(0.010)	(0.010)	(0.015)	(0.016)
Observations	221081	221081	221081	221081	507628	507628	507628	507628
R-squared	0.274	0.274	0.274	0.274	0.0939	0.0939	0.0939	0.0939
# Treated	11508	13326	4552	5023	15397	16863	7388	7976
Panel (B) Rural								
Mining	0.013***	0.016***	0.009*	0.018***	-0.046***	-0.048***	-0.066***	-0.046**
	(0.003)	(0.003)	(0.005)	(0.005)	(0.012)	(0.012)	(0.020)	(0.020)
Observations	1207644	1207644	1207644	1207644	263616	263616	263616	263616
R-squared	0.259	0.259	0.259	0.259	0.198	0.198	0.198	0.198
# Treated	69243	79790	19050	21889	12190	13902	4308	4839
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2 and 5-6) and first productions (Columns 3-4 and 7-8) on the probability of upward (Panel I) and downward (Panel II) blue-collar occupational mobility by urban (Panel A) and rural (Panel B) areas. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. * Indicates significance at 10% level, ** significance at 5% level, and *** significance at 1% level.

Table 5.25: Sensitivity: residency, white-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (I) Upward Mobility				**Panel (II) Downward mobility**			
	Discoveries		Productions		Discoveries		Productions	
	Disc-16	Disc-20	Prod-16	Prod-20	Disc-16	Disc-20	Prod-16	Prod-20
Panel (A) Urban								
Mining	0.006	0.009**	0.019**	0.029***	-0.013	0.006	-0.069*	-0.063*
	(0.005)	(0.004)	(0.009)	(0.009)	(0.023)	(0.023)	(0.036)	(0.037)
Observations	582314	582314	582314	582314	146395	146395	146395	146395
R-squared	0.256	0.256	0.256	0.256	0.277	0.277	0.277	0.277
# Treated	23033	25852	9993	10884	3872	4337	1947	2115
Panel (B) Rural								
Mining	0.014***	0.015***	0.001	0.008***	-0.086***	-0.047**	-0.105***	-0.078**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.020)	(0.020)	(0.033)	(0.032)
Observations	1404835	1404835	1404835	1404835	66425	66425	66425	66425
R-squared	0.250	0.250	0.250	0.250	0.328	0.328	0.328	0.328
# Treated	77823	89506	22421	25629	3610	4186	937	1099
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results for the effects of first mineral discoveries (Columns 1-2 and 5-6) and first productions (Columns 3-4 and 7-8) on the probability of upward (Panel I) and downward (Panel II) white-collar occupational mobility by urban (Panel A) and rural (Panel B) areas. Robust standard errors are in parentheses. Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and *** significance at 1% level.

5.8 Conclusion and Policy implications

In this paper, we empirically examine the impact of mineral discoveries and productions on intergenerational occupational mobility using a sample of around 1.5 million individuals across 2,690 districts from 27 African countries. We build absolute mobility measures and define upward and downward occupational mobility for blue- and white-collar jobs. We employ a generalized difference-in-differences model in a quasi-natural experiment to identify the causal relationship between mineral discoveries and productions and intergenerational occupational mobility. We find that mineral discoveries and productions positively affect blue- and white-collar intergenerational occupational mobility for individuals exposed to and living in areas with mining activities. They have contributed to an improvement of the labor market conditions in resource-rich districts. Moreover, we also show that the positive effects of mineral discoveries and productions also apply to individuals aged 16-20 years old entering in the labor market at the time of discovery and production, but interestingly, the positive effects are higher for those born after the discovery or production.

Furthermore, we unveil two underpinning transmission channels, including the demand for skilled workers channel (demand-side factor) and the educational channel (supply-side factor). First, we uncover that the creation of new jobs following the discoveries of mineral resources will increase the demand for skilled workers, thereby boosting the likelihood of intergenerational occupational mobility. Second, we find that children exposed to mineral activities tend to have higher educational mobility driven by higher return to education and new and higher income of their parents is invested in their education. Our results are robust to several robustness checks. In addition, we find heterogeneous effects depending on the African region's location, mineral discoveries' size, gender, and urban-rural residency.

Based on our findings, we can formulate two main policy recommendations. First, the positive effects of mining activities on occupational mobility will not materialize by themselves and need to be supported by public policies. In this regard, governments should enact reforms to facilitate the creation of jobs and entrepreneurship, particularly outside of the agricultural sector. As evidenced in this paper, education plays an important role. Therefore, policies to boost schooling infrastructure and education quality and ensuring that training are aligned with the local labor markets needs should be pursued. Second, to address unequal benefits of mining activities, authorities should implement targeted policies to ease access to female job opportunities in higher skilled jobs and enhance job opportunities in rural and urban areas based on the local conditions.

As an avenue for future research, it would be interesting to explore the effects of artisanal mining activities on intergenerational mobility in Africa. In this paper, we mainly focused on industrial mining because reliable data on artisanal mining activities are lacking.

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APPENDIX D

APPENDIX TO CHAPTER 5

D.1 Sample

Table D.1: Construction of sample from raw IPUMS data

(1) Country	(2) Year	(3) Nall	(4) Ndistrict	(5) Nocc	(6) Nliverelative	(7) Nlivebiop	(8) Nage	(9) Nsex	(10) Nurban	(11) Ncont	(12) Nim	(13) Nimbiop	(13) Inc.
Benin	1979	331 049	331 049	109 880	33 267	24 503	12 750	12 750	0	0	0	0	no
Benin	1992	498 419	498 419	204 190	63 452	55 000	37 071	37 071	37 071	30 715	11 619	11 170	yes
Benin	2002	685 467	685 467	307 826	100 577	63 802	56 690	56 690	56 690	28 405	15 702	15 132	yes
Benin	2013	1 009 693	1 009 693	324 468	98 931	63 343	63 984	63 984	63 984	34 399	16 306	15 894	yes
Total		**2 524 628**	**2 524 628**	**946 364**	**296 227**	**206 648**	**170 495**	**170 495**	**157 745**	**93 519**	**43 627**	**42 196**	
Botswana	1981	97 238	97 238	12 832	2 077	1 564	1 508	1 508	0	0	0	0	no
Botswana	1991	132 623	132 623	36 859	6 704	5 346	5 470	5 470	5 470	4 416	1 837	1 756	yes
Botswana	2001	168 676	168 676	43 610	7 983	6 404	7 477	7 477	0	0	0	0	no
Botswana	2011	201 752	201 752	62 597	10 682	8 405	10 050	10 050	0	0	0	0	no
Total		**600 289**	**600 289**	**155 898**	**27 446**	**21 719**	**24 505**	**24 505**	**5 470**	**4 416**	**1 837**	**1 756**	
Cameroon	1976	736 514	736 514	274 334	50 137	42 278	18 580	18 579	0	0	0	0	no
Cameroon	1987	897 211	897 211	0	0	0	0	0	0	0	0	0	no
Cameroon	2005	1 772 359	1 766 211	490 230	112 637	96 460	79 134	79 134	79 134	65 499	16 251	15 694	yes
Total		**3 406 084**	**3 399 936**	**764 564**	**162 774**	**138 738**	**97 714**	**97 713**	**79 134**	**65 499**	**16 251**	**15 694**	
Egypt	1986	6 799 093	6 799 093	1 585 317	514 199	479 223	440 545	440 545	440 545	416 614	119 104	117 344	yes
Egypt	1996	5 902 243	5 902 243	1 489 399	460 964	450 948	433 102	433 102	433 102	423 514	126 918	126 353	yes
Egypt	2006	7 282 434	7 282 434	1 997 466	536 234	519 591	507 304	507 304	507 304	491 971	166 265	165 668	yes
Total		**19 983 770**	**19 983 770**	**5 072 182**	**1 511 397**	**1 449 762**	**1 380 951**	**1 380 951**	**1 380 951**	**1 332 099**	**412 287**	**409 365**	
Ethiopia	1984	3 404 306	3 400 221	1 431 362	369 096	336 152	149 646	149 645	149 645	130 333	8 431	8 253	yes
Ethiopia	1994	5 044 598	5 044 598	2 397 145	782 287	759 404	403 625	403 625	403 625	384 960	74 029	73 450	yes
Ethiopia	2007	7 434 086	7 434 086	0	0	0	0	0	0	0	0	0	no
Total		**15 882 990**	**15 878 905**	**3 828 507**	**1 151 383**	**1 095 556**	**553 271**	**553 270**	**553 270**	**515 293**	**82 460**	**81 703**	
Ghana	1984	1 309 352	1 309 352	596 613	189 640	189 640	129 157	129 157	0	0	0	0	no
Ghana	2000	1 894 133	1 894 133	902 741	215 176	187 945	151 333	151 333	151 333	128 702	57 974	57 234	yes
Ghana	2010	2 466 289	2 466 289	1 116 271	285 078	253 527	207 340	207 340	207 340	180 404	81 150	79 223	yes
Total		**5 669 774**	**5 669 774**	**2 615 625**	**689 894**	**631 112**	**487 830**	**487 830**	**358 673**	**309 106**	**139 124**	**136 457**	
Guinea	1983	457 837	457 837	175 942	31 205	30 766	16 912	16 903	16 858	16 696	2 024	1 950	yes
Guinea	1996	729 071	729 071	328 774	117 641	96 034	62 222	62 222	62 222	45 716	8 868	8 006	yes
Guinea	2014	1 050 916	1 050 916	415 527	180 742	144 208	98 543	98 543	98 543	71 310	27 073	24 475	yes
Total		**2 237 824**	**2 237 824**	**920 243**	**329 588**	**271 008**	**177 677**	**177 668**	**177 623**	**133 722**	**37 965**	**34 431**	
Kenya	1969	659 310	659 310	0	0	0	0	0	0	0	0	0	no
Kenya	1979	1 033 769	1 033 769	0	0	0	0	0	0	0	0	0	no
Kenya	1989	1 074 098	1 074 098	368 386	73 444	68 280	48 400	48 400	48 400	44 979	16 591	16 542	yes
Kenya	1999	1 407 547	1 407 547	0	0	0	0	0	0	0	0	0	no
Kenya	2009	3 841 935	3 841 935	0	0	0	0	0	0	0	0	0	no
Total		**8 016 659**	**8 016 659**	**368 386**	**73 444**	**68 280**	**48 400**	**48 400**	**48 400**	**44 979**	**16 591**	**16 542**	
Lesotho	1996	187 795	187 776	42 373	13 021	11 577	11 096	11 096	11 096	9 920	3 455	3 433	yes
Lesotho	2006	180 208	180 208	50 168	12 810	11 703	12 027	12 027	12 027	10 959	5 076	5 058	yes
Total		**368 003**	**367 984**	**92 541**	**25 831**	**23 280**	**23 123**	**23 123**	**23 123**	**20 879**	**8 531**	**8 491**	
Liberia	1974	150 256	150 256	41 431	0	0	0	0	0	0	0	0	no
Liberia	2008	348 057	348 057	347 467	172 303	162 011	47 583	47 583	47 583	44 152	25 310	25 176	yes
Total		**498 313**	**498 313**	**388 898**	**172 303**	**162 011**	**47 583**	**47 583**	**47 583**	**44 152**	**25 310**	**25 176**	
Malawi	1987	798 669	798 669	337 666	32 254	31 105	23 112	23 112	23 112	22 258	2 213	2 211	yes
Malawi	1998	991 393	991 393	449 992	50 945	47 628	35 795	35 795	35 795	33 252	5 761	5 750	yes
Malawi	2008	1 341 977	1 341 977	406 989	62 384	60 654	30 805	30 805	30 543	28 976	10 926	10 891	yes
Total		**3 132 039**	**3 132 039**	**1 194 647**	**145 583**	**139 387**	**89 712**	**89 712**	**89 450**	**84 486**	**18 900**	**18 852**	
Mali	1987	785 384	784 096	344 048	130 756	121 263	54 945	54 945	0	0	0	0	no
Mali	1998	991 330	991 330	395 889	166 775	156 801	78 751	78 751	78 751	70 383	8 592	8 142	yes
Mali	2009	1 451 856	1 451 856	498 322	194 029	166 344	104 792	104 792	104 792	84 296	14 636	13 430	yes
Total		**3 228 570**	**3 227 282**	**1 238 259**	**491 560**	**444 408**	**238 488**	**238 488**	**183 543**	**154 679**	**23 228**	**21 572**	

Table D.2: Construction of sample from raw IPUMS data (continued)

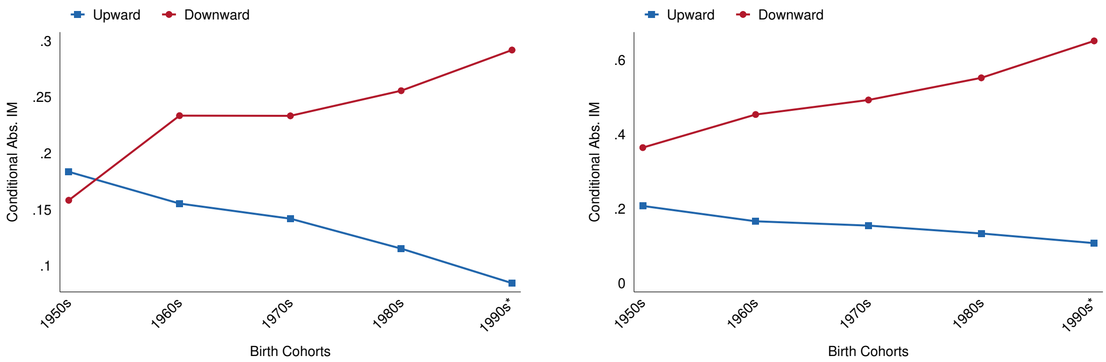
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(13)
Country	**Year**	**Nall**	**Ndistrict**	**Nocc**	**Nliverelative**	**Nlivebiop**	**Nage**	**Nsex**	**Nurban**	**Ncont**	**Nim**	**Nimbiop**	**Inc.**
Mauritius	1990	106 710	106 710	46 529	17 052	16 099	15 386	15 386	15 386	14 484	10 009	9 988	yes
Mauritius	2000	119 695	119 695	55 643	17 090	15 832	16 502	16 502	16 502	15 266	10 991	10 975	yes
Mauritius	2011	126 332	126 332	67 122	18 201	16 449	17 114	17 114	17 114	15 405	12 107	12 092	yes
Total		**352 737**	**352 737**	**169 294**	**52 343**	**48 380**	**49 002**	**49 002**	**49 002**	**45 155**	**33 107**	**33 055**	
Morocco	1982	1 012 873	1 012 873	312 573	136 613	131 883	93 554	93 554	0	0	0	0	no
Morocco	1994	1 294 026	1 294 026	365 908	171 658	165 034	144 312	144 312	0	0	0	0	no
Morocco	2004	1 482 720	1 482 720	470 790	223 756	214 699	204 772	204 772	0	0	0	0	no
Morocco	2014	3 341 426	3 340 830	1 008 595	420 771	408 203	392 308	392 308	391 297	380 269	146 362	144 937	yes
Total		**7 131 045**	**7 130 449**	**2 157 866**	**952 798**	**919 819**	**834 946**	**834 946**	**391 297**	**380 269**	**146 362**	**144 937**	
Mozambique	1997	1 551 517	1 551 517	656 841	155 616	134 092	81 109	81 109	81 109	64 018	15 578	15 531	yes
Mozambique	2007	2 047 048	2 047 048	798 873	164 695	141 071	95 558	95 558	95 558	75 623	24 729	24 652	yes
Total		**3 598 565**	**3 598 565**	**1 455 714**	**320 311**	**275 163**	**176 667**	**176 667**	**176 667**	**139 641**	**40 307**	**40 183**	
Nigeria	2006	83 700	83 700	0	0	0	0	0	0	0	0	0	no
Nigeria	2007	85 183	85 183	0	0	0	0	0	0	0	0	0	no
Nigeria	2008	107 425	107 425	37 768	6 629	6 243	4 549	4 542	4 529	4 227	1 653	1 632	yes
Nigeria	2009	77 896	77 896	21 018	4 542	4 184	2 941	2 934	2 934	2 678	580	551	yes
Nigeria	2010	72 191	72 191	31 184	8 315	7 896	4 588	4 588	4 588	4 254	1 014	996	yes
Total		**426 395**	**426 395**	**89 970**	**19 486**	**18 323**	**12 078**	**12 064**	**12 051**	**11 159**	**3 247**	**3 179**	
Rwanda	1991	742 918	742 918	0	0	0	0	0	0	0	0	0	no
Rwanda	2002	843 392	843 392	340 616	69 998	67 788	57 275	57 275	57 275	55 674	4 908	4 879	yes
Rwanda	2012	1 038 369	1 038 369	418 930	74 641	71 494	69 486	69 486	69 486	66 760	14 490	14 427	yes
Total		**2 624 679**	**2 624 679**	**759 546**	**144 639**	**139 282**	**126 761**	**126 761**	**126 761**	**122 434**	**19 398**	**19 306**	
Senegal	1988	700 199	700 199	236 666	83 509	73 854	43 653	43 653	0	0	0	0	no
Senegal	2002	994 562	994 562	304 799	131 466	122 017	99 860	99 860	99 860	91 955	29 957	27 315	yes
Senegal	2013	1 245 551	1 016 023	310 981	150 548	113 244	125 404	125 404	125 404	91 537	47 605	43 731	yes
Total		**2 940 312**	**2 710 784**	**852 446**	**365 523**	**309 115**	**268 917**	**268 917**	**225 264**	**183 492**	**77 562**	**71 046**	
Sierra Leone	2004	494 298	494 298	196 470	53 951	40 293	40 346	40 346	40 346	29 393	5 958	5 476	yes
Total		**494 298**	**494 298**	**196 470**	**53 951**	**40 293**	**40 346**	**40 346**	**40 346**	**29 393**	**5 958**	**5 476**	
South Africa	1996	3 621 164	3 621 164	769 123	122 338	108 233	114 158	114 158	114 157	102 642	39 289	38 580	yes
South Africa	2001	3 725 655	3 725 655	722 517	121 202	105 572	116 554	116 554	116 527	102 458	38 728	37 840	yes
South Africa	2007	1 047 657	1 047 657	198 958	37 683	33 457	36 120	36 120	36 120	32 353	13 698	13 409	yes
South Africa	2011	4 418 594	4 418 594	0	0	0	0	0	0	0	0	0	no
South Africa	2016	3 328 793	3 328 793	0	0	0	0	0	0	0	0	0	no
Total		**16 141 863**	**16 141 863**	**1 690 598**	**281 223**	**247 262**	**266 832**	**266 832**	**266 804**	**237 453**	**91 715**	**89 829**	
South Sudan	2008	542 765	542 765	224 390	74 766	65 949	40 312	40 312	40 312	34 113	14 602	14 334	yes
Total		**542 765**	**542 765**	**224 390**	**74 766**	**65 949**	**40 312**	**40 312**	**40 312**	**34 113**	**14 602**	**14 334**	
Sudan	2008	5 066 530	5 066 530	1 248 195	418 534	397 342	270 442	270 442	270 442	253 782	89 717	86 277	yes
Total		**5 066 530**	**5 066 530**	**1 248 195**	**418 534**	**397 342**	**270 442**	**270 442**	**270 442**	**253 782**	**89 717**	**86 277**	
Tanzania	1988	2 310 424	2 310 424	1 070 201	170 250	167 694	132 726	132 726	0	0	0	0	no
Tanzania	2002	3 732 735	3 732 735	1 613 633	333 568	308 362	234 853	234 853	234 853	213 802	35 620	35 459	yes
Tanzania	2012	4 498 022	4 498 022	1 771 740	357 612	329 837	265 895	265 895	265 895	243 429	47 409	46 875	yes
Total		**10 541 181**	**10 541 181**	**4 455 574**	**861 430**	**805 893**	**633 474**	**633 474**	**500 748**	**457 231**	**83 029**	**82 334**	
Togo	1960	13 759	13 759	5 041	803	534	0	0	0	0	0	0	no
Togo	1970	23 680	23 680	9 154	2 167	2 072	455	455	0	0	0	0	no
Togo	2010	584 859	584 859	215 269	4 854	3 496	3 732	3 732	3 732	2 816	355	365	yes
Total		**622 298**	**622 298**	**229 464**	**7 824**	**6 102**	**4 187**	**4 187**	**3 732**	**2 816**	**355**	**365**	
Uganda	1991	1 548 460	1 529 024	595 899	110 943	105 487	73 967	73 967	73 967	69 353	14 902	14 775	yes
Uganda	2002	2 497 449	2 497 449	750 654	109 251	105 530	79 309	79 309	79 309	76 365	16 536	16 269	yes
Uganda	2014	3 506 546	3 506 546	0	0	0	0	0	0	0	0	0	no
Total		**7 552 455**	**7 533 019**	**1 346 553**	**220 194**	**211 017**	**153 276**	**153 276**	**153 276**	**145 718**	**31 438**	**31 044**	
Zambia	1990	787 461	787 461	141 920	20 278	20 186	16 188	16 188	16 188	16 121	2 952	2 952	yes
Zambia	2000	996 117	996 117	282 149	62 742	42 194	51 896	51 896	51 896	33 037	6 197	5 946	yes
Zambia	2010	1 321 973	1 321 973	370 244	69 498	56 667	55 724	55 724	0	0	0	0	no
Total		**3 105 551**	**3 105 551**	**794 313**	**152 518**	**119 047**	**123 808**	**123 808**	**68 084**	**49 158**	**9 149**	**8 898**	
Zimbabwe	2012	654 688	654 688	216 786	27 708	25 208	25 061	25 061	25 061	22 828	6 360	6 287	yes
Total		**654 688**	**654 688**	**216 786**	**27 708**	**25 208**	**25 061**	**25 061**	**25 061**	**22 828**	**6 360**	**6 287**	
Total All		**127 344 305**	**127 083 205**	**33 473 293**	**9 030 678**	**8 280 104**	**6 365 858**	**6 365 833**	**5 454 812**	**4 917 471**	**1 478 417**	**1 448 785**	**51/79**

Notes: This table shows how we construct our final sample from the raw IPUMS data. Columns (1) and (2) give the country and census year, respectively. Columns (3) shows the initial number of observations in IPUMS data. Column (4) gives the number of observations with available information on district. Column (5) gives the number of observations with available information on occupation and district. Column (6) gives the number of observations for individuals living with at least one relative and for which information on occupation and district is available. Column (7) gives the number of observations for individuals living with at least one biological or step- parents and for which information on occupational and district is available. Column (8) gives the number of observations for individuals aged 20-50 years old and born after 1950 living with at least one relative and for which information on occupation and district is available. Column (9) gives the number of observations for individuals aged 20-50 years old and born after 1950 living with at least one relative and for which information on gender, occupation and district is available. Column (10) gives the number of observations for individuals aged 20-50 years old and born after 1950 living with at least one relative and for which information on residency (urban or rural areas), gender, occupation and district is available. Column (11) gives the number of observations for individuals aged 20-50 years old and born after 1950 living with at least one relative and for which information on residency (urban or rural areas), gender, occupation, district, and other control variables is available. Column (12) gives the final sample with data on occupational mobility where the reference group is the immediate older generation. Column (13) gives the final sample with data on occupational mobility where the reference group is the biological or step- parents (baseline). Column (14) gives the census/survey used in the final sample.

D.2 Stylized facts on Occupational mobility

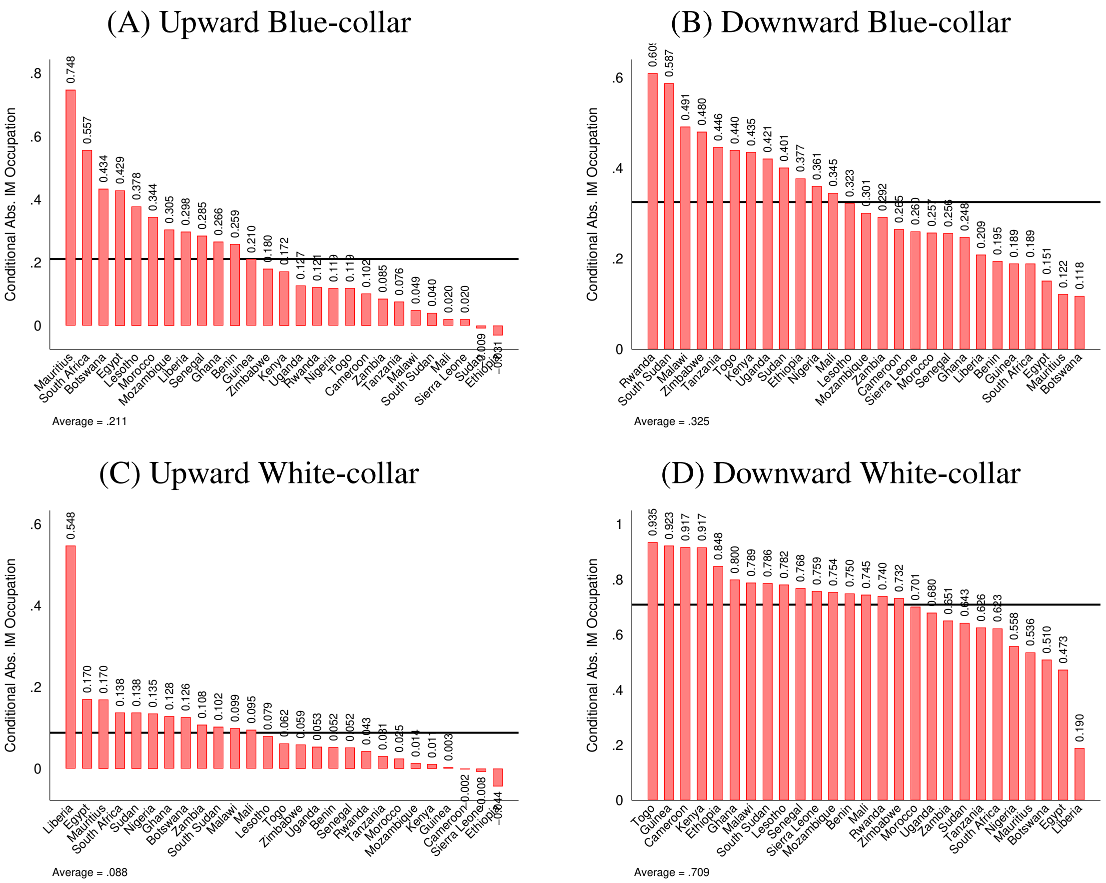
Figure D.1: Occupational mobility by birth cohorts

(A) Blue-collar (B) White-collar



Source: Authors' calculations based on IPUMS dataset
Notes: Conditional mobility is obtained from regressing occupational mobility indices on country or district fixed effects, cohort fixed effects and census-year fixed effects.

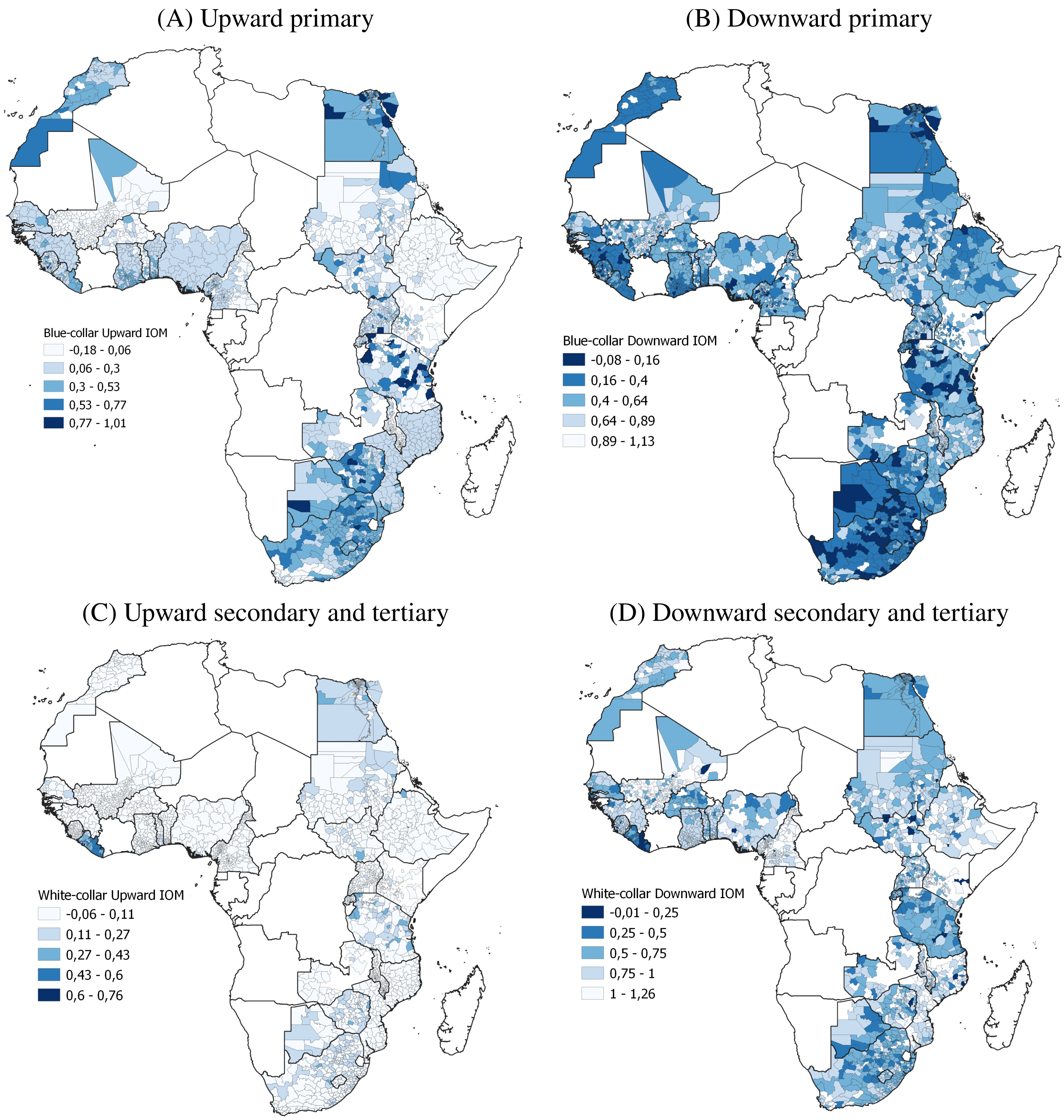
Figure D.2: Ranking: Country-level occupational mobility



Source: Authors' calculations based on IPUMS dataset

Notes: Conditional mobility is obtained from regressing occupational mobility indices on country or district fixed effects, cohort fixed effects and census-year fixed effects.

Figure D.3: District-level occupational IM



Source: Authors' calculations based on IPUMS dataset
Notes: Conditional mobility is obtained from regressing occupational mobility indices on country or district fixed effects, cohort fixed effects and census-year fixed effects.

D.3 Baseline results with control variables

Table D.3: Baseline results with control variables, Upward mobility for Blue-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Discoveries				Productions			
	Disc-B/A	Disc-10	Disc-16	Disc-20	Prod-B/A	Prod-10	Prod-16	Prod-20
Mining	0.013	0.009***	0.014***	0.017***	0.021	0.017**	0.014***	0.023***
	(0.011)	(0.003)	(0.003)	(0.003)	(0.016)	(0.007)	(0.005)	(0.005)
Males (base level)								
Female	0.002	0.002***	0.002***	0.003***	0.002	0.002***	0.002***	0.002***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Age	0.021***	0.021***	0.021***	0.021***	0.021***	0.021***	0.021***	0.021***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Single (base level)								
Married/in union	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Separated or divorced	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Widowed	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
No education (base level)								
Primary education completed	0.095***	0.095***	0.095***	0.095***	0.095***	0.095***	0.095***	0.095***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Secondary education completed	0.265***	0.265***	0.265***	0.265***	0.265***	0.265***	0.265***	0.265***
	(0.005)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)
Tertiary education completed	0.474***	0.474***	0.474***	0.474***	0.474***	0.474***	0.474***	0.474***
	(0.009)	(0.003)	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.003)
Parents: no education (base level)								
Parents: primary education completed	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Parents: secondary education completed	0.016**	0.016***	0.016***	0.016***	0.016**	0.016***	0.016***	0.016***
	(0.007)	(0.004)	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)
Parents: tertiary education completed	-0.082***	-0.082***	-0.082***	-0.082***	-0.082***	-0.082***	-0.082***	-0.082***
	(0.029)	(0.013)	(0.013)	(0.013)	(0.029)	(0.013)	(0.013)	(0.013)
Live with father/stepfather only (base level)								
Live with mother/stepmother only	0.003	0.003*	0.003*	0.003*	0.003	0.003*	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Live with father/stepfather and mother/stepmother	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
HH head male (base level)								
HH head female	0.004*	0.004***	0.004***	0.004***	0.004**	0.004***	0.004***	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Household size	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural (level)								
Urban	0.155***	0.155***	0.155***	0.155***	0.155***	0.155***	0.155***	0.155***
	(0.005)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)
Constant	-0.241***	-0.241***	-0.241***	-0.241***	-0.241***	-0.241***	-0.241***	-0.241***
	(0.015)	(0.006)	(0.006)	(0.006)	(0.015)	(0.006)	(0.006)	(0.006)
Observations	1428725	1428725	1428725	1428725	1428725	1428725	1428725	1428725
R-squared	0.307	0.307	0.307	0.307	0.307	0.307	0.307	0.307
# Treated	44135	65016	80751	93116	14236	18746	23602	26912
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the baseline results for the effects of first mineral discoveries (Columns 1-4) and first productions (Columns 5-8) on the probability of upward blue-collar occupational mobility. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group includes individuals born after the discovery (production) and the control group those born before the discovery (production) or in districts without discovery; Disc-10 (Prod-10) means that the treatment group includes individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production) or in districts without discovery; Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table D.4: Baseline results with control variables, Downward mobility for Blue-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Discoveries				Productions			
	Disc-B/A	Disc-10	Disc-16	Disc-20	Prod-B/A	Prod-10	Prod-16	Prod-20
Mining	-0.019	-0.008	-0.037***	-0.042***	-0.012	-0.034**	-0.042***	-0.035***
	(0.018)	(0.009)	(0.008)	(0.008)	(0.022)	(0.014)	(0.012)	(0.013)
Males (base level)								
Female	-0.037***	-0.037***	-0.037***	-0.037***	-0.037***	-0.037***	-0.037***	-0.037***
	(0.005)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)
Age	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Age squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Single (base level)								
Married/in union	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Separated or divorced	0.009*	0.009***	0.009***	0.009***	0.009*	0.009***	0.009***	0.009***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Widowed	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
No education (base level)								
Primary education completed	-0.063***	-0.063***	-0.063***	-0.063***	-0.063***	-0.063***	-0.063***	-0.063***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)
Secondary education completed	-0.139***	-0.139***	-0.139***	-0.139***	-0.139***	-0.139***	-0.139***	-0.139***
	(0.005)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)
Tertiary education completed	-0.183***	-0.183***	-0.183***	-0.183***	-0.183***	-0.183***	-0.183***	-0.183***
	(0.007)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.002)	(0.002)
Parents: no education (base level)								
Parents: primary education completed	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Parents: secondary education completed	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Parents: tertiary education completed	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Live with father/stepfather only (base level)								
Live with mother/stepmother only	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Live with father/stepfather and mother/stepmother	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
HH head male (base level)								
HH head female	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
Household size	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural (level)								
Urban	-0.172***	-0.172***	-0.172***	-0.172***	-0.172***	-0.172***	-0.172***	-0.172***
	(0.006)	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)
Constant	0.828***	0.828***	0.828***	0.828***	0.828***	0.828***	0.828***	0.828***
	(0.035)	(0.010)	(0.010)	(0.010)	(0.035)	(0.010)	(0.010)	(0.010)
Observations	771244	771244	771244	771244	771244	771244	771244	771244
R-squared	0.195	0.195	0.195	0.195	0.195	0.195	0.195	0.195
# Treated	17692	23452	27587	30765	7820	10203	11696	12815
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the baseline results for the effects of first mineral discoveries (Columns 1-4) and first productions (Columns 5-8) on the probability of downward blue-collar occupational mobility. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group includes individuals born after the discovery (production) and the control group those born before the discovery (production) or in districts without discovery; Disc-10 (Prod-10) means that the treatment group includes individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production) or in districts without discovery; Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level

Table D.5: Baseline results with control variables, Upward mobility for White-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Discoveries				Productions			
	Disc-B/A	Disc-10	Disc-16	Disc-20	Prod-B/A	Prod-10	Prod-16	Prod-20
Mining	0.015***	0.016***	0.014***	0.016***	0.007	0.010***	0.006**	0.013***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.005)	(0.003)	(0.003)	(0.003)
Males (base level)								
Female	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Age	0.008***	0.008***	0.008***	0.007***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Single (base level)								
Married/in union	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Separated or divorced	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Widowed	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No education (base level)								
Primary education completed	0.031***	0.031***	0.031***	0.031***	0.031***	0.031***	0.031***	0.031***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Secondary education completed	0.211***	0.211***	0.211***	0.211***	0.211***	0.211***	0.211***	0.211***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)
Tertiary education completed	0.631***	0.631***	0.631***	0.631***	0.631***	0.631***	0.631***	0.631***
	(0.008)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)	(0.002)
Parents: no education (base level)								
Parents: primary education completed	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parents: secondary education completed	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)
Parents: tertiary education completed	-0.017	-0.017**	-0.017**	-0.017**	-0.017	-0.017**	-0.017**	-0.017**
	(0.011)	(0.007)	(0.007)	(0.007)	(0.011)	(0.007)	(0.007)	(0.007)
Live with father/stepfather only (base level)								
Live with mother/stepmother only	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Live with father/stepfather and mother/stepmother	0.001	0.001*	0.001*	0.001*	0.001	0.001*	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HH head male (base level)								
HH head female	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household size	0.000	0.000**	0.000**	0.000**	0.000	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural (level)								
Urban	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.064***	-0.064***	-0.064***	-0.064***	-0.064***	-0.064***	-0.064***	-0.064***
	(0.008)	(0.003)	(0.003)	(0.003)	(0.008)	(0.003)	(0.003)	(0.003)
Observations	1987149	1987149	1987149	1987149	1987149	1987149	1987149	1987149
R-squared	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269
# Treated	57339	82336	100856	115358	20167	26550	32414	36513
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the baseline results for the effects of first mineral discoveries (Columns 1-4) and first productions (Columns 5-8) on the probability of upward white-collar occupational mobility. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group includes individuals born after the discovery (production) and the control group those born before the discovery (production) or in districts without discovery; Disc-10 (Prod-10) means that the treatment group includes individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production) or in districts without discovery; Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Table D.6: Baseline results with control variables, Downward mobility for White-collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Discoveries				Productions			
	Disc-B/A	Disc-10	Disc-16	Disc-20	Prod-B/A	Prod-10	Prod-16	Prod-20
Mining	-0.070	-0.104***	-0.087***	-0.058***	-0.041	-0.091***	-0.133***	-0.098***
	(0.049)	(0.018)	(0.015)	(0.015)	(0.048)	(0.031)	(0.024)	(0.024)
Males (base level)								
Female	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***
	(0.006)	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)
Age	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Age squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Single (base level)								
Married/in union	0.008*	0.008***	0.008***	0.008***	0.008*	0.008***	0.008***	0.008***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Separated or divorced	0.018**	0.018***	0.018***	0.018***	0.018**	0.018***	0.018***	0.018***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)	(0.006)
Widowed	-0.006	-0.007	-0.007	-0.007	-0.006	-0.006	-0.007	-0.007
	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
No education (base level)								
Primary education completed	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Secondary education completed	-0.227***	-0.227***	-0.227***	-0.227***	-0.227***	-0.227***	-0.227***	-0.227***
	(0.012)	(0.003)	(0.003)	(0.003)	(0.012)	(0.003)	(0.003)	(0.003)
Tertiary education completed	-0.597***	-0.597***	-0.597***	-0.597***	-0.597***	-0.597***	-0.597***	-0.597***
	(0.012)	(0.004)	(0.004)	(0.004)	(0.012)	(0.004)	(0.004)	(0.004)
Parents: no education (base level)								
Parents: primary education completed	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Parents: secondary education completed	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)
Parents: tertiary education completed	-0.071***	-0.071***	-0.071***	-0.071***	-0.071***	-0.071***	-0.071***	-0.071***
	(0.008)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)	(0.004)	(0.004)
Live with father/stepfather only (base level)								
Live with mother/stepmother only	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.010)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)	(0.007)	(0.007)
Live with father/stepfather and mother/stepmother	-0.011**	-0.011***	-0.011***	-0.011***	-0.011**	-0.011***	-0.011***	-0.011***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
HH head male (base level)								
HH head female	-0.022**	-0.022***	-0.022***	-0.022***	-0.021**	-0.022***	-0.022***	-0.022***
	(0.009)	(0.005)	(0.005)	(0.005)	(0.009)	(0.005)	(0.005)	(0.005)
Household size	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Rural (level)								
Urban	-0.009	-0.009***	-0.009***	-0.009***	-0.009	-0.009***	-0.009***	-0.009***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)
Constant	1.211***	1.210***	1.210***	1.210***	1.210***	1.210***	1.210***	1.210***
	(0.047)	(0.023)	(0.023)	(0.023)	(0.047)	(0.023)	(0.023)	(0.023)
Observations	212820	212820	212820	212820	212820	212820	212820	212820
R-squared	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
# Treated	4488	6132	7482	8523	1889	2399	2884	3214
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the baseline results for the effects of first mineral discoveries (Columns 1-4) and first productions (Columns 5-8) on the probability of downward white-collar occupational mobility. Robust standard errors are in parentheses. Disc-B/A (Prod-B/A) means that the treatment group includes individuals born after the discovery (production) and the control group those born before the discovery (production) or in districts without discovery; Disc-10 (Prod-10) means that the treatment group includes individuals born 10 years before the discovery (production) to after and the control group those born 11 years before the discovery (production) or in districts without discovery; Disc-16 (Prod-16) means that the treatment group includes individuals born 16 years before the discovery (production) to after and the control group those born 17 years before the discovery (production) or in districts without discovery; Disc-20 (Prod-20) means that the treatment group includes individuals born 20 years before the discovery (production) to after and the control group those born 21 years before the discovery (production) or in districts without discovery. *Indicates significance at 10% level, **significance at 5% level, and ***significance at 1% level.

Chapter 6

General Conclusion

At the end of this journey, it is essential to recall that the dissertation aimed to investigate the macroeconomic impacts of the giant discoveries of oil, gas, and minerals. From a macro standpoint, this dissertation analyzes the differentiated effects of giant discoveries on access to international financial markets proxied by sovereign debt ratings in developing and emerging countries. From a micro standpoint, it focuses exclusively on Africa and studies; and the microeconomic effects of mining discoveries and productions on intergenerational mobility in education and occupation. By covering the macro and micro aspects of giant discoveries, this dissertation provides a general overview of the potential effects of giant discoveries while contributing to the ongoing debate on whether countries are blessed or cursed to be rich in natural resources. Throughout its four chapters, this thesis reveals that the impact depends on, among others, how countries and populations react to the news of the discoveries, how governments conduct their macroeconomic policies in the aftermath of discoveries and use the windfalls from the resources, how the revenues from discoveries are used to impact the education, local development, and labor markets, improving the well-being of populations.

Specifically, from a macro standpoint, chapter 2 uses a sample of 28 developing and emerging countries and employs a random effect ordered probit model over the period 1990-2014 to analyze the impact of giant discoveries of oil, gas, and mineral on the sovereign debt ratings in the short and long term. It finds evidence of differentiated effects of giant discoveries in which some countries experience an improvement of their sovereign debt ratings while others experience a deterioration of financial conditions in the aftermath of discoveries. For a group of 13 countries in the sample, giant discoveries are associated with decreased ratings in the short term but increased ratings in the medium to long term. For another group of 15 countries, the effect is non-significant in the short term but is negative in the medium to long term. This paper also found evidence of learning effects in countries with improving sovereign debt ratings, as the history of past discoveries is positively associated with sovereign debt ratings. In addition, giant discoveries are found to be good predictors of access to financial markets, affecting both positively or negatively the ratings, which differentiated effects depend on the behavior of several macroeconomic variables and political indicators, including tax resources, public debt, development of financial markets, investments and quality of institutions. What seems to matter is not only the resources but also how governments respond to the news of the discovery. Indeed, this chapter shows that in countries with increasing ratings, on average, giant discoveries are associated with increased tax revenues to GDP, investments, decreased public debt to GDP, and improved government stability. Contrarily, in countries with decreasing ratings, giant discoveries are associated with a reduction in investments and an increase in corruption. These findings call for a careful assessment of governments' decisions in the aftermath of giant discoveries. Taking the right actions and policies will help countries to prevent a deterioration of their financial conditions.

Chapter 3 takes a different route from the previous papers in the literature by investigating the impact of the peak of giant discoveries rather than any giant discoveries or natural resources endowments. Indeed, the peak of discoveries appears to be more exogenous and could also be associated with more significant and amplified effects on sovereign debt ratings (Tsui 2011; Masi and Ricciuti 2019). It empirically studies the effects of the peak of oil and mineral giant discoveries on the institutional investor country rating using a Synthetic Control Method from 1985 to 2014 and considering five developing countries, including Angola, Kazakhstan, Romania, Gabon, and Cameroon. This chapter confirms the heterogeneous effects of natural resources discoveries on country ratings as found in the previous chapter, with improved ratings observed in the years following the peak of discoveries in Angola, Kazakhstan, and Romania, while deteriorated ratings have been found in Gabon and Cameroon in the aftermath of the peak of discoveries. The description of the case studies reveals that factors like diversification, sound macroeconomic and borrowing policies, strong governance, transparent resource management, appropriated investments in public goods and infrastructures, and improvements of the business climate matter a lot for natural resource discoveries to be a blessing for those countries.

From a micro standpoint, chapters 4 and 5 point out some positive effects of mineral discoveries and productions on intergenerational mobility in education and occupation in Africa. Chapter 4 uses a large dataset of 14 million individuals across 28 African countries and 2890 districts and examines the relationship between mining activities and intergenerational mobility in education. Firstly, it computes absolute measures of intergenerational educational mobility and provides some stylized facts on the dynamics of intergenerational educational mobility across African countries and regions. It shows that primary and secondary/tertiary educational mobility have improved in Africa over time, with a more significant increase in primary educational mobility. Moreover, the gender gap in favor of males has been reduced, with females doing better than males in recent decades; however, the residency gap in favor of people living in urban areas compared to those in rural areas remains significant. Secondly, it empirically employs a generalized difference-in-difference model in a quasi-natural experiment to analyze the relationship between mining activities and intergenerational educational mobility. Overall, this paper found positive effects of mineral discoveries on primary educational mobility. Specifically, the probability of upward primary educational mobility, i.e., the probability for a child born from uneducated parents or parents with less than primary education attainment to achieve at least primary education, increases by 2.7 percentage points (pp.) following mineral discoveries and 6.7 pp. following mineral productions. The probability of downward primary educational IM, i.e., the probability for a child born from parents with at least primary education attainment to be uneducated or have less than primary education attainment, decreases by 1.2 pp. following both mineral discoveries and productions. These positive effects are increasing for individuals born later after discoveries and productions, for males, and individuals living in urban areas. However, no significant evidence of intergenerational mobility for higher education, including both secondary and tertiary education, has been found. In addition, it unveils two transmission channels through which the positive effects of mineral discoveries and productions on primary educational mobility operate, including the income effect proxied by parents working in the mining sector and the returns to education. First, it shows that the mining sector creates new job and income opportunities for parents, allowing them to invest more in their child's educational attainment. Second, it uncovers that the economic dynamism and creation of new jobs following the discoveries of mineral resources lead to an increase in the demand for skilled workers, thereby boosting the returns to education.

Chapter 5 investigates the relationship between mining activities and intergenerational occupational mobility using a sample of around 1.5 million individuals across 27 African countries and 2690 districts. Like chapter 4, it employs a generalized difference-in-difference model and finds positive impacts of mineral discoveries and productions on blue- and white-collar mobility for individuals exposed to and living in districts with mining discoveries and productions, contributing, therefore, to an improvement of the labor market conditions in Africa. Specifically, the probability of upward blue-collar mobility increases by up to to 2.3 pp. following mineral activities. Downward blue-collar mobility decreases by around 4 pp. Likewise, the likelihood of upward white-collar mobility increases by up to 1.6 pp. following mining activities. Downward mobility decreases by up to 13.3 pp. These positive effects are also found for individuals aged

16–20 years old entering the labor market at the time of discovery or production, but interestingly, these effects are higher for those born after discoveries and productions. Moreover, our results show some heterogeneous effects depending on the African region's location, the mineral discoveries's size, gender, and the urban-rural divide. In addition, we explore the demand for skilled workers channel (demand-side factor) and the educational channel (supply-side factor) through which mineral discoveries and productions affect occupational mobility. Furthermore, two potential transmission channels, including the demand for skilled workers (demand-side facto) and the educational channel (supply-side factor) are observed. First, we uncover that the creation of new jobs following the discoveries of mineral resources will increase the demand for skilled workers, thereby boosting the likelihood of intergenerational occupational mobility. Second, we find that children exposed to mineral activities tend to have higher educational mobility driven by higher return to education and new and higher income of their parents is invested in their education.

Throughout the dissertation, we emphasize the nuanced or positive role of natural discoveries on sovereign debt ratings, educational and occupational intergenerational mobility, contrasting the "resource curse" result found by scholars and reconciling it with studies finding more positive effects at local levels. However, developing countries must fulfill certain conditions to turn natural resources from a curse to a blessing. Those policy recommendations are oriented into four main points.

First, governments should improve their macroeconomic and institutional framework by improving the quality of public administrations, reducing corruption levels, and above all, enhancing the transparency of natural resources revenue management. For instance, the public disclosure of agreements between governments and private companies that found the discoveries could reduce the optimism from citizens and allow financial experts to provide better estimates of the size of the boom and the time needed to benefit from the revenues. By doing so, authorities could comfortably make their projections regarding economic developments, investment plans, and access to international financial markets to finance their development while ensuring that their debt remains sustainable. The authorities should also set a sound framework to select the investment projects financed by the windfalls from the resources and improve their public financial management (Page and Tarp 2020).

Second, since it has been found that giant discoveries of natural resources could favor intergenerational mobility in education and occupation, revenues from resource production should be used to address existing inequality. Those revenues should be used to boost schooling infrastructure and education quality; implement targeted policies to support the creation of competitive local Small and Medium Enterprises (SMEs), strengthen the creation of female job opportunities in higher skilled jobs, favor better access to higher educational and occupational levels for females and individuals living in both rural and urban areas (IMF 2022).

Third, authorities should implement policies to save the resources revenues using policies aiming at smoothing commodity price volatility and investing them into populations so that they could benefit actual and future generations. One can create, for example, well-managed sustainable sovereign wealth funds aiming at building reserves and preserving a part of the windfalls from the discoveries productions to boost productivity, invest in public goods and infrastructures, finance the improvement in skills of youth, as in was the case with the Pula Fund established in Botswana in 1994 (Dixon 2016). In addition, it has been found by Cust et al. (2022) that governments could transfer natural-resource revenues directly to citizens and tax them back to finance public expenditure. This will lead to increased accountability towards the public system and improve the effectiveness of both public and private sectors in countries with abundant natural resources.

Fourth, diversification policies and optimal adequate investments are such great strategies to make natural resource discoveries more profitable for developing economies. Indeed, revenues from natural resources should be used to promote the growth of tradable services and agri-business, to make the countries less dependent on those hydrocarbon and mineral resources. Moreover, in the aftermath of giant discoveries, adequate public investments in the construction sector, for instance, should be selected to obtain a better return on investments necessary to develop economic growth. Finally, to make it possible, authorities should improve the quality of project appraisal and rentability by building skilled persons with solid training in project management. Also, they should ask for the expertise of international organizations like the World Bank, the International Monetary Fund, or the African Development Bank in designing their projections and estimations (Page and Tarp 2020).

Therefore, this dissertation changes the narrative regarding natural resources, particularly giant discoveries, generally perceived as a curse for many countries. Furthermore, it gives hope to the growing number of countries discovering oil, gas, and mineral these last decades by emphasizing that taking the right actions by governments between the announcement of discoveries and the entering of production, and even in the years after the event, matters to make natural resources profitable for citizen' well-being and turn them into a blessing.

As avenues of future research, three main analyses could be conducted. First, an analysis could weigh the relative importance of the different factors that are identified as conditioning the impact of natural resource discoveries on sovereign debt ratings. For instance, whether institutional factors matter more than debt dynamics and financial integration when it comes to reducing the risks for a country to experience a natural resource curse. We could also conduct further country case studies to learn better the experiences of countries that successfully manage their natural resources and turn them into equitable wealth shared among the population. Second, our analyses in the second part of this thesis focus on industrial mining. It could be interesting to explore the effects of artisanal mining activities on intergenerational mobility in Africa since there are good reasons to believe that artisanal mines could have fewer positive effects on intergenerational mobility in education and occupation. Third, given the richness of the dataset at the geolocalized level, one analysis could go beyond this thesis's scope to assess the potential environmental effects of mineral discoveries at district levels.

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Résumé extensif en français

CHAPTER 0

RÉSUMÉ EXTENSIF EN FRANÇAIS

Les pays sont-ils bénis ou maudits d'être riches en ressources naturelles? La manne des ressources est-elle une bénédiction qui apporte la prospérité ou une malédiction qui apporte le désespoir? Ces questions ont occupé une place centrale dans la littérature académique, mais aujourd'hui encore, les réponses sont ambiguës et peu concluantes. Dans cette thèse, nous tentons d'apporter une réponse et de contribuer au débat en cours sur les effets des découvertes de ressources naturelles en démontrant dans quatre essais que l'impact global dépend de divers facteurs. Pour plusieurs pays dans le monde, et particulièrement en Afrique, la découverte et l'exploitation des ressources naturelles est une grande opportunité, mais cette opportunité comporte des risques. En effet, l'histoire a montré que de nombreux pays riches en ressources naturelles, dotés d'une grande quantité de pétrole, de gaz et de mines, ont connu des épisodes prolongés de croissance négative et de croissance potentielle plus faible, un chômage plus élevé, des taux de pauvreté plus importants, une plus grande inégalité des revenus, des conflits aigus et une instabilité politique, plusieurs épisodes de crises financières, plus souvent que dans les économies moins dépendantes des ressources naturelles (Page and Tarp 2020). Heureusement, il existe aussi des histoires à succès avec ces pays riches en ressources qui ont réussi leur diversification et leur transformation économiques; et ont bénéficié d'une croissance et d'une prospérité plus élevées, d'un système éducatif et de santé bien développé, et d'un système politique stable grâce aux ressources naturelles.

Pour planter le décor de cette thèse, le chapitre relatif à l'introduction générale, est structuré en quatre sections principales. Premièrement, il présente la littérature sur la malédiction des ressources et discute des limites des mesures utilisées pour étudier l'impact des ressources naturelles. Deuxièmement, il développe l'utilisation des découvertes de ressources naturelles géantes dans la littérature, ses avantages par rapport aux mesures précédentes, ses impacts macroéconomiques et microéconomiques, et présente quelques faits stylisés - par exemple, sur son évolution dans le monde. Troisièmement, il décrit quelques études de cas de pays. Enfin, il présente les quatre autres chapitres de cette thèse et leurs contributions respectives à la littérature.

0.1 La littérature sur la malédiction des ressources et les critiques

0.1.1 La littérature sur la malédiction des ressources

Depuis Adam Smith et David Ricardo (avant les années 1980), les gisements de ressources naturelles, notamment le pétrole, le gaz et les mines, sont considérés comme une excellente opportunité pour les pays d'améliorer leur situation économique et sociale. Ils sont perçus comme un moyen pour l'économie de passer du sous-développement à l'industrialisation, comme cela a été le cas pour la Grande-Bretagne, l'Australie et les États-Unis (Viner 1952; Rostow 1959). Cependant, les articles pionniers sur les liens entre les ressources naturelles et le développement économique ont fait valoir que les ressources naturelles sont plus une malédiction qu'une bénédiction. Il s'agit de la littérature bien connue sur la "malédiction des ressources". L'idée de la malédiction des ressources, employée pour la première fois par Auty (1993), est définie comme le paradoxe selon lequel les pays riches en ressources naturels connaissent une absence de croissance économique soutenue ou élevée par rapport aux pays moins dépendants des ressources. Une littérature croissante décrivant la malédiction des ressources dans les pays riches en ressources est apparue suite à l'étude empirique séminale de Sachs and Warner (1995), qui a découvert que les pays ayant un ratio élevé d'exportations de ressources naturelles par rapport au PIB connaissaient des taux de croissance plus faibles. Parmi eux, par exemple, Corden and Neary (1982); Ross (2004, 2006); Kretzmann and Nooruddin (2005); Collier and Hoeffler (2005); Van Der Ploeg (2011); Keen (2012); Van Der Ploeg and Poelhekke (2017) montrent que les ressources naturelles ont généralement été associées à la détérioration des conditions économiques et institutionnelles, à l'apparition de conflits, ainsi qu'à une faible orientation de la politique budgétaire et à une accumulation de dettes insoutenables. En outre, cette littérature a révélé que les pays riches en ressources se caractérisent par un retard dans l'accumulation du capital humain et physique, une désindustrialisation, un faible taux d'épargne et une productivité stagnante ou en baisse (voir, par exemple, Budina et al. 2007; Mien and Goujon 2021). Une explication courante des effets négatifs des ressources naturelles est fournie par Corden and

Neary (1982) dans leur analyse du "syndrome hollandais". Ils constatent qu'une récession de l'industrie manufacturière aux Pays-Bas a été provoquée par une appréciation du taux de change réel causée par les découvertes de gaz naturel au cours des années 1960, qui a comprimé l'emploi dans les secteurs échangeables, induisant une désindustrialisation de l'économie et une perte de compétitivité. Une autre explication est élaborée par Torvik (2002). Il montre dans son modèle que l'abondance des ressources naturelles augmente le nombre d'entrepreneurs impliqués dans la recherche de rente et réduit le nombre d'entrepreneurs dirigeant des entreprises productives. Ainsi, les ressources naturelles entraînent une baisse du bien-être car la baisse de revenu due à la recherche de rente est supérieure à l'augmentation du revenu provenant des ressources.

0.1.2 Les critiques de la littérature sur la malédiction des ressources

Loin de faire un consensus, la littérature sur la malédiction des ressources a fait l'objet de nombreuses critiques. Parmi les articles récents passant en revue la littérature sur les ressources naturelles,[1] Badeeb et al. (2017) a conclu qu' "il n'existe actuellement aucun consensus concernant l'existence d'une malédiction des ressources naturelles. Si la malédiction est une préoccupation pertinente, la littérature disparate indique que son omniprésence ne doit pas être exagérée". En effet, ils ont révélé que plusieurs articles s'inscrivant dans cette littérature sur la malédiction des ressources présentent certaines lacunes empiriques. Ils se sont concentrés sur les effets moyens, et les variables qu'ils ont utilisées pour capter l'abondance, l'intensité ou la dépendance des ressources sont probablement endogènes: (Brunnschweiler and Bulte 2008; Van der Ploeg and Poelhekke 2009; James 2015). Plus précisément, Brunnschweiler and Bulte (2008) constatent que les mesures les plus utilisées dans la littérature antérieure (par exemple, les exportations de ressources naturelles par rapport au PIB, la part des exportations de ressources dans les exportations totales, les rentes de ressources naturelles par rapport au PIB) saisissent la "dépendance aux ressources" plutôt que leur "abondance" et sont endogènes aux facteurs structurels sous-jacents. En effet, ils soulignent que ces mesures utilisant le PIB au dénominateur ne sont pas indépendantes des politiques économiques et des institutions (voir également sur la même conclusion, Alexeev and Conrad (2009)). Ainsi, les articles qui trouvent un effet négatif de l'abondance des ressources naturelles sur l'activité économique et les institutions sont biaisés. Pour surmonter ce problème, ils proposent d'utiliser les actifs du sous-sol comme proxy de l'abondance des ressources, ce qui conduit à un effet positif des ressources naturelles plutôt qu'à une malédiction. Cependant, cette nouvelle mesure suggérée par les auteurs n'est pas non

[1] Pour une revue récente du débat sur les effets des ressources naturelles, veuillez consulter, par exemple, Frankel (2010), Venables (2016), Van Der Ploeg and Poelhekke (2017), Badeeb et al. (2017), Mien and Goujon (2021).

plus exogène en raison de sa forte corrélation avec les rentes de ressources, comme l'ont montré plusieurs auteurs, dont Van der Ploeg and Poelhekke (2010).

Face à ce débat, un effet positif des ressources naturelles est apparu dans des analyses plus récentes portant sur les pays africains ou d'autres pays en développement. Elles montrent que les ressources naturelles réduisent les inégalités et la pauvreté et augmentent le niveau de vie, les revenus et le bien-être. En effet, Goderis and Malone (2011) trouvent que les booms d'exploitation des ressources réduisent les inégalités de revenus dans les pays riches en ressources, pendant que Fisher et al. (2009) montrent des preuves de la réduction de la pauvreté dans la population des mineurs dans les mines artisanales d'or et de diamant en Tanzanie. Zabsonré et al. (2018) révèlent pour le Burkina Faso que l'exploitation de l'or a permis d'améliorer le niveau de vie, d'augmenter les dépenses des ménages par habitant et de réduire la pauvreté dans les zones minières. Marlet (2020), à partir de l'exploitation minière au Ghana, constate que les activités minières tendent à augmenter les flux migratoires jusqu'à 200 km du district traité en réduisant les coûts de migration par la construction de routes et d'infrastructures. En outre, elles induisent également une augmentation des revenus et une amélioration du bien-être de 1,3 %.[2]

0.2 Nouvelles approches pour mesurer l'abondance des ressources naturelles

Pour combler les lacunes de la littérature présentée dans la section précédente, les études récentes sur les ressources naturelles ont utilisé les découvertes géantes de pétrole, de gaz et de minéraux. En effet, les découvertes géantes de ressources naturelles présentent trois caractéristiques essentielles: la taille relativement importante, le retard de production et le moment exogène plausible des découvertes (Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019). Tout d'abord, les découvertes géantes représentent un montant substantiel de revenus de ressources naturelles pour un pays spécifique; elles peuvent donc avoir un impact significatif sur le développement socio-économique des pays. En représentant un choc économique important, elles peuvent transformer certains résultats macroéconomiques ou changer les conditions sociales liées à l'habitude des individus et à leurs attentes concernant leur propre avenir et celui de leurs enfants. Deuxièmement, les découvertes géantes ne se traduisent pas immédiatement en production. En effet, il existe un délai important entre l'annonce de la découverte et le début de la production, environ quatre à six ans après la découverte, selon les ressources, qui nécessitent

[2] En revanche, certains articles constatent que les activités minières peuvent créer certains problèmes environnementaux en augmentant la pollution et la toxicité des métaux (Hausermann et al. 2018; von der Goltz and Barnwal 2019).

des investissements considérables. Cela permet d'étudier les effets différenciés des découvertes géantes et des productions ultérieures. Troisièmement, le moment des découvertes géantes est plausiblement exogène et imprévisible en raison de la nature incertaine de l'exploration pétrolière. Plus précisément, bien que la technologie utilisée pour l'exploration se soit améliorée au fil du temps, il est encore très improbable de prédire le moment et la probabilité de réussite de la découverte d'un gisement minéral dans une région particulière: (Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019). De plus, l'emplacement exact des découvertes de ressources minérales est en quelque sorte exogène car il dépend de facteurs géographiques aléatoires de la région. Par conséquent, si certaines régions peuvent être dotées de ressources minérales, il est improbable d'en trouver dans d'autres. Dans ces conditions, il est plus plausible de traiter les découvertes géantes comme des expériences quasi-naturelles. Par conséquent, elles peuvent être considérées comme des chocs exogènes ayant d'énormes implications macroéconomiques et politiques pour les pays.

0.2.1 Sources de données sur les découvertes géantes et les faits stylisés

Trois types de découvertes géantes ont été considérés dans la littérature: le pétrole, le gaz et les minéraux. Premièrement, les découvertes géantes de pétrole et de gaz sont fournies par Horn (2011). Ils définissent les découvertes géantes de pétrole et de gaz comme des découvertes dont le volume récupérable est d'au moins 500 millions de barils d'équivalent pétrole (bep) récupérables à terme. Ces données couvrent une très longue période allant de 1868 à 2010. Elles couvrent de manière exhaustive les pays qui représentent 40 à 60% des réserves mondiales de pétrole, selon Mann et al. (2007). Elles s'appuient sur l'enquête initiale de Halbouty et al. (1970). Il fournit des informations très détaillées, notamment les tendances des champs pétroliers et gaziers, la taille (géant, méga-géant, super-géant), le type de gisement (onshore/offshore), la localisation géographique exacte (latitude, longitude), l'année de découverte, et bien d'autres encore. Deuxièmement, les découvertes géantes de minéraux sont fournies par MinexConsultingDataset (2019). Elle définit comme découvertes géantes celles qui génèrent un montant d'au moins 500 millions de dollars US de revenus par an pendant 20 ans ou plus. Elle englobe également les découvertes majeures et modérées, générant un flux de revenus annuels supérieur ou égal à 50 millions de dollars US (pour les découvertes majeures) sur une durée de vie plus courte (Bhattacharyya and Mamo 2021). En outre, cette base de données couvre environ 85% de toutes les découvertes réelles entre 1950 et 2019, 90% pour les gisements non massifs et environ 70% pour les gisements massifs. Elle fournit également des informations très détaillées sur le type et la classe de métal primaire (métaux en vrac et non en vrac), le statut de la mine (en exploitation, fermée, de faisabilité, d'exploration avancée, sous-développée, etc.), l'année de la découverte, le début et la fin de la production (année de démarrage de la mine, année de fermeture de la mine), la géolocalisation et le type de sociétés d'exploration.

Dans les Figure D.1 à Figure D.3, je présente quelques faits stylisés sur les découvertes géantes de pétrole, de gaz et de minéraux. Tout d'abord, la Figure D.1 représente le nombre de découvertes géantes par type de ressources naturelles et par décennies de 1950 à 2019. Dans l'ensemble, les découvertes géantes ne sont pas des phénomènes rares puisqu'elles ont eu lieu au cours de toutes les décennies, avec une augmentation des découvertes de minéraux par rapport aux découvertes de pétrole et de gaz qui ont diminué au fil du temps. Deuxièmement, dans les Figure D.2 et Figure D.3, je présente la géographie des découvertes de minéraux. Elle révèle que tous les types de découvertes géantes ont eu lieu dans toutes les régions. Cependant, il existe certaines disparités: environ 39% des découvertes géantes de pétrole ont eu lieu dans la région du Moyen-Orient et de l'Afrique du Nord, 31% des découvertes de gaz en Europe et en Asie Centrale, et 24,8% et 22,6% des découvertes de minéraux en Asie orientale et Pacifique et en Afrique Subsaharienne, respectivement.

0.2.2 La littérature sur les effets des découvertes géantes de ressources naturelles

Les découvertes géantes ont eu des impacts tant macroéconomiques que microéconomiques. En ce qui concerne les effets des découvertes au niveau des pays sur les variables et les politiques macroéconomiques, les institutions et les conflits, les études soulignent généralement des impacts négatifs. Par exemple, les découvertes géantes de ressources naturelles pourraient détériorer la conduite de la politique fiscale et augmenter les niveaux d'endettement et sont donc associées à une probabilité croissante de crises Kretzmann and Nooruddin (2005). De même, Ruzzante and Sobrinho (2022) montrent que la "fiscal presource curse" des découvertes de ressources naturelles (principalement le pétrole et le gaz) sur la viabilité de la dette publique conduit à une augmentation permanente de la dette publique et à des épisodes de surendettement avant que la "première goutte de pétrole soit pompée". En outre, d'autres articles montrent que les découvertes géantes sont associées à une surévaluation du taux de change Harding et al. (2020), à une augmentation de l'incidence des conflits armés et à un changement du cadre institutionnel vers l'autocratie (Tsui 2011; Lei and Michaels 2014), à une augmentation de la corruption (Vicente 2010) et à une augmentation de la pauvreté et des inégalités (Smith and Wills 2018). En revanche, peu d'articles soulignent les effets positifs ou ambigus des découvertes géantes. Par exemple, Toews and Vezina (2017) trouvent que les découvertes géantes de pétrole et de gaz favorisent une augmentation des fonds plus stables comme les investissements directs étrangers dans les secteurs non liés aux ressources. Au lendemain des découvertes, Arezki et al. (2017) trouvent des preuves d'un important "effet d'anticipation". Ils montrent que le compte courant et le taux d'épargne diminuent pendant les cinq premières années avant de redevenir fortement positifs au cours des années suivantes; l'investissement augmente de manière robuste peu après l'annonce de la nouvelle, le PIB n'augmente pas avant la cinquième année et les taux d'emploi baissent légèrement pendant une période prolongée.

En ce qui concerne les impacts microéconomiques et locaux, la littérature montre que les découvertes de ressources naturelles ont contribué à améliorer le développement économique local, la gouvernance, la fourniture de biens publics et le bien-être et à réduire la probabilité de conflits. En effet, Cavalcanti et al. (2019) trouvent des preuves d'un impact positif des découvertes de pétrole et de gaz sur le développement local et l'urbanisation au Brésil. Cust and Mensah (2020) révèlent que les découvertes de pétrole, de gaz et de minéraux ont un impact positif sur les attentes des citoyens, ce qui se matérialise par une diminution de la migration vers l'extérieur et une augmentation de la fertilité à court terme. Bhattacharyya and Mamo (2021) montrent que les découvertes de pétrole et de minerais réduisent la probabilité de conflit dans 48 pays africains, principalement grâce à l'amélioration du développement économique et à une distribution politique efficace du patronage dans les districts où se trouvent les découvertes.

Dans l'ensemble, les impacts des découvertes géantes, ou plus largement des ressources naturelles, sont mitigés et peu concluants. Dans ce contexte, la section suivante décrit quelques études de cas nationales afin de présenter la manière dont les pays ont réagi (par exemple, en modifiant leurs politiques économiques) aux découvertes géantes de ressources naturelles et d'explorer les effets sur les indicateurs et les mécanismes socio-économiques.

0.3 Études de cas par pays

Il est essentiel de comprendre comment les pays et les gouvernements réagissent aux nouvelles concernant la découverte de ressources naturelles. En général, l'ampleur d'un boom anticipé est surestimée, et le délai de perception des revenus est sous-estimé. Alors que la plupart des pays augmenteront leurs emprunts de manière non durable et seront confrontés à des problèmes de viabilité de la dette, choisiront des projets à faible rendement et ne mettront pas en place un cadre de gouvernance solide pour la gestion des ressources, d'autres, au contraire, commenceront prudemment à investir dans des projets à rendement élevé afin de diversifier leur économie, d'accroître leur capital humain et leur productivité et de conserver les bénéfices pour les générations futures.

0.3.1 Mozambique

Les découvertes géantes de gaz en 2012 dans la province de Cabo Delgado au Mozambique ont suscité beaucoup d'espoir de la part du gouvernement et des communautés locales. Cependant, le pays a été confronté à de nombreux problèmes avant d'extraire la ressource (Roe 2018). Tout d'abord, une poussée des investissements directs étrangers (IDE) dans le secteur extractif a été associée à un boom des IDE dans les secteurs non extractifs. Plus précisément, à la suite des découvertes, les investissements ont augmenté de plus de 20 points de pourcentage du PIB. Cette forte variation des investissements est due à une poussée de l'IDE dans les secteurs non extractifs, qui a augmenté de 58% au cours des deux années qui ont suivi la découverte. En outre, le nombre de projets d'IDE a augmenté de 30% et le nombre d'emplois créés de 54% (Toews and Vezina 2017). Deuxièmement, les différents gouvernements ont contracté d'énormes prêts externes pour financer les investissements publics, qui ont également explosé, en supposant que le Mozambique deviendrait un exportateur de gaz clé. Ces prêts ont été contractés au mépris des bonnes pratiques en matière de gestion des finances publiques, car la sélection des projets et les conditions des contrats de prêt ont suscité de vives inquiétudes. Contrairement aux conclusions de Alfaro and Charlton (2013), et Roe (2018), qui montrent que l'afflux d'IDE dans les secteurs non extractifs (principalement les services et l'industrie manufacturière) est associé à une activité économique plus élevée, le Mozambique a connu une croissance plus faible dans les années qui ont suivi les découvertes.

Pourquoi le Mozambique ne s'est-il pas envolé comme prévu par les autorités et la population? Roe (2018) montre, parmi de nombreuses raisons, que le comportement des emprunts publics et ses implications pour la viabilité de la dette est un facteur crucial. En effet, le plan d'emprunt aurait dû mieux intégrer l'estimation du produit des ressources et la durée entre la découverte et le début de la production. Par exemple, l'émission d'obligations EMATUM de 2013 a expiré en 2020 avant que le gouvernement n'ait perçu le premier dollar de revenu de la ressource. Ainsi, le service de la dette de cette obligation reposait sur des revenus gouvernementaux préexistants. Dans le même temps, les financements des donateurs, en particulier les dons, ont diminué suite à la suspension du programme du FMI en avril 2016, ce qui n'a pas contribué à améliorer la trajectoire de la dette. En conséquence, le ratio dette/PIB est passé de 40% en 2012 à environ 130% en 2020. Le comportement du gouvernement, en contractant de lourds emprunts internationaux et nationaux et, à partir de 2013, en émettant des garanties publiques sur des prêts s'élevant à 2,3 milliards de dollars américains (environ 20 pour cent du PIB), a détérioré le cadre macroéconomique, créant une situation de surendettement (IMF 2016; Khan et al. 2016; Page and Tarp 2020).

En outre, les autorités n'ont pas intégré les retards dans les projets conduisant à la production.

Initialement prévue pour 2021, les nouvelles projections montrent que les productions ne devraient pas démarrer avant 2024 et 2025. En d'autres termes, la production commencerait alors que la situation budgétaire s'est considérablement détériorée et qu'il sera nécessaire d'établir des priorités en matière de dépenses, malgré les retombées des ressources utilisées pour assurer la viabilité de la dette. Dans un contexte différent, les recettes prévues auraient été utilisées pour combler le déficit d'éducation (4% du PIB par an) et le déficit de santé (plus de 50% du PIB). Mais aujourd'hui, une part importante de ces ressources serait consacrée au service de la dette, laissant les déficits de protection sociale non comblés. La triste réalité est que les détenteurs d'obligations du Mozambique devraient recevoir des portions des futurs revenus du gaz naturel du Mozambique dans le cadre de la restructuration de la dette de 2018 des euro-obligations du pays.

0.3.2 Ghana

Tout comme le cas du Mozambique, le Ghana illustre bien la "fiscal presource curse" dans les années qui suivent les découvertes, comme l'explique Ruzzante and Sobrinho (2022). En effet, le Ghana a connu deux découvertes géantes de pétrole en 2007 et 2010, pour un total de 2 milliards de barils équivalent pétrole (bep). À cette époque, les gouvernements et les citoyens jubilent, anticipant la prospérité que ces découvertes annoncent, et l'ancien Président Ghanéen, John Kufuor, proclame en 2007: "Même sans pétrole, nous nous portons bien... Avec le pétrole comme coup de fouet, nous allons voler". Malheureusement, aujourd'hui, le Ghana ne vole pas. Les prévisions de la Banque Mondiale estiment les revenus de la production à environ 20 milliards de dollars US pour la période 2012-30. Cependant, les solides prédictions économiques ne se sont pas concrétisées. La croissance est tombée en dessous de 4% entre 2014 et 2016, la plus faible depuis 20 ans, et la contribution du pétrole aux recettes publiques était inférieure à 10%, avec une moyenne d'environ 7,5% pour les cinq premières années de production de pétrole (Benkenstein 2016). Le ratio dette extérieure/PIB est passé de 37% à 50% entre 2009 et 2016. Les conditions financières se sont rapidement détériorées, comme l'illustre le prêt d'urgence d'un milliard de dollars dans le cadre d'un programme soutenu par le FMI demandé en 2015 par les autorités ghanéennes. La liesse prend fin à cause d'imprudences économiques et de la malchance: dépenses excessives, emprunts importants (sur cette période, le Ghana a emprunté 4,5 milliards de dollars sur les marchés internationaux et n'a gardé que 484 millions de dollars de recettes pétrolières pour les jours de "pluie"), et la chute des prix du pétrole en 2014 (Bawumia and Halland 2017; Page and Tarp 2020) (FMI, 2017). D'autres pays comme la Sierra Leone avec la découverte de gisements de minerais de fer en 2009 ou l'Ouganda avec ceux de pétrole en 2006, ont connu une détérioration de leurs conditions financières, et des chutes de croissance dans la foulée des découvertes géantes en raison d'anticipations mal calculées et de décisions désastreuses liées aux emprunts publics hors budget (Khan et al. 2016). Si le Ghana a tiré les leçons de l'expérience d'autres pays et consacré des efforts à la création d'un cadre solide pour la gouvernance et la gestion des ressources pétrolières, les autorités n'ont pas correctement mis en oeuvre les bonnes normes internationales en termes de responsabilité, de collecte des revenus, y compris les loyers de surface, et de distribution équitable des mannes issues des ressources.

0.3.3 Botswana

Heureusement, le tableau apparaît nuancé avec quelques exemples de réussite qui donnent de l'espoir aux pays confrontés à des découvertes géantes de ressources naturelles. En Afrique, le Botswana est l'un des pays les plus prospères qui a bâti son économie sur la manne de l'extraction des diamants. Depuis les découvertes de diamants à la fin des années 1960 et au début des années 1980, le Botswana a rapidement amélioré son environnement économique, social et institutionnel et est devenu un pays à revenu intermédiaire. Depuis lors, le Botswana a bénéficié de bonnes conditions financières et d'un accès permanent au marché international. À titre d'illustration, la notation souveraine de la dette à long terme du Botswana a toujours été classée dans la catégorie d'investissement supérieure-moyenne par Standard and Poor depuis 2001. Malgré un accès permanent au marché international, le Botswana a développé un marché des capitaux domestique depuis 1989, devenant la Bourse du Botswana en 1995. Au fil des ans, le marché boursier national s'est considérablement développé. À mesure que l'environnement réglementaire s'est amélioré, de nouveaux produits ont été introduits et divers programmes de sensibilisation ont été mis en oeuvre pour attirer les émetteurs et les investisseurs. Le Botswana a surmonté la menace de la malédiction des ressources principalement grâce aux investissements du gouvernement dans les biens publics et les infrastructures, aux mesures prises pour stimuler la productivité, à la création de fonds d'épargne pour lisser l'économie pendant les turbulences financières, et à l'excellente gouvernance poursuivie par les autorités. Par exemple, en 1994, le Pula Fund a été créé en vertu de la loi sur la Banque du Botswana en tant que fonds souverain pour détenir un investissement à long terme dans le but de constituer des réserves et de préserver une partie de la manne provenant des exportations de diamants pour les générations futures. [3] Comme le montre Dixon (2016), le Pula Fund est le plus ancien et le troisième plus grand fonds d'Afrique, et il s'élevait à 5,4 milliards de dollars américains en 2016. Le Botswana a pu réinvestir dans l'amélioration de la santé et de l'éducation grâce à l'absence de dépenses

[3] Veuillez suivre ce lien pour plus de détails sur le Pula Fund : https://www.bankofbotswana.bw/content/pula-fund.

publiques inutiles, à une faible inflation ou à une augmentation des réserves de change tout en évitant les problèmes de surendettement (Acemoglu et al. 2003; Leith 2005).

0.3.4 Malaysia

En dehors de l'Afrique, la Malaisie a réussi à convertir les découvertes de ressources naturelles en un moteur essentiel de sa croissance durable et inclusive. Le secteur du pétrole et du gaz a apporté de nombreux avantages. Depuis la découverte du pétrole et du gaz, grâce à la technologie dans les années 1970, la Malaisie s'est appuyée sur les revenus du pétrole et du gaz pour réduire les inégalités économiques et construire une croissance économique durable. En effet, après les émeutes ethniques de 1969, le gouvernement malaisien s'est engagé à utiliser le développement économique pour réduire les inégalités raciales et économiques. Le nationalisme croissant en Malaisie et l'idée qu'il est essentiel de maintenir un contrôle souverain sur les ressources naturelles ont conduit le gouvernement à s'assurer un plus grand contrôle sur le secteur du pétrole et du gaz et à renégocier les accords de production avec les majors pétrolières internationales. Par ailleurs, les gouvernements ont également poursuivi des stratégies de diversification en utilisant les revenus pour soutenir des secteurs d'investissement non directement liés aux ressources. Ils ont multiplié les programmes d'investissement dans les secteurs de l'agriculture, de la fabrication et des services grâce à une gestion saine des ressources. Dans l'agriculture, les programmes d'investissement ont permis d'augmenter la productivité et de réaliser une transition de la production de caoutchouc à celle d'huile de palme. Dans le secteur manufacturier, l'économie s'est ouverte au commerce et aux investissements directs étrangers. Une politique industrielle a été menée (y compris le développement des infrastructures, notamment dans les zones économiques spéciales) qui a permis de développer une série d'activités à forte intensité de main-d'oeuvre, notamment le secteur de l'électronique. En outre, la stabilité macroéconomique a été maintenue par la prudence budgétaire et certains éléments de chance, comme lorsque l'augmentation rapide des volumes de pétrole a compensé la chute des prix des années 1980. La compagnie pétrolière nationale de Malaisie a également mené cette stratégie de diversification, qui a commencé à investir à l'étranger dans les économies émergentes de l'Asie, notamment au Myanmar, au Cambodge, en Thaïlande et au Vietnam.

0.3.5 Principaux points à retenir

Le contraste frappant offert par les études de cas par pays entre le Ghana et le Mozambique (les histoires d'expansion et de récession), et le Botswana et la Malaisie (les histoires de réussite résident) pourrait résider dans six aspects selon Page and Tarp (2020):

- les expériences (durée) en matière de gestion des ressources naturelles ;
- les cinq caractéristiques communes du Warner en matière de prise de décision sur les investissements publics suite à la découverte (Warner 2014; Roe 2018), notamment:
  - une incapacité à sélectionner les investissements publics en se référant à des critères économiques solides;
  - une tendance systématique à utiliser des prévisions de prix, de coûts et d'impacts trop optimistes;
  - un manque d'informations au moment de la mise en oeuvre pour identifier les taux de rendement probables (réels) des investissements;
  - l'inertie des programmes d'investissement: les investissements une fois lancés sont susceptibles de continuer à être financés même lorsque les conditions nécessaires à leur réussite se détériorent;
  - un haut dégrée de vulnérabilité des décisions d'investissement public aux abus pour des motifs personnels ou politiques.

En effet, le temps d'exposition dans la gestion des ressources naturelles est essentiel pour comprendre comment elles affectent la trajectoire de développement socio-économique et la vie des gens. Ceci est bien illustré dans Cust and Mihalyi (2017) et Ruzzante and Sobrinho (2022), qui ont utilisé le terme "presource curse" et l'ont distingué de la "resource curse". En effet, la "presource curse" concerne la période généralement relativement courte (mais incertaine) entre la découverte et le début de la production. Cust and Mihalyi (2017) montrent des résultats mitigés en fonction de la qualité des institutions. Ils constatent que les pays dotés d'institutions politiques plus faibles ont connu une croissance plus faible pendant la période de "présource", inférieure aux prévisions du FMI et à la croissance avant la découverte, tandis que ceux dotés d'institutions solides connaissent au moins une croissance conforme aux prévisions du FMI et à la croissance avant la découverte. De même, Ruzzante and Sobrinho (2022) trouvent des preuves d'une "fiscal presource curse", c'est-à-dire que les ressources naturelles peuvent mettre en péril la viabilité fiscale avant même que "la première goutte de pétrole soit pompée". Plus précisément, ils montrent que les découvertes géantes de pétrole et de gaz entraînent une augmentation permanente de la dette publique et, finalement, des épisodes de surendettement, en particulier dans les pays dont les institutions politiques et la gouvernance sont plus faibles. Dans l'ensemble, ces résultats montrent qu'il est important de dissocier l'annonce de la découverte et le début de la production. Ce sont généralement les réactions du gouvernement à la découverte et l'exubérance de la population, également présentées dans les cinq caractéristiques communes de la prise de décision de Warner, plutôt que le début de la production, qui donnent lieu à la probabilité d'une malédiction des ressources. Ces preuves suggèrent que la malédiction peut être atténuée et même évitée en poursuivant des politiques fiscales et des stratégies d'emprunt prudentes, en renforçant la gouvernance, en mettant en oeuvre des cadres fiscaux transparents et solides pour la gestion des ressources, en épargnant par le biais de fonds souverains pour les générations futures et en investissant dans des projets solides dans les domaines de l'éducation, de la santé et des infrastructures pour améliorer le capital humain et la productivité.

0.4 La valeur ajoutée de cette thèse et les contributions

En résumé, la littérature empirique sur les effets des ressources naturelles est mitigée et peu concluante. Au niveau macroéconomique, les études ont généralement trouvé des effets négatifs, tandis que des effets positifs sont apparus au niveau microéconomique ou local. Certaines analyses ont montré que la méthodologie et les variables utilisées pour mesurer les ressources naturelles jouent un rôle clé dans la capture des "véritables" effets des ressources naturelles. Cela conduit de nombreux articles à considérer les découvertes géantes comme un bon indicateur des ressources naturelles, étant donné leur taille relativement importante, le décalage de production et le moment exogène plausible des découvertes. D'autre part, les études de cas par pays ont montré que ce qui importe pour les effets des ressources naturelles est la façon dont les gouvernements et la population réagissent à la nouvelle des découvertes. Par conséquent, les effets moyens saisis dans la plupart des analyses sont moins susceptibles de donner une image claire des effets des ressources naturelles et des mécanismes.

Alors qu'il existe une littérature abondante sur les avantages ou les conséquences négatives des ressources naturelles, mon intérêt est de contribuer au débat et d'approfondir les effets des découvertes géantes à la fois i) au niveau macroéconomique sur la notation de la dette souveraine et l'accès aux marchés financiers et ii) au niveau microéconomique sur la mobilité intergénérationnelle éducative et professionnelle. En outre, cette thèse vise à formuler des recommandations politiques pour aider les pays à mieux utiliser leurs ressources.

Cette dissertation présente les résultats de la recherche, structurés en deux parties et quatre chapitres. La première partie, divisée en deux chapitres, étudie la relation entre les découvertes géantes de ressources naturelles (pétrole, gaz, minéraux) et l'accès aux marchés financiers. Dans le deuxième chapitre, je fais la lumière sur les effets des découvertes géantes de ressources naturelles (pétrole, gaz naturel, minéraux) sur la notation de la dette souveraine à court et à long terme. Pour ce faire, j'utilise 28 pays en développement et émergents sur la période 1990-2014. J'applique un modèle probit ordonné à effet aléatoire sur deux ensembles différents d'échantillons. Je trouve des preuves des effets différenciés (positifs et négatifs) des découvertes géantes sur les notations. Plus précisément, pour 13 pays, je constate que les découvertes géantes sont associées à une détérioration des notations de la dette souveraine à court terme, mais à une augmentation de ces notations à moyen et long terme. Pour les 15 autres pays, je montre que les découvertes géantes n'ont aucun effet à court terme mais réduisent les notations à moyen et long terme. Ces effets différenciés dépendent du comportement des indicateurs macroéconomiques et politiques résultant des actions et des politiques prises à la suite des découvertes. Je révèle également qu'il existe certains effets d'apprentissage des découvertes géantes dans les pays dont la notation de la dette souveraine augmente. Les pays ayant un historique de découvertes géantes ont tendance à avoir des notations plus élevées. Ce qui semble compter, ce ne sont pas seulement les ressources, mais aussi la façon dont les gouvernements réagissent à la nouvelle de la découverte. En effet, je montre que dans les pays dont la notation augmente, les découvertes géantes sont en moyenne associées à une augmentation des recettes fiscales par rapport au PIB, des investissements, une diminution de la dette publique par rapport au PIB et une amélioration de la stabilité gouvernementale. En revanche, je constate que dans les pays dont la notation est en baisse, les découvertes géantes sont associées à une réduction des investissements et à une augmentation de la corruption. Ces résultats appellent à une évaluation minutieuse des décisions des gouvernements à la suite de découvertes géantes. En effet, en prenant les bonnes mesures et politiques, les pays pourront éviter une détérioration de leurs conditions financières.

Dans le troisième chapitre, un document complémentaire au chapitre 2, j'examine les effets causaux du pic des découvertes géantes de pétrole et de minerais sur la notation de Institutional Country Credit Ratings (ICR). J'ai utilisé la Synthetic Control Method (SCM) et l'ai appliquée à cinq pays en développement, dont l'Angola, le Kazakhstan, la Roumanie, le Gabon et le Cameroun, de 1985 à 2014. La SCM permet de capter l'effet causal spécifique au pays du pic des découvertes géantes et est plus appropriée pour les études de cas comparatives. Nous nous concentrons sur le pic des découvertes de géants plutôt que sur les découvertes de géants, comme dans le chapitre 2. La raison en est que le pic des découvertes géantes est plus susceptible d'être exogène et pourrait induire des effets amplifiés sur les conditions financières (Tsui 2011; Masi and Ricciuti 2019). Nous constatons que le pic de découvertes a un impact à la fois positif et négatif sur les notations de crédit des pays investisseurs, en fonction des caractéristiques spécifiques des gouvernements. Par conséquent, nous confirmons les effets hétérogènes de (le pic de) découvertes géantes sur l'accès aux conditions financières, comme indiqué au chapitre 2. Plus précisément, nous constatons que les cotes de crédit des pays investisseurs se sont considérablement améliorées en Angola, au Kazakhstan et en Roumanie après le pic des découvertes. En revanche, les cotes de crédit des pays investisseurs se sont considérablement détériorées au Gabon et au Cameroun après le pic des découvertes géantes. Ces résultats confirment que les effets moyens des découvertes géantes présentés dans la littérature peuvent cacher le développement réel des pays qui peut différer d'un pays à l'autre.

La deuxième partie s'intéresse aux effets plus granulaires des découvertes minérales et se concentre sur l'Afrique, où les ressources minérales sont abondantes. Elle étudie la relation entre les découvertes minérales et la mobilité intergénérationnelle en matière d'éducation et de profession. Dans le quatrième chapitre, nous adoptons une approche innovante en explorant les effets des découvertes et des productions minérales sur la mobilité intergénérationnelle en matière d'éducation, en reliant les parents aux niveaux d'éducation de leurs enfants pour plus de 14 millions d'individus dans 28 pays africains et 2 890 districts. Nous utilisons une méthode de différence de différences généralisée dans une expérience quasi-naturelle. Notre expérience quasi-naturelle s'appuie sur l'exogénéité plausible des découvertes de minéraux qui renvoient des caractéristiques spécifiques, en particulier le moment non prévu des découvertes, l'emplacement géographique non prévu et le décalage entre les découvertes de ressources naturelles et le début de la production (Horn 2011; Khan et al. 2016; Arezki et al. 2017; Cavalcanti et al. 2019). Nous constatons que les découvertes et les productions de minerais affectent positivement la mobilité éducative pour l'enseignement primaire en Afrique pour les individus exposés aux sites miniers et vivant dans des districts avec des découvertes. Plus précisément, la probabilité de mobilité éducative primaire ascendante, c'est-à-dire la probabilité pour un enfant né de parents non éduqués ou de parents ayant un niveau d'éducation inférieur au primaire d'atteindre au moins l'éducation primaire, augmente de 2,7 points de pourcentage (pp.) après les découvertes de minéraux et de 6,7 pp. après les productions de minéraux. La probabilité d'un IM de niveau primaire descendant, c'est-à-dire la probabilité qu'un enfant né de parents ayant atteint au moins le niveau d'éducation primaire soit non éduqué ou ait atteint un niveau d'éducation inférieur au niveau primaire, diminue de 1,2 pp. après les découvertes et les productions minérales. Ces effets positifs augmentent pour les individus nés plus tard après les découvertes et les productions, les hommes et les individus vivant dans des zones urbaines. Cependant, nous ne trouvons aucune preuve significative de mobilité intergénérationnelle pour l'enseignement supérieur, y compris l'enseignement secondaire et tertiaire. En outre, nous discutons de deux canaux de transmission par lesquels les effets positifs des découvertes et productions minières sur la mobilité de l'éducation primaire opèrent, y compris l'effet de revenu représenté par les parents travaillant dans le secteur minier et les rendements de l'éducation. Premièrement, nos résultats montrent que le secteur minier crée de nouvelles opportunités d'emploi et de revenu pour les parents, ce qui leur permet d'investir davantage dans le niveau d'éducation de leurs enfants (Becker and Tomes 1979). Deuxièmement, nous découvrons que le dynamisme économique et la création de nouveaux emplois à la suite de la découverte de ressources minérales entraînent une augmentation de la demande de travailleurs qualifiés, ce qui accroît le rendement de l'éducation (Torche 2014).

Le cinquième et dernier chapitre, un document complémentaire au chapitre 4, étudie la relation entre les découvertes et les productions de minéraux et la mobilité professionnelle intergénérationnelle. Plus précisément, nous considérons 1,5 million d'individus dans 27 pays Africains et 2 690 districts, en reliant les professions des enfants à celles de leurs parents. Nos principaux résultats montrent que les découvertes et les productions minérales augmentent la mobilité professionnelle des cols bleus et blancs; elles ont donc contribué à améliorer les conditions du marché du travail africain. En ce qui concerne la mobilité des cols bleus, la probabilité que les individus nés de parents travaillant dans l'agriculture ou dans des emplois élémentaires aient de meilleures chances d'occuper au moins un emploi de col bleu s'ils sont exposés et vivent dans un district où il y a une découverte ou une production minière augmente de 0,9 à 1,7 point de pourcentage (pp.) pour les découvertes, et de 1,7 à 2,3 pp. pour les productions. De même, la probabilité que les individus nés de parents travaillant dans des emplois de cols bleus ou blancs fassent moins que leurs parents et travaillent dans des emplois agricoles et élémentaires s'ils sont exposés et vivent dans un district avec une découverte minière diminue d'environ 4 pp. pour les découvertes et les productions. De même, en ce qui concerne la mobilité des cols blancs, la probabilité que les individus nés de parents travaillant dans des emplois agricoles ou élémentaires ou dans des emplois d'ouvriers aient de meilleures chances de travailler dans des emplois de cols blancs s'ils sont exposés à une découverte ou à une production minière et qu'ils vivent dans une zone de découverte ou de production minière augmente de 1,6 pp pour les découvertes, et de 0,6 à 1,3 pp pour les productions. De même, la probabilité que les individus nés de parents travaillant dans des emplois de cols blancs fassent moins que leurs parents et travaillent dans des emplois agricoles et élémentaires ou des emplois de cols bleus s'ils sont exposés et vivent dans un district avec une découverte minière diminue d'environ 5,8 à 10,4 pp. pour les découvertes, et de 9,1 à 13,3 pp. pour les productions. En outre, nous constatons que les effets positifs des découvertes minières et de la production s'appliquent également aux individus âgés de 16 à 20 ans qui entrent sur le marché du travail au moment de la découverte et de la production. Cependant, il est intéressant de noter qu'ils sont de plus en plus positifs pour ceux qui sont nés après la découverte ou la production. Cette probabilité plus élevée pour les personnes nées plus tard après la découverte ou la production pourrait s'expliquer par le fait qu'il faut du temps pour que les activités minières aient un impact sur les communautés locales, notamment en termes de niveaux d'éducation, de fourniture d'infrastructures et de biens publics, et de structure du marché du travail. En outre, nous montrons que les effets positifs des découvertes et des productions minières sur la mobilité des cols bleus et blancs opèrent à travers i) le canal de la demande de travailleurs qualifiés (facteur lié à la demande) et ii) le canal de l'éducation (facteur lié à l'offre). Premièrement, nous découvrons que le dynamisme économique, la transformation structurelle et la création de nouveaux emplois à la suite de la découverte de ressources minérales vont accroître la demande de travailleurs qualifiés, augmentant ainsi la probabilité d'une mobilité professionnelle intergénérationnelle: (Torche 2014; Cavalcanti et al. 2019). Deuxièmement, le canal éducatif est basé sur le fait que les enfants exposés aux activités minières auront tendance à augmenter leur éducation afin d'obtenir des rendements plus élevés de l'éducation, et parce que les activités minières généreront de nouveaux revenus plus élevés pour les parents (Becker and Tomes 1979; Weber-Fahr 2002; Loayza et al. 2013) pour investir dans l'éducation de leurs enfants (Atsebi et al. 2022).

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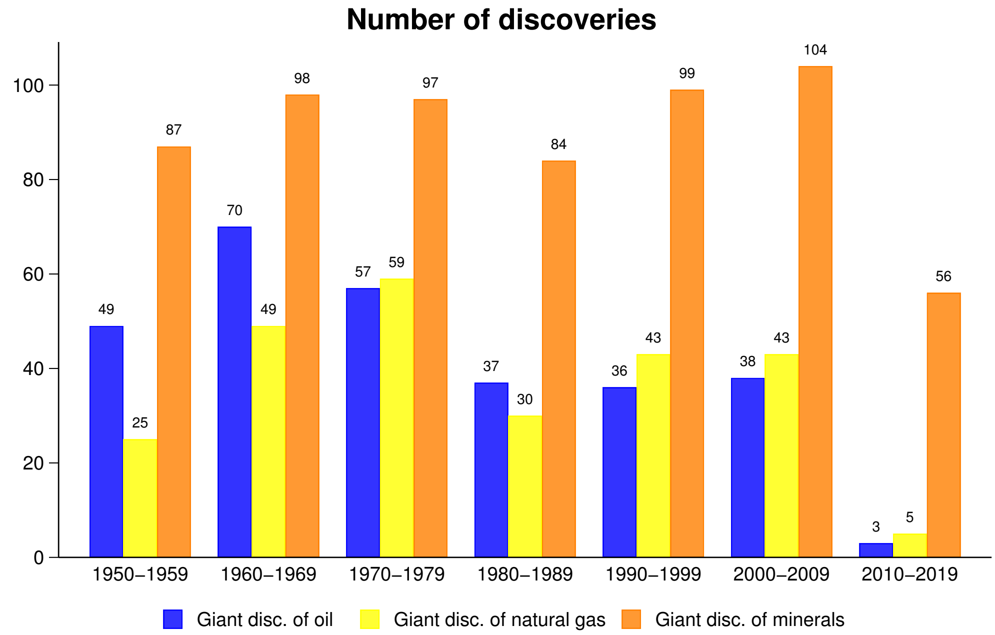
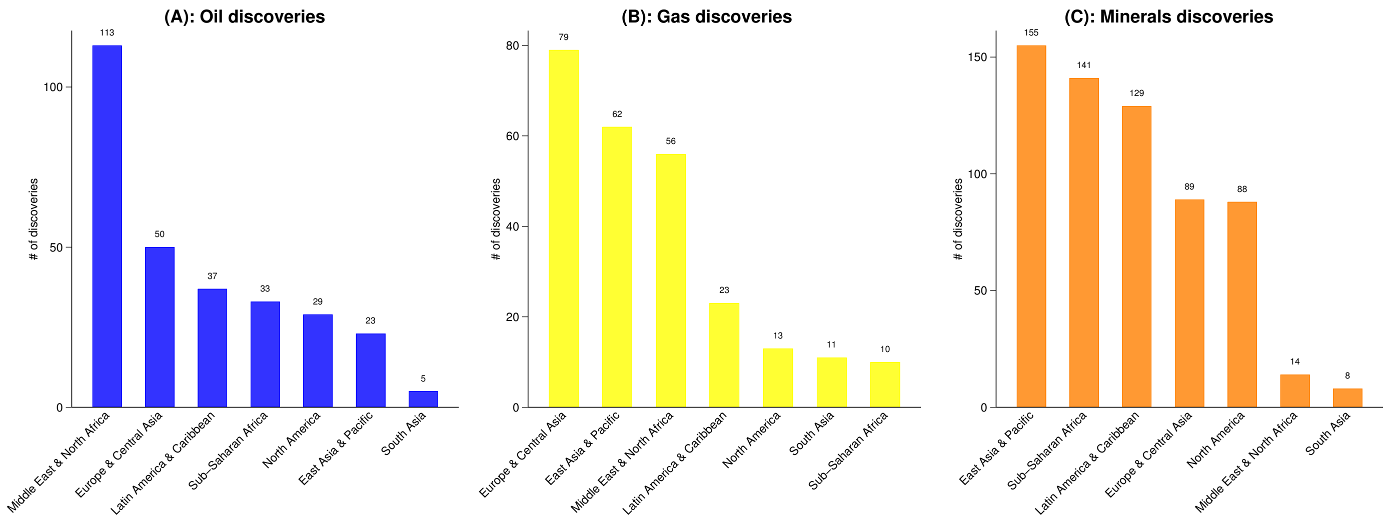
Figure D.1: Total number of discoveries since 1950



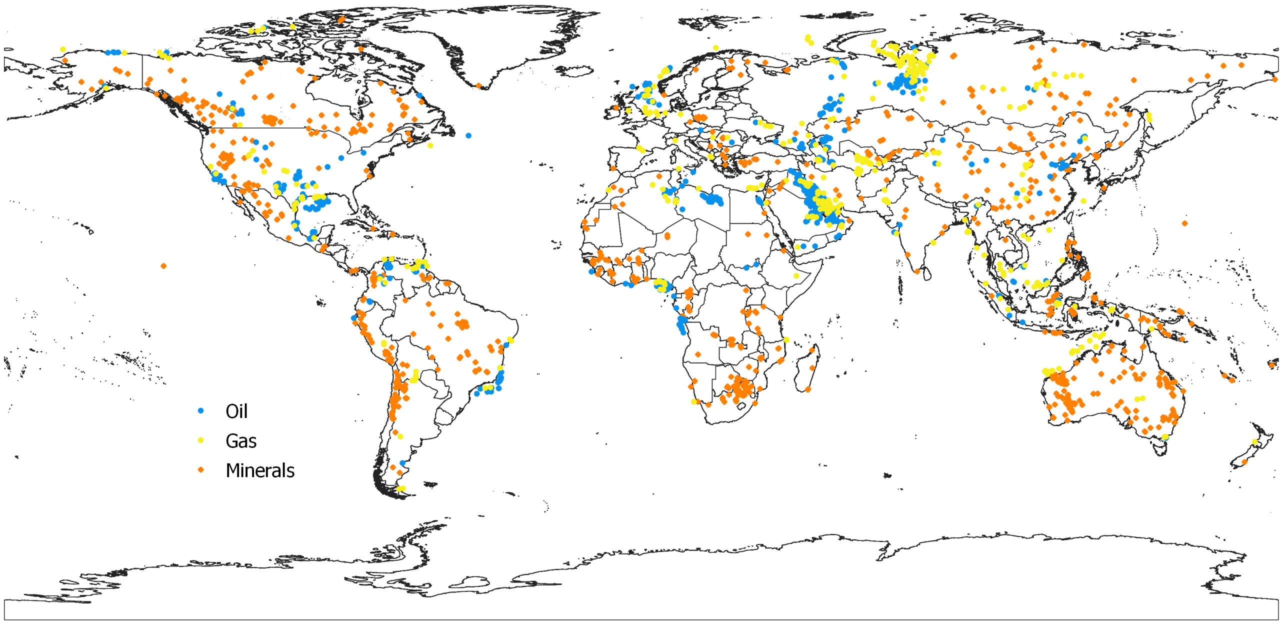
Source: Horn (2011); MinexConsultingDataset (2019)

Figure D.2: Total number of discoveries by field of natural resources and by region



Source: Horn (2011); MinexConsultingDataset (2019)

Figure D.3: Geographical location of giant discoveries of natural resources, 1950-2018



Source: Horn (2011); MinexConsultingDataset (2019)