University of Sussex

Essays on Natural Resources in Africa

Local Economic Development, Multi-Ethnic Coalitions and Armed Conflict

Nemera Gebeyehu Mamo

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Declaration

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

However, the thesis incorporates some materials from Chapter 2 and 4 that are already released as working papers and under review with journals on the date of submission. The journal version of the paper is a joint work with my supervisors, and I hereby confirm that I contributed to each paper.

In the following paragraphs, I will provide clearer statements about the exact nature of my contribution to the papers which are co-authored with my supervisors Dr Alexander Moradi and Dr Sambit Bhattacharyya.

On the second chapter, I worked collaboratively with my supervisors where we explored the effect of mineral production and discovery on local economic development in sub-Saharan Africa by using satellite data on night lights as a measure of economic development. I collected annual industry specific information, and constructed large longitudinal dataset containing information on industrial size mining productions in Africa for more than two decades using IntierraRMG (currently known as SNL Metals based in London). Where IntierraRMG did not provide relevant information such as production start-up date, I consulted other sources and added the information into the panel data. In addition, I constructed the natural resource discovery panel data which we acquired from MinEx Consulting.

I also constructed a panel dataset on night lights for 3,635 districts from 42 Sub-Saharan African countries over the period 1992 to 2012 using ArcGIS. The satellite data on night lights are freely provided by the US National Oceanic and Atmospheric Administration (NOAA). Yet converting them into district specific has required months of researching activities (including taking PhD trainings on ArcGIS). Once the data has been organised, I run regressions, analyse the results with my supervisors and convert the results into a tabular and graphical illustrations. As a PhD student, I have duly shown the courage and independence of contributing towards the journal version of the paper.

On the fourth chapter, which I co-authored with Dr Sambit Bhattacharyya, we explored the effect of oil and mineral discoveries on intra-state armed conflict onset, intensity, and incidence in Africa at the grid level. From data constructions to running regressions, analysing results and converting the results into a tabular and graphical illustrations, I have predominantly contributed to the development of the paper. More on the data front, I have constructed huge grid-level conflict data using three geocoded datasets of conflict events in Africa: PRIO-GRID conflict dataset, Armed Conflict Location and Event Dataset (ACLED) and Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED). This paper is currently to be revised and resubmitted to Economic Development and Cultural Change journal.

Finally, I declare that the organisation of this thesis in terms of presenting the results and writing up, my supervisors have no direct impact. Yet I have enormously gained from their research motivations and guidance, for which I am always grateful and my deepest gratitude to them.

Signature: Nemera Gebeyehu Mamo

UNIVERSITY OF SUSSEX

Nemera Gebeyehu Mamo, Doctor of Philosophy

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Summary

This thesis consists of three stand-alone papers. It examines the economic and political effects of natural resources in Africa. In the first paper, we investigate the effect of mining activity on subnational economic development by using satellite data on night lights as a measure of economic development. We find that mineral production and discovery improves local economy. However, we do not observe (strong) general equilibrium effect beyond the confines of a district.

In the second paper, we test the link between natural resources and multi-ethnic power sharing coalitions in Africa. We find that resource discoveries and rising commodity prices increase the probability of representation at the executive branches of government. Our finding supports the idea that resource discoveries and rising commodity prices provide rulers with more revenues to expand the state cabinet sizes; hence they build broader multi-ethnic coalitions.

In the third paper, we investigate the association between natural resources and intra-state local armed conflict in Africa. We find that natural resource discoveries do not trigger armed conflict in Africa at the local level. Consistent with the finding in the first paper (positive economic effect) and second paper (positive political effect), resource discovery appears to reduce the likelihood of armed conflict by increasing the opportunity cost of joining armed rebellion.

Acknowledgements

The Ph.D journey has been a truly life-changing experience and it would not have been possible to do without the guidance and support of many people and I would like to take this opportunity to express them my deepest gratitude.

First and foremost I would like to thank my supervisors Dr Alexander Moradi and Dr Sambit Bhattacharyya. They have taught me, both consciously and unconsciously, how good research in development economics is done. I appreciate all their contributions of time, ideas, and encouragement to make my Ph.D experience productive. The interest and commitment they have for the research was contagious and motivational for me. My deepest gratitude to them.

Choosing Sussex for studying MSc + Ph.D (1+3) was one of the best decisions I have ever made not only because of its encouraging academic environment but also for the great human qualities of its community. I truly benefitted from my interactions with the Staffs at the Department of Economics, and the Administrators at the School of Business, Management and Economics, and Doctoral School (ESRC Doctoral Training Centre). I do not just take the services and help I received from you for granted, but I am grateful for every aspect of it.

My time at Sussex was also made enjoyable due to the many friends and groups, who have been a source of inspiration, support and learning. I am grateful for time spent with classmates during the MSc, and Ph.D buddies for advices and support. Thank you very much and all the best for you my friends.

I am very grateful for the 1+3 funding opportunity I received from the Economic and Social Research Council (ESRC). It was a pleasure and a privilege to have won funding from the UK's leading research and training agency in economic and social researches, without which I would not have been able to study in the UK. As ESRC-funded student, I also profited from the attendance of research training and events organised by National Centre for Research Centres. All for subsidised prices. I also acknowledge financial support from the Department of Economics for data subscription, and travel and accommodation allowances for conference attendance. The willingness of the Department to help its students is encouraging.

I would like to extend special thanks to participants in seminars and workshops in which I presented versions of chapters in this thesis in the CSAE (Oxford University), RES Junior Research Symposium, LSE Spatial Economics Research Centre, Working Group in African Political Economy (WGAPE), Nordic Conference in Development Economics and African Economic History Network, who provided me insightful comments and suggestions.

To my friends and families in Ethiopia and outside Ethiopia, who have helped me in the process, thank you very much. I must mention the name of my mother, Maaramee Fufaa Arbee, who literally gave up her life for her children. I first learned *Pareto Optimality Hypothesis*, not from the textbook but from her. All her children (Qonjit, Nemera, Mitiku, Bedilu and Coraa, in birth order) have gained and live on a higher indifference curve today because of her unreserved compromises and forgoing her individual best preferences.

Finally, special recognition goes out to my wife, Aduu Teshale Joba, whose love and support proved invaluable in the overall learning experience and life in the UK, particularly during the very tough times. I dedicate this thesis to you and to our two precious gifts of God, Soortuu Nemera and Guutamaa Nemera.

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CHAPTER 1

Introduction

Resource rich African economies have played a significant role in supplying raw materials to the global market (Humphreys, 2009). These supplies have generated large fiscal revenues and export earnings in spite of resource wealth management challenges (van der Ploeg and Venables, 2011; Venables, 2016). During a period of rising commodity prices since 2000s, natural resource sector contributed to the general economic rent about 28 percent of GDP, total export earnings over 77 percent and governments revenues over 42 percent in Africa (World Bank, 2014). Economic importance of the sector, through the revenues they generate, is still expanding. Many discoveries were made and the extraction of these new resources are yet to take place in the future (Collier, 2010a). Since the turn of the century, the share of Africa's resource discoveries in the world has more than doubled compared to the trend before 2000 (MinEx Consulting, 2014).

Should resource rich African countries that discover new natural resources rejoice or mourn? Existing evidence suggests that natural resource abundance is likely to hinder economic performance. Consistent with the resource curse notion, Africa has experienced mixed moments with its natural resource sector since independence. Resource abundance in post-independence period were largely attributed to corruption and political violences. The main challenges of using natural resources for development in resource rich African economies is that they have weak governance that are further undermined by the political forces (Venables, 2016). For this reason, political causal mechanisms is widely recognised as the foundations of the resource curse (Robinson et al., 2006).

In this thesis, we study the economics and politics of natural resources in Africa. We contribute to the resource curse debate by examining the effects of large scale natural resource discoveries and productions on local economic development, political power distributions and intra-state (local) armed conflict. This thesis consists of three stand-alone papers.

We start by exploring the effect of mineral production and discovery on local economic development in sub-Saharan Africa. We measure economic activity at different levels of spatial stratification using satellite data on night lights (Henderson et al., 2012). The standard GDP measures on any consistent basis are widely unavailable at the subnational level in Africa. As a consequence, most recent subnational studies make effective use of night lights data (Michalopoulos and Papaioannou, 2013a; Hodler and Raschky, 2014). We combine the night lights data with a mine level geo-referenced data on discovery and production. We find mineral production and discovery improves economic development at the district level in 42 sub-Saharan African countries over the period 1992 to 2012. We observe that the mineral production effect is largely driven by the startup of new mining activity. Moreover, we observe strong positive effect of the discovery. Comparing to districts without any discoveries, the average effect of mineral discovery shocks on night lights density turns positive and significant 6 years post discovery. The discovery effect is associated with 19-44 percent increase of a district's night lights density between 6-10 years post discovery.

In the second paper, we investigate the role of natural resources in political power sharing arrangements in Africa. We find that multi-ethnic cabinet positions sharing in Africa is significantly associated with natural resources. Leaders appoint more elites from ethnicities with abundant natural resources. Within 2-8 years of resource discovery, ethnicity with resource discovery could receive between 0.7-2 more ministerial appointments compared to ethnicity with no discovery. We also observe significant association between ethnic specific commodity prices and ethnic cabinet shares. Within 3-10 years, increased ethnic specific commodity prices is associated with 1.17-2.2 more ministerial appointments.

Our finding in the second paper rejects clearly the hypothesis of political power being allocated exclusively based on population sizes and other political variables. We test three potential mechanisms explaining the role of natural resources in cabinet positions sharing. First, risk of political violence by excluded ethnicities is not a significant mechanism linking natural resources to cabinet positions sharing. Second, we find mixed evidence on the association between natural resources and social actors collective contentious action (e.g., demonstrations and riots) as a potential explanation of cabinet positions sharing. Third, our finding supports the idea that resource abundance provide rulers with more revenues to expand cabinet sizes; hence they build broader multi-ethnic coalitions.

In the final paper, we investigate the association between natural resource discoveries and intra-state armed conflict in Africa at spatial resolution of 0.5 x 0.5 degrees latitude and longitude (approximately 55km x 55km) covering all African countries. We combine the onset, intensity, and incidence of intra-state armed conflict with a oilfield and mine level geo-referenced data on discovery. Contrary to the conventional resource-conflict association, we find that oilfield and mineral discoveries reduce the likelihood of armed conflict onset at the local level. Within 10 years post discovery, the cross-section comparison (using the standard pooled OLS regressions) shows natural resource discovery reduces the probability of conflict by 0.01 percent. This probability increases to about 0.03 percent when identifying the association using grid fixed effect estimates.

Consistent with the finding in the first and second papers, we argue that positive economic and political effect of resource discoveries plausibly explain the association between resources and localised armed conflict in Africa. We find that resource discovery improves luminosity at the grid level which in turn reduces armed conflict, which we interpret as purely economic mechanism. Based on the finding in the second paper, we argue that multi-ethnic distribution of ministerial appointments by the ruler reduces the probability of armed conflict.

Our work contributes to the resource curse literature. In the following sections, we review the related literature and relate our contribution to the emerging within-country econometric analysis of the effect of natural resources.

1.1 The Resource Curse: What Have We Learned?

Our main contribution is to the broader literature on the natural resources and economic development. A large body of macro literature note that resource rich countries on average grow slower than resource poor countries (Auty, 2001; Gylfason, 2001; Sachs and Warner, 2001).[1] The cross-country findings have been contested. For instance, Brunnschweiler and Bulte (2008) argue that cross-country studies have used an explanatory variable that suffers from endogeneity issues and omitted variable bias. There are a multitude of variables at the country level that might confound the association between resources and macro outcomes. To minimise the risk, an emerging literature has shifted the focus towards exploiting within-country variation using subnational evidences.[2]

The finding at the subnational level is (still) mixed. One of the key contribution to the literature was made by Michaels (2011), Allcott and Keniston (2014) and Haas and Poelhekke (2016) who investigate the association between natural resource abundance and the manufacturing (business) sector. Michaels (2011) finds positive long-run effect of oil-based specialisation on the overall manufacturing employment density in the United States. Similarly, Allcott and Keniston (2014) find that oil and gas booms in the United States have positive effect on manufacturing employment and output. Local manufacturing sector in resource endowed counties supply inputs to the natural resource sector, and other manufacturing sectors also benefit from increases in local demand by supplying locally-traded goods and services. However, Haas and Poelhekke (2016) document that subnational natural resource extraction could hinder local business environment through "congestion effects" on the availability of local inputs and infrastructure. Their evidence come from eight resource rich countries: Brazil, Chile, China, Kazakhstan, Mexico, Mongolia, Russia and Ukraine.

The emerging literature has also investigated how the extractive industries have an effect on the agricultural sector, and the findings are mixed. Lippert (2014) exploits variation in copper production in Zambia and find that copper

[1] See van der Ploeg (2011) for a survey of this literature.

[2] See Aragón et al. (2015) and Cust and Poelhekke (2015) for surveys of the literature on local and regional studies of natural resources. Similarly, van der Ploeg and Poelhekke (2017) provide a survey of recent quantitative evidence.

boom improved the demand for locally produced agricultural goods and services. However, Fafchamps et al. (2016) used gold production dataset in Ghana and document locations near gold mining have more sophisticated non-agricultural forms of economic activity. In contrast, Aragón and Rud (2015) find that farmers in the vicinity of mining industries in Ghana face a significant reduction in agricultural output and total factor productivity.

Other sub-national evidences focused on conventional mechanisms. For instance, Aragón and Rud (2013) analyses the effect of a large Peruvian gold mine on the real income of households and find positive effects. Their study offers support for the local backward linkages hypothesis, implying that extractive industries can increase the real return to local factors of production via local procurement of goods and services. The study by Loayza and Rigolini (2016) uses mining dataset in Peru and their results are consistent with the results of Aragón and Rud (2013). They find that mining boom leads to larger average consumption per capita and lower poverty rates in mining districts. However, Kotsadam and Tolonen (2016) document the existence of gender inequality in economic opportunities that may arise due to mining booms in Africa. They find a mixed blessing for women. They document that mine opening causes women shift to the service sector, yet overall female employment shrinks.

Recent advances in within-country econometric analysis are also exploiting the wide array of hitherto unavailable data to estimate persistent (long-run) effects of mining activities. A pioneering contribution was made by Dell (2010) who investigates the long-run impacts of an extensive forced mining labor system known as *mita* in Peru and Bolivia. Districts exposed to the *mita* between 1573 and 1812 have lower household consumption and prevalence of stunted growth in children today. The paper documented that the effect persisted through its impacts on land tenure system and public goods provisions. Another persistent effects of mining activity is through its impact on infrastructure development. Bonfatti and Poelhekke (2017) estimate the effect of mining-related transport infrastructure on the pattern of bilateral trade flows in Africa. They find that such infrastructure - which connects mines to the coast - reduces intra-African trade by favouring overseas trade. Mining activity has favoured connecting the mines with the coast than with the neighbouring countries, hence it lowers trading cost with overseas countries compared to the neighbours.

1.2 Natural Resources and Political Power

Our bigger contribution is to the literature on the political economics of natural resources. Several studies have argued that natural resources may lower the economic performance because they strengthen powerful groups, weaken legal frameworks, and foster rent-seeking activities (Ross, 1999; Tornell and Lane, 1999; Auty, 2001; Torvik, 2002; Collier, 2010b). There is an empirical regularity indicating the perverse incentive of rulers as a plausible political mechanism that lead to country level resource curse (Caselli and Cunningham, 2009). More crucially, natural resources can create perverse incentives and enable politicians to survive in office for undefined period. The core finding that more natural resources is associated with rulers' survival in office is unambiguous (Omgba, 2009; Cuaresma et al., 2010; de Mesquita and Smith, 2010; Andersen and Aslaksen, 2013). To stay longer in office, rulers use windfall revenues to increase public goods provisions to buy off the opposition, or influence the outcome of election (Robinson et al., 2006). Furthermore, rulers could strengthen military or security technology in the shadow of resource booms (Cotet and Tsui, 2013; Bazzi and Blattman, 2014). The hypothesis is that military technology enhance government's repressive, or counter-insurgency capacity to tighten grip on power by effectively repressing any latent opposition (Besley and Persson, 2009).

Natural resources can also heighten the autocratic nature of political systems, where incumbents choose the degree of political contestability by deciding how much to spend on political forces (Caselli and Tesei, 2016). Jensen and Wantchekon (2004) also pointed out that the executive discretion by the incumbent over the distribution of resource rents has a significant impact on political regimes. Other studies demonstrate how natural resources can feed corruption (Bhattacharyya and Hodler, 2010; Brollo et al., 2013; Knutsen et al., 2016).

1.3 Natural Resources and Internal Armed Conflict

We also contribute to the literature on the association between resources and conflict (Cotet and Tsui, 2013; Dube and Vargas, 2013; Lei and Michaels, 2014). The effect of resources on the risk and intensity of conflict could be ambiguous (Besley and Persson, 2011). There is a wide range of plausible rival mechanisms of the resource-conflict association (Humphreys, 2005). We highlight a set of mechanisms that could underlie a potential (positive or negative) association between natural resources and intra-state armed conflict. This will help us to understand the net effect of natural resources on armed conflict.

The opportunity cost mechanism treats conflict as an economic activity.[3] The hypothesis states that if the returns from conventional economic activities such as farming or wage labour are high then the likelihood of armed conflict reduces (Collier and Hoeffler, 1998, 2004; Miguel et al., 2004). In the event of resource booms the returns from non-fighting activity could potentially increase thereby reducing the likelihood of armed conflict.[4]

The empirical literature on resource shocks and conflict however produced mixed results. Dube and Vargas (2013) find support for the labour vis-à-vis capital intensity argument in case of Colombia where price shocks tend to increase conflict. However, they qualify their argument by stating that the results are very much dependent on the type of primary commodities. Bazzi and Blattman (2014) show that the revenue from capital-intensive minerals and oil accrue mainly to the state and therefore do not affect individual incomes directly. This in fact reduces the likelihood of conflict by strengthening state institutions.

Another causal mechanism is the "State as a Prize". Natural resources may increase the prize value of state capture and in turn increase the incentive for armed conflict (Fearon, 2005). There are two prominent variants of this argument. The first focuses on the local rebels engaging in direct armed conflict against the state to benefit from natural resources (Collier and Hoeffler, 2004).

[3]The logic originates from the economic analysis of crime by Becker (1968). A risk-neutral individual will commit a crime if his private benefit exceeds the expected costs for doing so.

[4]A labour market mechanism operates via factor intensity. Dal Bó and Dal Bó (2011) demonstrate that resource extraction could affect wages of low skilled low income households as the former activity is predominantly capital intensive.

The second focuses more on the role of geography as oppositions in resource rich regions fight to secede from the state (Humphreys, 2005; Morelli and Rohner, 2015). Africa has experienced several episodes of secessionist movements and some studies observe that natural resources play a significant role (Fearon, 2005).

The political patronage mechanism stipulates that resources generate political incentives for incumbents to distribute political patronage more widely to survive longer in power (Robinson et al., 2006; Cuaresma et al., 2010; Andersen and Aslaksen, 2013). Distribution of patronage to the elites and citizens ensures that the incumbent dissuades a militant subset of the society from attempting armed rebellion (Francois et al., 2015). Patronage distribution may take the form of public sector employment offers, ethnic brokerage, or personal networks that connect the co-opted elites in the centre to local citizens (Roessler, 2011). Patronage distribution also influences the voting behaviour of citizens (Robinson et al., 2006). In summary, the political patronage mechanism predicts an inverse association between resource discovery and conflict.

Furthermore, the state capacity mechanism stipulates that natural resources increase state's counter insurgency capacity through enabling it with additional revenue which could then be used to strengthen the military and other security infrastructure (Besley and Persson, 2009; Bell and Wolford, 2014). For example, Cotet and Tsui (2013) find that increased defence burden and enhanced military technology increases the government's counterinsurgency capacity and thereby reducing the likelihood of armed conflict. Note that the state capacity mechanism is somewhat similar to the political patronage mechanism and they often complement each other within a political system (Bazzi and Blattman, 2014).

The rest of the thesis is organised as follows: Chapter 2 examines the association between mining and local economic development in sub-Saharan African countries. Chapter 3 examines the effects that changes in natural resource discoveries and global commodity prices have on the allocation of cabinet positions across diverse ethnicities in Africa. Chapter 4 investigates the empirical association between resource discoveries and intra-state armed conflict at the grid level corresponding to a spatial resolution of 0.5 x 0.5 degrees covering all African countries. Chapter 5 concludes the thesis.

1.4 Measurement Challenges and Discovery Data

Most of the econometric analysis of the impact of natural resources is hindered by several challenges, but a main limitation is the challenges in the measurement of natural resources. Some studies have questioned the robustness of the resource curse findings largely based on endogeneity issues (i.e., using endogenous variable as an explanatory variable). For instance, Brunnschweiler and Bulte (2008) stated that the negative impact of natural resources on growth and development at the cross-country level arises due to the use of an endogenous resource dependence as an explanatory variable (i.e., the ratio of natural resource exports to GDP). Yet their proposed natural resource measurement (i.e., resource abundance) itself is not free from measurement challenges. Because the measurement of the total amount of resource wealth (or, abundance) is an endogenous variable by construction. The resource abundance measures are constructed by the World Bank and still depend on the prevalent price of resources and cost of extraction to assign dollar values (van der Ploeg and Poelhekke, 2010).

Few emerging literature on the impact of natural resources, however, has shifted the focus towards exploiting hitherto unutilised measurement of natural resources (i.e., natural resource discovery data) (Cotet and Tsui, 2013; Lei and Michaels, 2014; Arezki et al., 2017; Mamo et al., 2017). In this context, this thesis essentially relies on the assumption that discovery dates of natural resources (oilfield and mineral deposit) are exogenous at the sub-national level. This is a departure from the existing cross-country and most sub-national level literature, which are of course fraught with endogeneity issues. The dates of natural resource discoveries are random due to the uncertain nature of exploration investment in Africa. The exploration intensity and strategy are strongly influenced by external conditions such as global business cycles and market. The critics may still argue that global business cycles and market have link with the discovery announcement. Nevertheless, these external conditions themselves are still exogenous to African political economy and development.

Even though it is possible to identify the area where oilfield or mineral deposits are likely to be found using geological as well as historical information, it is not possible to accurately predict the timing of discoveries. Therefore, the discovery dates of oilfield and mineral deposits are exogenous. Again one might argue that political elites and government could manipulate the announcement of the precise timing of discovery. Our data is immune to such possibility as the discovery dates are independently verified and documented using multiple sources. Therefore, exploiting such random variation in the timing of discoveries allows us to conduct a quasi-natural experiment, and our approach is less subject to potential reverse causality challenges. More discussion on the details of data sources and measurement is available under data sections in each chapter.

In most cases, we restrict discovery variable to first discovery where there were no mining or oil drilling activity before. Restricting the discovery variable to first discovery address some main identification concerns. There is no concern that natural resource discoveries are serially correlated over time during the sample period. Moreover, the timing of the discovery represents to economic agents, and this element of surprise is particularly likely where there no any mining or drilling history. Therefore, our finding in this thesis is not undermined by endogenous issues of natural resource measurement.

CHAPTER 2

Mining and Local Economic Development

2.1 Introduction

The industrial age of eighteenth and nineteenth century witnessed a coming together of coal, iron and steel, and steam power which propelled mass production and living standards to a level unprecedented in human history. Britain and other continental European countries were able to successfully utilise natural resources to industrialise and improve living standards. The post-independence development experience of resource rich developing nations especially in Africa however has been dismal giving rise to the view that natural resources are a curse rather than a blessing for development.

Indeed, a large body of predominantly macro literature document a negative correlation between growth rates of GDP per capita and resource reliance by exploiting variation in cross-national data. This literature broadly identifies three potential channels through which natural resources could hinder development. First, natural resource exports could appreciate the real exchange rate thereby disadvantaging the tradable non-resource sector (or the modern sector) of an economy (Corden and Neary, 1982). Adverse development outcomes may be permanent, if competitiveness cannot be regained.[1] Second, over-reliance on natural resources for government revenue could give rise to corruption and weak institutions as the state would no longer require relying on the non-resource sec-

[1] We wonder whether this argument is relevant in the context of Sub-Saharan Africa. The manufacturing sector is tiny - even in non-mining countries. Besides, the exchange rate is not seen as a key constraint for manufacturing firms in Africa (Bigsten and Söderbom, 2006).

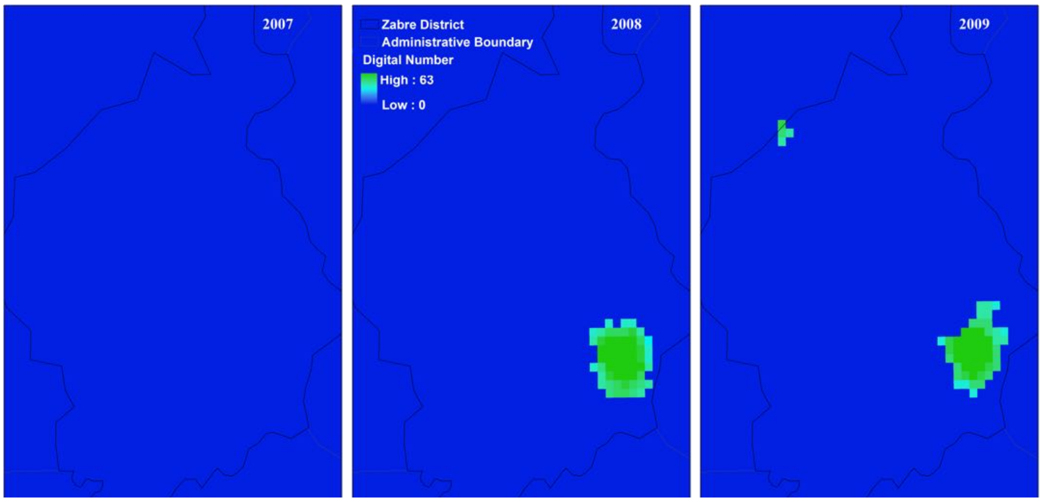
tor as a major source of revenue (Robinson et al., 2006). Third, the high volatilty of global commodity prices could disadvantage resource rich developing countries as they become more exposed to global shocks and macroeconomic instability (Deaton, 1999; Ramey and Ramey, 1995).

A significant intellectual efforts went into documenting the adverse consequences of natural resources in resource rich developing countries. Yet establishing causality has remained somewhat illusive in the cross-country studies. In this chapter we aim to explore whether natural resources improve development at the subnational level. We contribute to the resource curse debate by examining the local impacts of large scale mineral discovery and extractions in the context of sub-Saharan African countries. We show that mining has a positive impact on the local economy, as reflected in the satellite data on night lights at the second level subnational administrative unit (district level). However, we do not observe (strong) general equilibrium effect beyond the confines of a district.

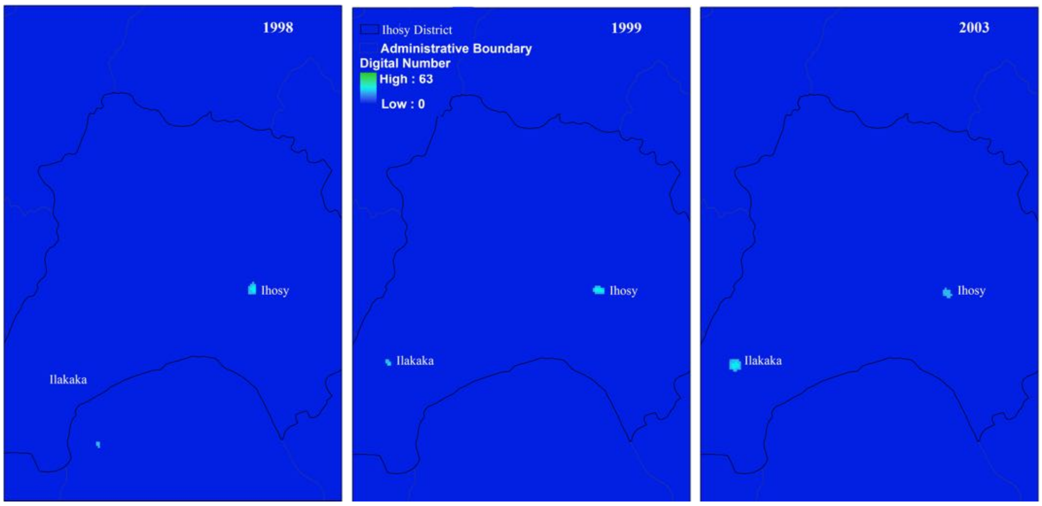
A quick snapshot in Figure 2.1 reveal that mineral production and mining discovery leads to significant improvements in economic activity measured by night lights. The upper panel in Figure 2.1 zooms into Zabre District in the Boulgou Region of Burkina Faso. Zabre has produced her first mineral commodity, gold, in 2008. The change in the economic fortunes of Zabre is visually apparent here via the satellite images of night lights before and after gold production. In 2007 before gold production, the mean pixel value of night lights in Zabre is 0.006. But in 2008 the mean pixel value increased to 0.31. The following year 2009, Zabre again experienced an increase in night lights. So much for night lights, what about population? In 2007, the Socioeconomic Data and Applications Centre estimates Zabre's population to be 135,582 and the population five years later in 2012 is estimated to be 160,150. Again an 18 percent increase. The lower panel reveals a similar story before and after the discovery of a Sapphire mine in 1998 in the town of Ilakaka in the Ihosy district of Madagascar. The town Ilakaka did not exist before 1998.

We find that mineral production and discovery improves economic development at the district level in 42 sub-Saharan African countries over the period 1992 to 2012. We distinguish between the effects of mineral production volume expansion in the existing mines (intensive margin) and new mineral production (extensive margin). We observe that night lights increase due to mining expansion at the intensive margin. However, large effects are observed at the extensive margin following new production.

Figure 2.1: Mineral Production, Discovery and Night Lights



(**a**)



(**b**)

Notes: The upper panel shows Zabre District in Burkina Faso starting gold production in 2008. The lower panel shows Ihosy District in Madagascar. After the discovery of Sapphire deposits at Ilakaka-a village with about 40 households-in 1998, the place saw an influx of migrants and turned into a major trading centre for sapphires and a town with an estimated population of now larger than 30,000. Until 1998 there were no night lights visible in Ilakaka. After the discovery, the number of pixels with visible lights increased. Ihosy town, in contrast, has not experienced such growth; lights got smaller. Overall, however, the aggregate lit pixels have increased in Ihosy District. The lower panel is a replication of Figure 5 in Henderson et al. (2012).

We also notice that the positive impact of mineral production kicking in approximately two years prior to the actual start of mineral production. This is consistent with the fact that installation of mining infrastructure and worker arrival typically predates production.

In order to precisely identify the effect of mining on development we exploit the exogenous variation in the discovery dates of giant and major deposits of 21 minerals. We find that the positive effect of discovery kicks in on night lights approximately six years after the first discovery. For giant and major discoveries, this time frame is eight years. These results are consistent with the view that it takes approximately six to eight years for production to start following a discovery. The magnitude of the effect of first discovery is 19 percent on the sixth year and continues to rise to 44 percent on the tenth year. The effect is robust to the inclusion of population density, average annual rainfall, district fixed effects, and year fixed effects as controls.

A skeptic's view of the positive effect of mining on night lights is that it is driven entirely by lights emanating from the mines, particularly if the location of lights coincides with the mining location. Even though plausible, this view is not supported by mining industry facts on the ground in Africa (Banerjee et al., 2015).[2] Furthermore, using GIS we exclude all lights around 2 kilometre radius of a mine from our sample our results remain qualitatively unchanged.

Economic development is a general equilibrium phenomenon. Looking at the subnational district level data might mask the fact that mining districts gain at the expense of non-mining districts and the net effect of mining for a country is still negative. In order to unmask such patterns in the data we redefine the unit of interest. We test our model at the regional and country level using both production and discovery data. We find that there is very little evidence for positive effect of mineral production and discovery at the region and country level.

Why mineral discovery and extractions might affect local economic development? Our finding is consistent with the emerging sub-national literature that are largely motivated by theories of demand side linkage of extractive in-

[2]Governments and mining corporations often try to keep workers near the mining site for lengthy periods of time by offering fixed contracts and prearranged wages to miners. This creates mass migration and hence growth of mining towns and cities nearby that offer services. The mineral revolution in South Africa from the 1870s onwards is a good example, which had an impact on urbanisation, agriculture, infrastructure and local politics. The migration prompted changes in rural areas, as farms lost workers to the mines and demand for food increased.

dustries and development. The theories predict that development opportunities are likely to emerge from mineral discoveries and extractions via the potential backward linkages implying increases in return to local factors of production in post-resource discoveries and extractions (Aragón and Rud, 2013). Similarly,our finding can be explained by the effect of local demand shocks on agricultural sector. Mining boom can improve the demand for locally produced agricultural commodities (Lippert, 2014). Moreover, the theories also predict that the positive economic consequences of mining activity might likely to emerge via the labour market opportunities (Kotsadam and Tolonen, 2016). The other important economic reason explaining the positive relationship between mining activity and local development is likely to be sophistication in non-agricultural forms of economic activity and agglomeration economies (Fafchamps et al., 2016). The argument for agglomeration economies links natural resource abundance to the manufacturing (business) sector, where local non-agricultural business sectors benefit from local demand demand shocks due to natural resource abundance (Michaels, 2011; Allcott and Keniston, 2014).

Our work is related to the literature on natural resources and economic development. Auty (2001), Gylfason (2001) and Sachs and Warner (2001) note that resource rich countries on average grow much slower than resource poor countries. Subsequent studies have argued that natural resources may lower the economic performance because they weaken legal frameworks and foster rent-seeking activities (Ross, 1999; Tornell and Lane, 1999; Auty, 2001; Collier, 2000; Torvik, 2002). Others have argued whether natural resources are a curse or a blessing depends on country-specific circumstances especially institutional quality and governance (Mehlum et al., 2006; Robinson et al., 2006; Bhattacharyya and Hodler, 2010, 2014a; Bhattacharyya and Collier, 2014; Venables, 2016), natural resource type (Isham et al., 2005a) and ethnic fractionalisation (Hodler, 2006). While these and related studies not imply that resource rents inevitably reduce living standards, they show that it is entirely possible. Even though these studies are relevant for sub-Saharan Africa they mainly explore the cross-national dimension. They do not investigate the role of natural resources and especially mining at the local, regional and national levels which we undertake here. These studies are focused not exclusively on sub-Saharan Africa and casual interpretations of their results are often problematic.[3] We do well on both counts here as we utilise a new mine level dataset on mineral production and discovery in sub-Saharan Africa and relate it to night lights. The satellite data on night lights have been used by others recently as a credible measure of economic development at the local, regional and country levels (Henderson et al., 2012).

Resource curse thesis suggests that resource curse is a general equilibrium phenomenon. Therefore, the cross-national focus of the early empirical literature is understandable. However, there has been a shift in the focus more recently with several studies focusing on the local effects of resource extraction. For example, Aragón and Rud (2013) analyse the effect of a Peruvian gold mine on the real income of local households using household survey data and find positive effects. Caselli and Michaels (2013) and Allcott and Keniston (2014) focus on the local effects of oil boom in Brazil and shale oil and gas boom in the United States respectively. In spite of the growing interest on the local effects of resource boom, most of the studies remain country or mine specific calling into question the external validity of their findings. Furthermore, studies on sub-Saharan African countries remain a rarity barring a few exceptions.[4] In contrast, we study the entire sub-Saharan Africa which appears to be unmatched in this literature. We utilise discovery dates of giant and major mining deposits to set up a quasi-natural experiment which none of the other studies do.

Our work is also related to a more recent literature on the determinants of development at the subnational level. This literature makes use of satellite data on night lights and city growth to measure development at the regional and subnational levels. Michalopoulos and Papaioannou (2013a, 2014) and Hodler and Raschky (2014) are examples of studies that use night lights whereas Jedwab et al. (2016) and Jedwab and Moradi (2016) use city growth. The factors identified as

[3]Recent cross-country studies relating mainly oil and conflict have used information on giant oil discovery to mitigate the causality challenge. Cotet and Tsui (2013) and Lei and Michaels (2014) study the effect of oil on conflict. Arezki et al. (2017) analyse the impact of oil discovery on macro variables.

[4]Aragón and Rud (2015), Kotsadam and Tolonen (2016), and Fafchamps et al. (2016) are examples of such exceptions. Aragón and Rud (2015) study the pollution effect of gold mining on agricultural prodictivity. Kotsadam and Tolonen (2016) study the effect of natural resources on local employment in Africa, and Fafchamps et al. (2016) investigate whether gold mining is a catalyst for early stages of urbanisation (proto-urbanisation).

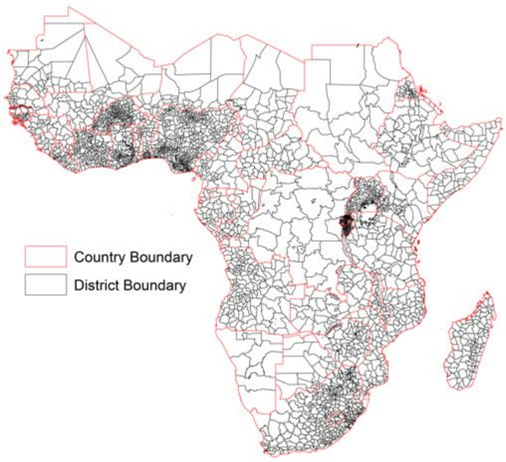
key determinants of African subnational development by this literature are pre-colonial ethnic institutions (Michalopoulos and Papaioannou, 2013a, 2014), birth region of rulers (Hodler and Raschky, 2014), and colonial railroads (Jedwab et al., 2016; Jedwab and Moradi, 2016). Michalopoulos and Papaioannou (2014) also show that national institutions do not explain subnational variation in development in Africa. Note that Michalopoulos and Papaioannou (2013a, 2014) exploit cross-sectional variation while Hodler and Raschky (2014) use panel data.

The remainder of the chapter is structured as follows: Section 2.2 presents the data sources and descriptions. Section 2.3 discusses the empirical strategy to identify the local effects of mining activity. Section 2.4 presents the results and discussion. Section 2.5 deal with robustness. Section 2.6 concludes.

2.2 Data Sources and Measurement

We construct a panel of 3,635 districts from 42 Sub-Saharan African countries over the period 1992 to 2012.[5] Districts are the main units of observation in our study. They correspond to the second level subnational administrative classification of sub-Saharan Africa in 2000 obtained from (FAO GeoNetwork, 2013). The average size of a district in our sample is 6,585 square kilometres. Table A.1 in the Appendix reports basic summary statistics.

Figure 2.2: District Level Map of Sub-Saharan Africa



Notes: This map shows the second level administrative units that we use in our analysis. We exclude small island countries (Saint Helena, Seychelles, Sao Tome and Principe, Reunion, Mayotte, Mauritius, Cape Verde and Comoros) and Djibouti.

[5]In the Appendix we present a list of countries included in the sample.

2.2.1 Local Economy: Satellite Data on Night Lights

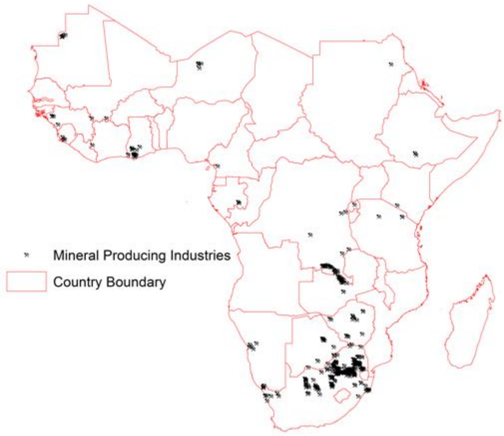
As our main measure of local economic development we use satellite data on night lights provided by the US National Oceanic and Atmospheric Administration (NOAA). Note that the data we use here is cleaned luminosity, after filtering for cloud coverage, other ephemeral lights, and background noise. The measure comes on a scale from 0 to 63 (digital number), where higher values imply greater luminosity. The data are available at pixels of 30 arc-second dimension (equivalent to one square kilometre). The very high resolution helps us calculate economic activity at the local level. We calculate light density by dividing the sum of all night lights pixel values within a district by the area. As an alternative measure, we also construct luminosity per capita.

The distribution of night lights across districts is not normal. A substantial number of observations (about 31.5 percent of the sample) take the value zero. There are also a few extreme observations on the right tail of the distribution. To account for this, we follow Michalopoulos and Papaioannou (2013a) and Hodler and Raschky (2014) and define the dependent variable as the natural log of night lights density plus 0.01. Such transformation ensures that all available observations are used and the problem of outliers minimised. Note that the absence of reported night lights typically does not imply darkness, and certainly not absence of economic activity (Hodler and Raschky, 2014). There are also issues with the difference between true lights emanating into space and what is recorded by a satellite (Henderson et al., 2012). In particular, there is variation in recorded lights data across satellites. Measurement error of this nature is unlikely to be a concern here as it is orthogonal to our model in section 3.1. Furthermore, because all districts in a particular year are covered by the same satellite, any cross-satellite variation in night lights is accounted by the year fixed effects.

2.2.2 Natural Resources: Mineral Discovery and Production

Information on mining comes from two sources. The first source is IntierraRMG (2014). It provides data on production, start-up year and mining status for industrial size mines for the period 1992-2012. Our dataset contains 548 industrial size mining industries producing 21 different mineral commodities. All the mines are matched to district administrative units. Where IntierraRMG did not provide a start-up date, we consulted other sources (including the website of each mining company) and added the information. Moreover, the mineral value is calculated using price data from the U.S. Geological Survey (Kelly and Matos, 2013).

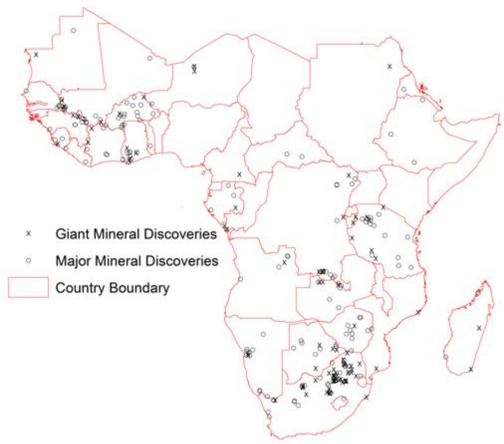
Figure 2.3: Geographical Locations of Mine Producing Industries



Notes: The map shows the location of active mines in sub-Saharan Africa. These mines are owned or operated by either large multinationals or state owned companies. We exclude small-scale mines and informal or illegal mines.

The second source is MinEx Consulting (2014). It reports discovery and production start-up dates of 259 giant and major mineral deposits from 1950 to 2012. MinEx codes a mineral deposit as giant if it has the capacity to generate at least USD 500 million of annual revenue for 20 years or more accounting for fluctuations in commodity price. A major mineral deposit is defined as one that could generate an annual revenue stream of at least USD 50 million but may not last as long as a giant deposit.

Figure 2.4: Geographical Locations of Mineral Deposit Discoveries



Notes: The map shows the location of major and giant mine discoveries in Sub-Saharan Africa over the period 1950-2012.

2.2.3 Other District Specific Variables

Population density is an important control variable, as it exhibits strong positive correlation with light density (Cogneau and Dupraz, 2014).[6] Population data is obtained from the Socioeconomic Data and Applications Centre-Centre for International Earth Science Information Network (SEDAC-CIESIN). Population estimates are available for 1990, 1995, and 2000, and projections for 2005, 2010, and 2015. We follow Hodler and Raschky (2014) and aggregate the gridded population dataset to second level administrative units. We then construct annual district population 1992-2012 replacing missing years by linear interpolation.

We use a set of geography, climate, political economy and infrastructure variables as observable characteristics between treated and control districts.[7] The geography variables are altitude, ruggedness, soil fertility, distance to the coast, and land surface area. From the 90m Digital Elevation Database of the NASA Shuttle Radar Topographic Mission (SRTM), we construct mean and standard deviation of elevation. Soil fertility is expressed as the percentage of a district's land area with fertile soils for agricultural crops and is constructed from the index in FAO/UNESCO Digital Soil Map of the World. The climate variables are annual

[6]Despite its consistency and spatially explicit population distribution, gridded population estimates may not match the actual population at the district level. This could be seen as a standard measurement error because population projections are not based on night lights.

[7]With the exception of rainfall and population, our observable characteristics are time-invariant at the district level. The summary statistics on all variables can be found in Appendix.

rainfall from Tropical Applications of Meteorology using Satellite data (TAMSAT), and the district's land area classified as tropical climate, arid climate and temperate climate (Kottek et al., 2006). The infrastructure variables are paved road density (i.e. paved road length per square kilometre), railway density (i.e. railway length per square kilometre) and electric grid density (i.e. electric transmission cable length per square kilometre). They are derived from the African Development Bank and DIVA-GIS for the year 2000. Finally, the political economy variables are a "capital" dummy variable equal to one if the district contains the capital city of the country, or if the district itself is the capital city, distance to the capital city and ethnic fractionalisation constructed from the Ethnographic Atlas by Murdock (1959). The implicit assumption here is that proximity to the capital city is associated with better quality institutions whereas high levels of ethnic fractionalisation is associated with poor institutional quality.

2.3 Empirical Strategy

2.3.1 Local Effects of Mineral Production

We start with exploring the effect of mining activity and our main specification uses annual data for the period 1992-2012:

$$Luminosity_{d,t} = \alpha_d + \eta_t + X_{d,t}\beta + \gamma Mining\ Production_{d,t} + \epsilon_{d,t} \qquad (2.1)$$

where $Luminosity_{d,t}$ is the natural log of night lights density plus 0.01 in district d in year t, $Mining\ Production_{d,t}$ is the natural log of mineral production value, α_d are district fixed effects, η_t are year fixed effects, and $X_{d,t}$ is a vector of time-variant control variables that includes the natural log of population density and rainfall. The coefficient of interest is γ, the elasticity of mineral production.

Identification comes from temporal variation within mineral producing districts. The validity of this strategy rests on the assumption that fluctuations in mineral production are driven by factors external to the district. This may not be true. For example, shocks - such as power cuts or violent conflicts - may affect both mining and economic activity during a certain district-year and are not absorbed by the district fixed effect. The same reasoning applies to the extensive margin. The opening of a mine can be delayed or coincide with conditions (such as a road). Keeping these caveats in mind, the results nevertheless help to establish stylised facts that we probe more thoroughly later.

2.3.2 Local Effects of Mineral Discovery

Similarly, we identify the effect of mine discovery shocks on local economic development by estimating the following model:

$$Luminosity_{d,t} = \tilde{\alpha}_d + \tilde{\eta}_t + X_{d,t}\tilde{\beta} + \sum_{j=0}^{10} \tilde{\gamma}_j Discovery_{d,t-j} + \tilde{\epsilon}_{d,t} \qquad (2.2)$$

where $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a mineral discovery has been made in year $t-j$, 0 if no discovery has been made and missing for every year post-discovery other than $t-10$.

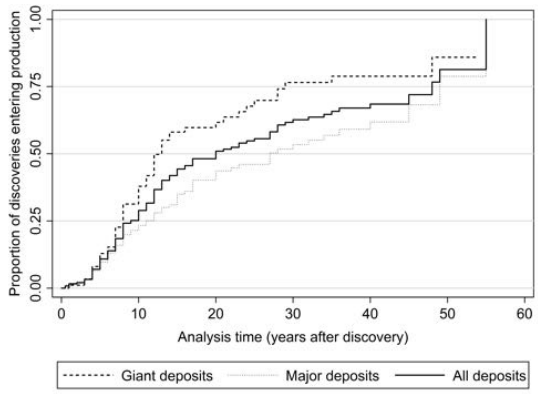
We restrict $Discovery_{d,t-j}$ to *first discoveries*, that is to discoveries in districts that never had any mining activity before, and the comparison group to districts without any discoveries. This restriction serves two purposes. First, existing mining activities may affect local development and it is difficult to disentangle this effect from the effect of a new discovery. Second, economic agents may arguably anticipate repeated discoveries due to the knowledge of past discoveries and geology. In contrast, a discovery and its exact timing is much harder to predict for "virgin" non-mining districts.[8] Thus, setting $Discovery_{d,t-j} = 1$ for first discoveries is the cleanest treatment group. In fact, the coefficient $\tilde{\gamma}_0$ tests whether there is a significant level difference between non-mining districts and districts in which a discovery has just been made. Overall, the coefficients $\tilde{\gamma}_j$ measure the difference in night lights j years after a discovery.

Analysing *mineral discoveries* enables us to explore and mitigate potential endogeneity challenges associated with *mineral production*. First, one potential concern is that districts with better unobservable fundamentals may be more likely to enter production. Discoveries are likely to follow a different, less se-

[8] Mineral discoveries in virgin districts are not heavily clustered in administrative regions with pre-existing mining activities either. For the 1992-2012 period, 36 out of the 73 first discoveries occurred in districts, where the corresponding region had no recorded mining activity as well.

lective model, because they require less capital, and returns are largely driven by the size of the deposit which is unknown *exante*. Certain discoveries may not enter production at all. Discoveries can be interpreted as intention-to-treat. Second, the timing of the discovery can be considered exogenous, if discovery represents 'news' to economic agents. We believe that this element of surprise is particularly likely in districts without any mining history. Third, there may be a significant delay between discovery and start of production.

Figure 2.5: Estimates of Discoveries Entering Production



Notes: The graph shows Kaplan-Meier failure estimates, whereby mineral deposits become "at risk" when discovered and "fail" when entering production. Analysis at mineral discovery level 1950-2013. Discoveries that have not started production are those which current status is coded as "Undeveloped" or "Feasibility". We excluded mineral discoveries (N=12), for which the start-up year was missing but current status was coded as "unknown", "operating" and "closed". N(major discoveries/giant discoveries at risk)=(156/88). Data is from MinEx Consulting (2014).

Our data indicates that 10 years after a discovery, only 27.2% of the sites entered production. After 20 years, the figure rises to 48.3% (Figure 2.5). Setting up mining infrastructure and attracting the labour force to work in the mines constitute economic activity *caused by mining* but it typically predates production. This effect could be wrongly attributed to the pre-mining era comparison group. In contrast, mining discovery constitutes a clean start of the experiment. Overall, we can treat the discovery date as an exogenous news shock, much more in line with the start of the experiment, enabling us to mitigate potential reverse causality challenges associated with mineral production.

2.4 Results and Discussion

2.4.1 Mineral Production and Local Economic Development

In this section, we report the main results following the empirical strategy discussed in the previous section. Table 2.1 presents evidence on the effect of mineral production on night lights density. All the specification include time varying population density and average rainfall, and district and year fixed effects.

We distinguish between value and quantity by expressing mineral production in 1992 constant USD and 1992 constant commodity prices respectively. We expect quantity to be more important. Commodity prices are determined at the world market and can fluctuate widely (Deaton, 1999). However, mining companies may have little incentive to adjust production to price fluctuations in the short-term. Therefore, prices and demand for local inputs may be less affected. Windfall gains and losses may then largely accrue to capital owners.

We start with exploring the effect of production at the intensive margin. Our main specification is based on Equation 2.1 by using annual data for the period 1992-2012, and results are reported in columns (1)-(3) in Table 2.1. Column (1) points to a positive association between production values and night lights. The association, however, is stronger when using production volumes instead (column (2)), and in a horserace it is the latter that wins (column (3)).

To study the extensive margin, we replace $Mining\ Production_{d,t}$ with a dummy equal to one if the district has - or ever had - a producing mine. Under this specification the sample includes all districts. The estimated coefficient identifies the change in night lights associated with a change in a district's status from non-mining to mining, or in other words the start of mineral production. This because we use district fixed effects which absorb night lights differences in districts that do not change status. In column (4) we examine the effect of mining at the extensive margin on night lights and find that a switch from a non-mining district to a mining district is associated with an increase in night lights by 55.4 percent. This is approximately more than 13 times the effect of mining expansion at the intensive margin and hence a large effect.

Table 2.1: Intensive and Extensive Margins of Mineral Production

	Intensive Margin			Extensive Margin
	(1)	(2)	(3)	(4)
Ln(Mineral Production)	0.024*		-0.061	
	(0.014)		(0.047)	
Ln(Mineral Production in 1992 Commodity Prices)		0.038**	0.102*	
		(0.018)	(0.057)	
Mineral Production (1=yes)				0.554***
				(0.117)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,802	1,802	1,802	76,335

Notes: This table shows the association between night lights and various measures of mining activity in a panel of district-year observations for the period 1992-2012. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. column 4 uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

How big are the economic significance of these effects. A simple test would be tally them with district level real GDP data. Henderson et al. (2012) find that for low and middle income countries, the structural elasticity of growth of night lights with respect to GDP growth in the long-term is close to one. Michalopoulos and Papaioannou (2013a) use the Demographic and Health Survey (DHS) data at the subnational level and estimate the elasticity between luminosity and composite wealth index to be 0.7. Based on such estimates we could speculate that a switch from non-mining to mining would increase a district's GDP by 38.78 percent (this number is the estimate in Table 2.1 column (4) multiplied by 0.7).

2.4.2 Mineral Production Onset and Local Economy

So much for mineral production, how about the effect of the onset of production? For this analysis the most important concern is the violation of the unconfoundedness assumption: districts that enter mineral production may do so because of certain unobservable characteristics that are associated both with the start of mineral production (the 'assignment') and with the potential outcomes. For example, the geology of mineral resources may be correlated with soil quality and water availability (riverbeds); profitability of mineral extraction may depend on the presence of infrastructure (railroads, roads, ports, electricity) and labour; and certain underlying factors may facilitate local opposition to mining. Overall, districts with better unobservable characteristics may start production earlier, and it could be the former-not the latter-that would cause development.

We divide the data into a control and treatment group. The aim is to identify a suitable control group that matches the treatment group in every respect except the treatment. We define two control groups. Firstly, we take districts that never have had any mining activity as of 2012 (control 1). While one would not expect this to be a valid control group, the comparison is interesting in its own right. Secondly, we take districts yet to be mined but with mineral deposits (control 2). The potential of these districts are examined in a feasibility study as of 2012. Mining companies assess profitability of a site going through several stages (grassroots, exploration, advanced exploration, pre-feasibility, feasibility, construction) of filtering. Feasibility studies are the final stage before construction. Thus, most of the selection has taken place by this stage.[9] Still, only a subset of districts may pass from the feasibility stage to construction and finally production. We therefore rely on the same pre-treatment trends to lend confidence to the parallel trend assumption. In order to facilitate pre-treatment comparison, we define the treatment group as those districts that started production for the first time between 2003 and 2012, hence we a have a symmetric pre- and post-treatment period of 1992-2002 and 2003-2012 respectively.

We first examine whether there is any systematic difference in observable characteristics between treated and control districts. Table 2.2, Panel A, column (1) presents the mean values for each observable characteristic and columns (2) and (3) present the normalized mean difference between treatment and the two control groups.[10] All observables are time-invariant (referring to the year 2000). Column (2) indicates that treated districts are at a relatively higher altitude and are more rugged than never mined districts. They also have a larger land surface

[9]We do not use the construction stage as control group, because construction by itself already constitutes economic activity caused by mining. We aim to present an even cleaner strategy when investigating mineral discoveries, see subsection 2.4.4.

[10]The normalised difference between treatment t and control group c is defined as $\Delta_X = (\bar{X}_t - \bar{X}_c)/\sqrt{(S_t^2 + S_c^2)/2}$ where $\bar{X}$ and S^2 refer to sample means and variances respectively.

area, less rainfall, a more temperate climate, an ethnically more fractionalised, and a higher railway density. In contrast, column (3) suggests that the treated districts are fairly similar to feasible districts.

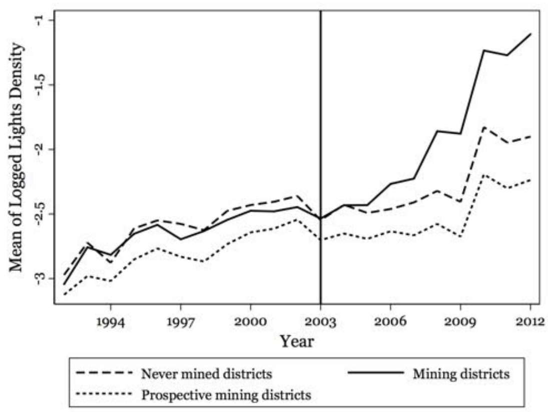
Table 2.2: Comparison of Treated and Control Districts

		Normalized Difference	
	Treated	Treated-Control 1 Never mined	Treated-Control 2 Feasibility
	(1)	(2)	(3)
Number of Districts	53	3284	156
Panel A: Time-Invariant Cross-Sectional Variables			
Ln(Altitude in m)	6.18	0.14*	-0.00
Ln(Ruggedness)	4.31	0.14*	-0.04
Share of district with fertile soil	16.09	-0.04	-0.09
Ln(Distance to the Coast in km)	5.76	0.09	0.05
Ln(Land surface area in sq. km)	8.40	0.36***	-0.03
Ln(Average annual rainfall in mm)	4.73	-0.15**	0.03
Share of district with tropical climate	50.88	-0.11*	-0.09
Share of district with dry/arid climate	27.17	0.03	0.00
Share of district with temperate climate	21.94	0.12**	0.11
Capital city (1=yes)	0	-0.11	-0.08
Ln (Distance to the capital city in km)	5.56	0.05	-0.03
Ethnic FractionalizatioObservations	0.31	0.24***	0.02
Ln(Paved road density per sq. km in 2000)	0.02	-0.05	0.10
Ln(Railway density per sq. km in 2000)	1.66	0.21***	0.03
Ln(Electric-grid density per sq. km in 2000)	0.06	-0.05	0.16**
Panel B: Trend Comparison			
Ln (0.01+night lights Density)			
Pre-treatment growth 1992-2002	0.60	-0.00	0.00
Post-treatment growth 2003-2012	1.33	0.41***	0.53***
Ln (0.01+night lights Per Capita)			
Pre-treatment growth 1992-2002	0.40	0.01	0.02
Post-treatment growth 2003-2012	1.17	0.44***	0.55***

Notes: This table shows the difference in observables and outcomes between treated and control districts. Treated districts started mineral production for the first time between 2003 and 2012. The control groups are defined as i) districts that never had any mining activity (control group 1) and ii) districts yet without mining but with mineral deposits, which potential is examined in a feasibility study (control group 2). In column (1), coefficients represent the mean value of each variable for the treatment group. In columns (2) and (3), we present the normalised mean difference relative to the control group as in Imbens and Wooldridge (2009). Panel A presents the comparison of time invariant variables. Panel B presents decadal growth rates before treatment (1992-2002) and after treatment (2003-2012). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level.

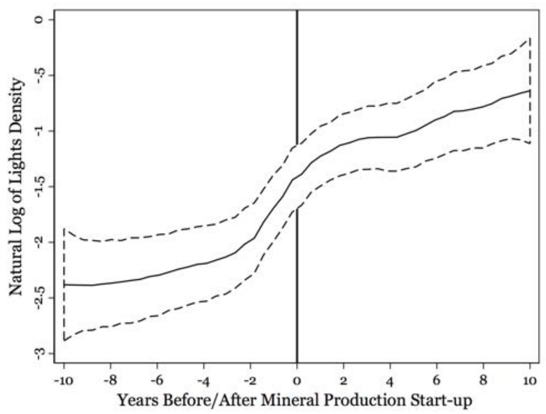
In Table 2.2, Panel B we report decadal growth rates in the outcome variables for the 1992-2002 and 2003-2012 period by treatment status. We do not find any pre-existing divergent trend in night lights across treated and control districts prior to the production treatment. In contrast, during the treatment period trends significantly diverge. After a decade night lights in the treated districts have grown by about 50 percentage points more. Figure 2.6 shows the development in night lights of treated and control groups on an annual basis.

Figure 2.6: Evolution of Lights in Three Categories of Districts



Notes: The graph shows the evolution of night lights for three categories of districts: i) districts that started mineral production after 2002 (treatment), ii) districts that never had any mining activity (control group 1) and iii) districts that are yet to be mined but with mineral deposits identified in feasibility studies (control group 2). Data is from IntierraRMG.

Figure 2.7: Evolution of Lights in Mining Districts



Notes: The graph shows the evolution of night lights in mining districts in the run-up to production and the years thereafter. Production starts at time t=0. Data is from IntierraRMG.

Figure 2.7 shows the evolution of night lights in mining districts the 10 years before and after the start of production. We observe that night lights start improving two years prior to the actual production start date. This is consistent with the view that infrastructure moves closer to the site one or two years prior to the actual start of production. We also observe steady increase in lights even ten years after the actual start of production. In sum, the evidence suggests that, contrary to the conventional wisdom of resource curse, mineral production improves living standards at the local level in sub-Saharan Africa.

2.4.3 Mineral Discovery and Local Economic Development

In this section we relate the news shock of mineral discoveries to development. Table 2.3 displays the effect of discovery shocks on night lights density. In column (1), the coefficients reflect the change in night lights j ={0, 1, ..., 10} years after a discovery relative to the pre-discovery era and trends in night lights of non-mining districts in the same year. The coefficient $\tilde{\gamma}_0$ is indeed very close to zero and remains small and insignificant up to four years. After year 6, however, point estimates become significantly positive and they increase with j. It is important to stress that this is an average treatment effect which may be explained by both, number of districts entering production and night lights still expanding in districts that started mining.

The coefficients in column (1) do not necessarily measure the effect of a single discovery, as more discoveries may follow after the first discovery. There are districts that had more than one discovery. In column (2), we limit the sample to the time when there was no subsequent discovery. Coefficients remain unchanged. Having an additional discovery after the first discovery does not seem to matter much, possibly pointing to a decreasing marginal product.

We would expect heterogeneous effects with respect to the size of mineral deposits. In particular, giant deposits should have a larger effect because of their higher economic value and because they tend to enter production more quickly than major deposits (Figure 2.5). We test this idea using the same specification as in equation 2.2, but with dummy variables MD_{drt-j} indicating the first discovery of giant (major) deposits exclusively.

Columns (3) and (4) in Table 2.3 shows the estimates for giant deposits and major deposits respectively. While standard errors are large indicating that there are no statistically significant differences between giant and major deposits, point estimates indeed confirm a pattern by which night lights take off slightly earlier (at about year 5) and at a steeper rate after a discovery of giant mineral deposits.[11] At year 10 after the discovery, the increase in night lights corresponds to 54 percentage points for giant deposits compared to a 37 percentage points for major deposits. These are indeed large effects.

[11] There are an average of 25 giant and 48 major deposits in our 10 year time horizon on average.

Table 2.3: Mine Discovery and Night Lights Density

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.029	-0.028	-0.032	-0.024
	(0.061)	(0.063)	(0.098)	(0.081)
$j=1$	0.023	0.024	0.100	-0.005
	(0.073)	(0.075)	(0.111)	(0.091)
$j=2$	-0.011	-0.008	0.075	-0.043
	(0.079)	(0.081)	(0.106)	(0.098)
$j=3$	0.019	0.006	-0.015	0.039
	(0.086)	(0.087)	(0.131)	(0.094)
$j=4$	0.071	0.068	0.085	0.070
	(0.100)	(0.104)	(0.167)	(0.111)
$j=5$	0.126	0.114	0.146	0.122
	(0.104)	(0.109)	(0.174)	(0.114)
$j=6$	0.194*	0.190*	0.314	0.134
	(0.112)	(0.118)	(0.220)	(0.118)
$j=7$	0.242**	0.218*	0.342	0.190
	(0.121)	(0.126)	(0.235)	(0.123)
$j=8$	0.387***	0.391***	0.484**	0.331**
	(0.137)	(0.147)	(0.235)	(0.161)
$j=9$	0.401***	0.402***	0.477**	0.355**
	(0.149)	(0.155)	(0.247)	(0.171)
$j=10$	0.438***	0.431***	0.538**	0.373**
	(0.149)	(0.156)	(0.253)	(0.166)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	74,234	74,178	73,150	73,828

Notes: This table reports the effect of mineral resource discoveries on night lights in a panel of district-year observations. Districts with pre-existing mining activities were dropped from the regression. In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

2.4.4 Why Mining Matters for Local Economic Development?

We find that mineral discovery and production have a positive effect on night lights density at the district level in 42 sub-Saharan African countries over the period 1992 to 2012. In particular, a startup of new mining activity is associated with a 55.4 percent increase in night lights density. Similarly, a mineral discovery effect is associated with 19-44 percent increase in district's night lights density between 6-10 years post discovery. We subsequently present a set of economic factors that explain the patterns shown between mining activity and local economic development in Africa.

There is an emerging literature exploiting within country variation to analyse the effect of natural resource booms. Within this literature, our finding is closely related to the finding of Aragón and Rud (2013), Lippert (2014), Loayza and Rigolini (2016) and Fafchamps et al. (2016). Our finding can be explained by the effect of local demand shocks on agricultural sector. Mining boom can improve the demand for locally produced agricultural commodities (Lippert, 2014). In turn, this translates into better living standards for local communities. The patterns shown in our study can also be explained by the fact that local mining activity promote local procurement (or demand for local inputs) and employment. For example, Aragón and Rud (2013) offers support for the local backward linkages hypothesis, implying that extractive industries can increase the real return to local factors of production via local procurement of goods and services. Such demand shocks due to mining boom are likely to improve average consumption per capita and lower poverty rates in mining districts (Loayza and Rigolini, 2016). Moreover, our finding can be explained by agglomeration economies. The study by Fafchamps et al. (2016) used gold production dataset in Ghana and document locations near gold mining have more sophisticated non-agricultural forms of economic activity. The argument for agglomeration economies links natural resource abundance to the manufacturing (business) sector, where local non-agricultural business sectors benefit from local demand demand shocks due to natural resource abundance (Michaels, 2011; Allcott and Keniston, 2014).

2.4.5 General Equilibrium: Regional and Country Level Effects

In this section, we explore the general equilibrium effects of mining activity by redefining the units of interest. An alternative solution to explore general equilibrium effects is to redefine the unit of interest. Districts are likely to make interactions, which makes the no-interaction assumption less plausible to identify the effect of mining. There is well-defined economic and political interaction between districts within the same region as well as within the same country. We, therefore, study the next higher aggregates than districts using the 1st level administrative unit (region level) and countries as unit of observation.

Interactions decline with geographical distance; hence the effect at the district level is large, and the effect at the regional level may be smaller or even zero. This is consistent with the finding of other studies. In their study of gold mining in Peru, Aragón and Rud (2013) found income effects declining with distance and being insignificant at 100 km from the mine. Similarly Kotsadam and Tolonen (2016) found effects on female employment up to a distance of 75 km.

We study both mineral production and discovery data. Table 2.4 starts with administrative regions, and the specification include region and year fixed effects. We have two variables of interests measuring the mineral production value and the number of mineral producing districts in the region. We test the effect of mineral production on night lights density by using two alternative outcome variable. We observe statistically significant effect of mineral production at the region level when using the sum of night lights in all the districts in the region. However, when we exclude the night lights from the mineral producing districts, the statistical significance disappears but remains positive. This implies that the significant effect of mineral production on night lights density is largely coming from the mining districts in the regional.

Table 2.4: Mineral Production and Night Lights Density at the Region Level

	(1)	(2)	(3)	(4)
Ln(Mineral Production Value)	0.018***		0.007	
	(0.005)		(0.014)	
Ln(Number of Mining Districts)		0.298***		0.055
		(0.104)		(0.287)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes
Observations	10,228	10,898	10,141	10,709

Notes: This table reports the effects of mineral production at the regional level. We have two main variables of interest: the value of mineral production and the number of mining districts. In columns (1)-(2), the outcome variable include the sum of night lights from all the districts in the region. In columns (3)-(4), the outcome variable exclude night lights from the mineral producing districts from which we know that there is a positive effect. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

The mineral discovery data displays similar phenomenon, where we find weak evidence for a positive effect of discovery at the region level. The OLS estimates are reported in Table 2.5. We use the same model as in Equation 2.2 with year and region fixed effects. We observe no heterogeneity between giant and major discovery effects.

Table 2.5: Mine Discovery and Night Lights Density at the Region Level

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	0.023	-0.012	-0.042	-0.007
	(0.079)	(0.056)	(0.103)	(0.063)
$j=1$	0.133	0.040	0.105	0.005
	(0.089)	(0.072)	(0.117)	(0.084)
$j=2$	0.111	-0.006	-0.013	-0.010
	(0.110)	(0.083)	(0.112)	(0.100)
$j=3$	0.100	-0.007	-0.117	0.040
	(0.110)	(0.085)	(0.101)	(0.100)
$j=4$	0.110	0.018	-0.067	0.062
	(0.115)	(0.091)	(0.111)	(0.111)
$j=5$	0.138	0.036	-0.099	0.097
	(0.120)	(0.091)	(0.108)	(0.109)
$j=6$	0.190	0.067	0.014	0.087
	(0.116)	(0.090)	(0.104)	(0.111)
$j=7$	0.183	0.068	0.032	0.091
	(0.112)	(0.097)	(0.091)	(0.124)
$j=8$	0.201*	0.117	0.136	0.095
	(0.116)	(0.106)	(0.098)	(0.137)
$j=9$	0.202*	0.076	0.102	0.061
	(0.122)	(0.113)	(0.099)	(0.144)
$j=10$	0.213*	0.148	0.159	0.115
	(0.114)	(0.104)	(0.098)	(0.135)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,155	9,541	8,960	9,370

Notes: This table reports the effect of mineral resource discoveries on night lights in a panel of region-year observations. In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j>10$. In column (2), the dummy is set missing the year a second discovery was made in the same district. In column (3) and (4), the dummy is for giant and major deposit discoveries respectively. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

In Table 2.6, we repeat the exercise with country level data using year and country fixed effects. Likewise, we use two alternative measurement of an outcome variable: the sum of night lights in all the districts in a country, and the sum of night lights in the non-mining districts by excluding night lights from the mining districts. The OLS estimates shows very similar effect with the region level analysis, and we conclude that there is very little evidence for significant effect of mining activity at the higher administrative units.

Table 2.6: Mineral Production and Discovery at the Country Level

	Ln(0.01 + Night Lights Density per sq. km)					
	Mineral Production				Mineral Discovery	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
Ln(Mineral Production Value)	-0.0001	-0.001				
	(0.003)	(0.003)				
Ln(Number of Mining Districts)			0.072	0.072		
			(0.094)	(0.094)		
Discovery in the past 5 years					0.022	0.021
					(0.019)	(0.022)
Discovery in the past 6-10 years					0.027	0.025
					(0.020)	(0.020)
Discovery more than 10 years ago					0.015	0.006
					(0.015)	(0.015)
Pop Density & Rainfall	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	882	882	882	882	882	882

Notes: This table reports the effects of mining activity on night lights at the country level. For mineral production analysis in columns (1)-(4), we have two main variables of interest measuring the natural logarithm of the value of mineral production and the natural logarithm of the number of mining districts. For mineral discovery analysis in columns (5) and (6), we have three explanatory variables indicating a dummy variable equal to 1 if a giant or major mine deposit was discovered in the past 5 years, in the past 6-10 years and more than 10 years ago, 0 if no discovery has been made. In columns (1), (3) and (5), the outcome variable include the sum of night lights from all the districts in a country. In columns (2), (4) and (6), we exclude night lights from mineral discovery or producing districts from which we know that there is a positive effect. Robust standard errors clustered by country are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

2.5 Robustness and Sensitivity Analysis

Recent studies raised valid concerns regarding night lights data and districts as units of observation. Robustness results are shown in the Appendix. Min (2008) and Cogneau and Dupraz (2014) argue that in sparsely populated areas light intensity is dominated by noise. Min (2008) pointed to a minimum population threshold above which one can reliably assume that the lack of visible night lights indicate lack of electrification and outdoor lights. We followed Min (2008) and excluded sparsely populated places with less than 4 people per square kilometre from the sample. The results for excluding sparsely populated districts are reported in Tables A.2 and A.9 in the Appendix. Furthermore, we followed Cogneau and Dupraz (2014) and dropped zero luminosity districts from the sample. The main estimates reported in Tables 2.1 and 2.3 remain unchanged. The results for dropping districts with zero luminosity from the sample are reported in Tables A.3 and A.10 in the Appendix.

In the main regressions we use night lights density as the main outcome variable. However, lights density may not be a better predictor of local economic development. Cogneau and Dupraz (2014) make a case for using log luminosity per capita (i.e. log light density minus log population density). They argue that economic development in Africa should be judged in light of today's African population and not surface area. We re-estimate Tables 2.1 and 2.3 by reweighing the lights intensity measure by population. The results are reported in tables A.4 and A.11 in the Appendix and our results remain unaltered.

Countries with a larger population and number of districts could be disproportionately represented in our sample. To correct for this potential bias we weight districts by the inverse of the total number of districts in the country. This mimics the process of assigning equal weights to each country in the sample. We re-estimate Tables 2.1 and 2.3 and the results in fact become stronger. The results are reported in Tables A.5 and A.12 in the Appendix

We also address concerns that subnational administrative boundaries are endogenous by construction. Administrative demarcations in a country are typically determined by geographic and demographic characteristics of the area, which could be the determinants of local economic development. To mitigate this concern, we use 0.5 x 0.5 degree grid cells as units of observation (i.e. around 55 x 55 kilometres at the equator). In the panel of cell-year observations we investigate how mineral discoveries and production affect the cell level economic development measured by night lights density in a given cell-year. Several recent studies have implemented similar grid-cell level approach (Michalopoulos and Papaioannou (2013a) and Berman et al. (2014)). Our results in Tables 2.1

and 2.3 remain unaffected by this change in the unit of analysis. The results are reported in Tables A.6 and A.13 in the Appendix

Moreover, the positive effect of mining might be driven by night lights emanating from the mining industries. We address this concern by ignoring all lights around a 2 kilometre radius of a mine and re-estimate the regressions reported in Tables 2.1 and 2.3.[12]. The results are reported in Tables A.7 and A.13 in the Appendix and our results remain qualitatively unchanged.

In Table 2.1 we replaced missing values in production quantities by linear interpolation. This may affect estimates of the intensive margin. To check we drop district-year observations from the dataset and rerun Table 2.1. The results are reported in Tables A.8 in the Appendix and our results remain qualitatively unchanged.

2.6 Conclusion

We investigate how mining affects local economic development in the context of sub-Saharan African countries. Economic development is measured using satellite data on night lights. We find that both mineral extraction and discovery expands economic activity in a panel of 3,635 districts from 42 Sub-Saharan African countries observed over the period 1992 to 2012. The study finds positive effects of mining at the intensive margin, however large effects are associated with mining at the extensive margin.

Our finding is consistent with the emerging sub-national literature that are largely motivated by theories of demand side linkage of extractive industries and development. The theories predict that mineral discoveries and extraction are likely to impact local economic development in sub-Saharan Africa, as reflected in the night lights intensity, via the potential backward linkages implying increases in return to local factors of production. Moreover, positive economic consequences of mining activity are also likely to emerge via the labour market opportunities. The other important economic reason explaining the positive relationship between mining activity and local development is likely to be im-

[12]The choice of 2 kilometre is somewhat arbitrary. Note however that increasing the radius increasingly excludes lights not directly produced by the mine.

provement in the sophisticated non-agricultural forms of economic activity and agglomeration economies.

Our findings imply that resource depletion in sub-Saharan African countries provide an opportunity to improve local economic development. Limited access to the international credit market is a defining feature of governments and private sectors in sub-Saharan Africa because they are insufficiently credit worthy. However, the conjunction of relatively high global commodity prices and new natural resource discoveries can provide a major new source of development finance for sub-Saharan Africa. It can also trigger agglomeration effects via new cities and new infrastructure especially at the extensive margin. This is an opportunity not to be missed by sub-Saharan Africa.

CHAPTER 3

Natural Resources and Multi-Ethnic Coalitions

3.1 Introduction

How is cabinet positions allocated across diverse ethnicities in Africa? The most widely stated attributes of power sharing in Africa is the manner in which rulers use state resources to expand state cabinet offices and allocate ministerial positions across elites. It could very well be that natural resources play a decisive role in the power sharing dynamic within the African political system. In other words, ethnicities from resource rich regions empowered by their enhanced economic and political power could demand additional representation in the central government in the form of cabinet posts. The incumbent leader or the ruling elite could respond by ignoring these demands and resorting to coercion. Alternatively, the incumbent elite could also co-opt these resource rich ethnic groups using political patronage.

We examine the effects that changes in natural resource discoveries and global commodity prices have on the allocation of cabinet positions across diverse ethnicities in Africa. The study employs ethnic ministerial appointments to the cabinet, or ethnic representation in the cabinet offices as a measure of multi-ethnic power sharing coalitions. The results show that ethnic ministerial appointment in Africa is systematically related to changes in natural resource discoveries and ethnic specific commodity price indices. The effect of natural resource discoveries on ethnic ministerial appointment is positive and statistically significant within 2-8 years of resource discovery. Similarly, the effect of commodity prices is also positive and statistically significant. The significant and positive relation between natural resources and ethnic ministerial appointment implies that rulers appoint more elites from ethnicities with abundant natural resources, as reflected in natural resource discoveries and ethnic specific commodity price indices. This reject the commonly held view that state cabinet positions being allocated exclusively based on population sizes.

Why do natural resources matter for multi-ethnic power sharing coalitions in Africa? We test three potential mechanisms linking natural resources to ethnic power sharing coalitions. First, risk of political violence by excluded ethnicities is not a significant mechanism linking natural resources to power sharing coalitions. Second, we find mixed evidence on the association between natural resources and social actors collective contentious action (e.g., demonstrations and riots) as a potential explanation for power sharing coalitions. Third, our finding supports the idea that rising resource discoveries and commodity prices provide rulers with more revenues to expand the cabinet sizes; hence they build broader multi-ethnic coalitions.

Do ministerial appointments come with real power to impact meaningful distributive politics? We find that the effect of natural resources on both top and low cabinet positions sharing is statistically significant and positive.[1] We argue this complements the assertion that appointment to top inner circle of the cabinet offices do not imply that elites are just assigned for symbolic representation. These positions come with real distributive power politics. We find evidence that ethnicities that share the ethnicity of the head of cabinet positions receive larger economic benefit, as reflected in night lights intensity. In contrast, excluded ethnicities do not enjoy higher intensity of night lights, i.e., excluded ethnicities receive less public or economic opportunities.

We contribute to the literature by adopting an innovative approach towards geocoding the ethnic share of cabinet posts dataset and relating it to Murdock (1967) Ethnographic Atlas. Furthermore we marry this data with our georeferenced data of resource discovery and commodity prices to estimate the effect of

[1] Based on Francois et al. (2015) , we experiment different categorisations of cabinet positions into top and low. For example, we categorise the Defence, Finance, Economy, Foreign Affairs, Trade, Education, etc. as top ministerial appointments. The low ministerial appointments may include Environment, Civil Service, Cultural Affairs, Social Service, Youth and Sport, etc.

natural resource discovery and price shocks on ethnicity level power politics in Africa. The ethnicity level political consequences of natural resources in Africa is not widely studied. To the best of our knowledge, our study is the first attempt to systematically analyse these effects using rigorous empirical methods.

Similar to Mamo et al. (2017), our cleanest identification strategy relies on the exclusivity and randomness of the single first discovery of natural resources in a particular ethnic homeland. This refers to the virgin ethnic homelands which receives their one and only resource discovery during the sample period. We use multiple layers of clustering starting from ethnic homeland to country levels to account for cross-sectional and intertemporal dependence. In addition we also use a strategy similar to Cotet and Tsui (2013), Bhattacharyya et al. (2017), and Arezki et al. (2017) which relies on the stochastic nature of the discovery dates of giant and supergiant mineral and oil discoveries. A mineral deposit is coded as giant if it has the capacity to generate at least USD 0.5 billion of annual revenue for 20 years or more accounting for fluctuations in commodity price. A giant oil or/and gas (including condensate) field is a deposit that contains at least a total of 500 million barrels of ultimate recoverable oil or gas equivalent. This would be able to generate an annual revenue stream of approximately USD 0.4 billion under the assumptions that over the sample period the average gestation lag between production and discovery is 5 years, the average price of a barrel is USD 25, and the average discount rate including the country specific risk premium is 10 percent.[2] Therefore, it is reasonable to assume that both the giant oil and mineral discovery shocks are approximately of the same size on average. However, it is important to note that these value calculations are based on parametric assumptions which could be revised in subsequent years.

Exploration effort could drive resource discovery in a country. This may not be an issue in the specifications with the first discovery variable but it could be a source of bias in the specifications based on giant or major discoveries. We do not have ethnic homeland level measures of exploration effort. However, we could be reasonably confident that the country specific time varying effects in our

[2] Some studies claim that the risk premium augmented discount rate should be as high as 14-15 percent. Arezki et al. (2017) presents a more sophisticated analysis of net present value of giant oil discoveries and find that the median size of a giant discovery is approximately 5-6 percent of GDP.

specifications are controlling for exploration effort.

A recent literature study the nature of cabinet post allocations in Africa and its consequences. For example, Arriola (2009) and Roessler (2011) study how cabinet appointments prolong the tenure of an incumbent and influence the risk of political violence. Burgess et al. (2015) and Kramon and Posner (2016a) study the motivations behind cabinet post allocations and find ethnic favoritism to be playing a significant part. In contrast, Francois et al. (2015) find ethnic population share to be the prime driver of cabinet post allocation in Africa. None of these studies look into the role of natural resources and especially point source resources which we actively pursue here.

Our work is related to the literature on political resource curse (Robinson et al., 2006; Caselli and Cunningham, 2009). Understanding the impact of natural resources on political outcomes is central to this predominantly cross-country macro literature. However, this literature do not engage with the ethnicity level patronage mechanism following a natural resource shock so common in resource rich African countries. We explicitly study this phenomenon using detailed micro data which undoubtedly moves this literature forward.

A large and predominantly macro literature document the harmful role of ethnic politics in African economic development (Easterly and Levine, 1997; Gennaioli and Rainer, 2007; Michalopoulos and Papaioannou, 2013b). These studies by design do not focus on the micro ethnicity level political dynamics.

Finally, our paper is also related to the resource curse literature. Auty (2001), Gylfason (2001) and Sachs and Warner (2001, 2005) note that resource rich countries on average grow much slower than resource poor countries. Subsequent studies have argued that natural resources may lower the economic performance because they strengthen powerful groups, weaken legal frameworks, and foster rent-seeking activities (e.g., Tornell and Lane (1999), and Besley (2007)). Others have argued whether natural resources are a curse or a blessing depends on country-specific circumstances especially institutional quality (eg., Mehlum et al. (2006), Robinson et al. (2006), Bhattacharyya and Hodler (2010, 2014a), and Bhattacharyya and Collier (2014)), natural resource type (Isham et al., 2005b) and ethnic fractionalisation (Hodler, 2006).

The remainder of the chapter is structured as follows: Section 3.2 describes the types of dataset, sources and measurement of the main variables of interest. Section 3.3 discusses our empirical strategy to investigate the effect of natural resources on power sharing coalitions. Section 3.4 presents the main results on the effects of natural resources and discusses the mechanisms. Section 3.5 presents the battery of robustness checks. Section 3.6 concludes.

3.2 Data Sources and Measurement

Ethnicity is our main unit of interest, as it is the organising principle and the basis of political institutions in Africa (Posner, 2005). We focus on ethnic composition of executive branch of government, where the ministers are responsible for implementing government policy (Rainer and Trebbi, 2012). It is also regarded as an instrument for managing elite relations (Arriola, 2009).

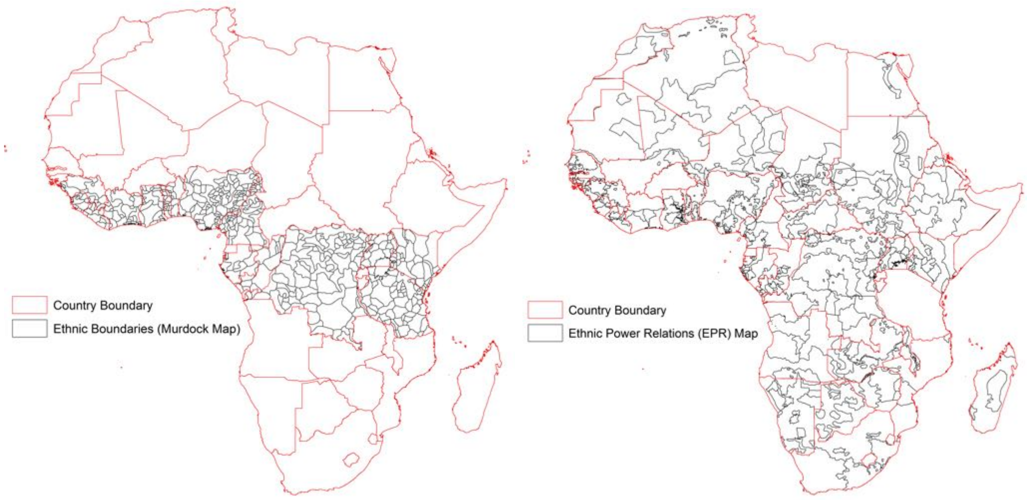
3.2.1 Multi-Ethnic Power Sharing Dataset

The study uses two datasets on multi-ethnic power sharing coalitions in Africa. First, the paper utilises the novel dataset constructed by Francois et al. (2015) on ethnic composition of government coalitions in post-colonial African countries, hereinafter called FRT15 dataset. The dataset emphasise the executive branch of the government, as it plays a central role in all national political systems. The ethnicity of national ministries have been identified since independence (until 2004) in 15 equatorial African countries, and they constitute 45% of African population. Second, the paper utilises Ethnic Power Relations (EPR) dataset to estimate the effect natural resources have on ethnic access to executive state power (Wucherpfennig et al., 2011). EPR provides information on ethnic group' access to national level executive power in 39 African countries from 1946 to 2010.

FRT15 dataset reports ethnic share of cabinet positions, population sizes, ruler's ethnicity indicator, largest ethnicity indicator and coalition member indicator. We generate geo-coordinates of each ethnicity, by utilising ethnicity database from Joshua Project (U.S. Centre for World Mission), and different boundary maps of ethnicities including University of Texas Libraries. We match about

60% of ethnicities from Francois et al. (2015) to Murdock (1967) map of ethnic homeland. We have a panel of 161 ethnicities in 15 African countries (see Figure 3.1 Map (a)). We argue that this does not give rise to the issue of selection bias. Table B.1 in the Appendix reports basic summary statistics for the matched ethnicities. The cross-sectional sample size is not significantly reduced and the mean values are comparable. The mean value of group's share of cabinet positions is 0.059 in our sample, and 0.054 in the sample of Francois et al. (2015). In addition, the number of ethnicities represented in the national politics varies across countries (see Tables B.2 and B.3 in the Appendix). Tanzania and Democratic Republic of Congo's share of ethnicities is the largest over the sample period, 18.01% and 13.66% respectively. In contrast, Benin (with 0.62%) and Republic of Congo (with 1.24%) share is the lowest over the sample period.

Figure 3.1: Geographical Boundary of Ethnic Groups in Africa



(a) **(b)**

Notes: The map shows the geographical boundary of our sample countries and ethnic group polygons. Map (a) constitute 15 equatorial African countries: Benin, Cameroon, Cote d'Ivoire, Democratic Republic of Congo, Gabon, Ghana, Guinea, Liberia, Nigeria, Republic of Congo, Sierra Leone, Tanzania, Togo, Kenya, and Uganda. The ethnic polygons portray the spatial distribution of ethnicities based on Murdock map of ethnic boundaries. Map (b) is a geocoded version of the Ethnic Power Relations (GeoEPR) dataset that charts politically relevant ethnicities across 39 African countries.

The main advantage of FRT15 is that power sharing is measured at individual minister level and each single position is identified. It allows to calculate share of cabinet positions hold by each ethnicity in the country. Moreover, FRT15 use a fine classification of ethnicities, and it is much closer to the standard ethnicity classifications (Alesina et al., 2003; Fearon and Laitin, 2003).

EPR dataset provides annual data on politically relevant ethnicities, and their access to executive state power in 39 African countries where ethnicity has been politicised. Political power in this dataset also refers to executives only, disregarding access to legislative and judicial institutions. Unlike FRT15, EPR codes access to power as a categorical variable.[3] The EPR dataset present a higher coverage of 39 African countries, and covers the time period between 1950 and 2010 in our sample. The summary statistics of the number of ethnicities represented in the national politics is reported in Table B.2 in the Appendix.

We use four of EPR's access to power coding as a categorical variable: *included* denotes ethnicity represented in the central government, *excluded* denotes ethnicity not represented in central government, *autonomy* denotes ethnicity elites dominate provincial government, and *separatist* denotes ethnicity elites dominate a breakaway region. The *included* category further divided into sub-categories: *monopoly* denotes elite members hold monopoly power in the executive to the exclusion of elites of all other ethnicities, and *dominance* denotes elite members of the group hold dominant power in the executive but there is some limited inclusion of other groups who however do not have real influence.

3.2.2 Natural Resources: Production and Discovery Dataset

We use two datasets on natural resources in Africa. First, we use ethnic specific mineral and agricultural commodity production that are sourced from IntierraRMG (2014) and the Spatial Production Allocation Model (SPAM) (You et al., 2012), respectively. Second, we use ethnic specific natural resource discoveries that are sourced from MinEx Consulting (2014) database for mine deposits, and Horn (2011) for oilfield discoveries.

[3]The inclusion or exclusion criterion is based on the standard definition of PREG (Politically Relevant Ethnic Group). An ethnicity is politically relevant if either at least one significant political actor claims to represent the interests of that group in the national political arena or if group members are systematically and intentionally discriminated against in the domain of public politics. EPR dataset is flexible and dynamic, as list of PREG may change over time in order to account for possible shifts of the most relevant ethnic cleavages within a country, or to account for a change of the power status of any groups. All ethnicities are categorised according to the degree of access to central state power by those who claimed to represent them. The executive power, whether political power is effectively exercised or not, can be the presidency, the cabinet, and senior or top positions including army command. The regimes type could be democratic, military dictatorships, one-party or dominant-party states.

The IntierraRMG (2014) dataset, currently known as SNL Metals and Mining, contains information on 548 industrial size mines in Africa in our sample, geocoded with point coordinates and annual information on production levels. All the mines are matched to ethnic boundaries, and ethnic specific mineral production is constructed using industry specific mineral production.

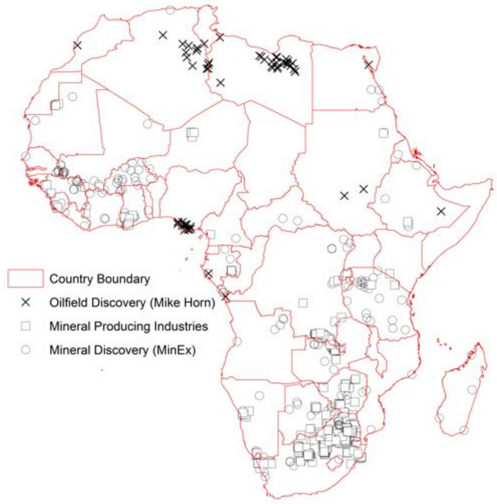
The Spatial Production Allocation Model (SPAM) contains time invariant data on agricultural production in the year 2000. It provides 10x10 km grid-level crop production for a range of major agricultural crops across the world. We exploit the time invariant production data of SPAM to construct ethnic specific commodity price indices. The time invariant production patterns capture overall subnational or regional patterns of agricultural commodity in Africa. We focus on major agricultural commodities where price statistics are available.

Our discovery datasets cover different geo-politics in Africa to analyse the effect of natural resources on power sharing. Figure 3.2 shows the geographical distribution of discoveries. MinEx Consulting (2014) dataset covers a time period between 1950 and 2012 for 32 African countries, whereas Horn (2011) dataset covers discoveries of oilfield between 1955 and 2010 for 9 African countries.

MinEx reports 263 discoveries of mine deposits, and gold represents about 48% of the discoveries (see Table B.4 in the Appendix). Horn (2011) reports 59 onshore giant oilfield discoveries in Africa over the 1955-2010 period. To minimise the risk associated with the potential measurement error arising from the estimated size of discoveries, we simply construct an indicator whether an ethnicity has discovered at least one mine deposit or oilfield in each given year.

The summary statistics about the discoveries and list of primary commodities appear in the appendix. Countries are heterogenous in terms of the number of discoveries, and the geographical distribution of discoveries within a country (see Tables B.5 and B.6 in the Appendix). The following countries experience more than 4% share of mineral discoveries individually in the continent over the sample: Botswana, Burkina Faso, Democratic Republic of Congo, Ghana, Mali, Namibia, South Africa, Tanzania and Zimbabwe. In the Mike Horn's oilfield discovery dataset, Libya and Nigeria display 45.8% and 23.7% share of oilfield discovery, respectively.

Figure 3.2: Geographical Location of Resource Production and Discoveries



Notes: The map shows the geographical location of mineral production, mineral deposit and oilfield discoveries.

3.2.3 Other Ethnic Specific Variables

Information on *de facto* political power of ethnicities come from Ethnic Armed Conflict Dataset (EACD), which is based on UCDP/PRIO (Wimmer et al., 2009). We exploit two main variations: year in which a new ethnic violence starts, and year in which high intensity ethnic violence starts. Information on collective contentious action come from Social Conflict Analysis Database (SCAD). This dataset contains information on protests, riots, strikes, and other social movements in Africa (Salehyan and Hendrix, 2016). We rely on the reported motivation behind the collective action, and we are only interested in peaceful social movement directed toward government authorities. We also use satellite data on night lights as proxy measure of rent re-distribution, as there are no widely available data on rent re-distribution at the subnational level (Hodler and Raschky, 2014). We adjust night lights by ethnic land surface area. The night lights data come from Defence Meteorological Satellite Program's Operational Linescan System.

3.3 Empirical Strategy

Our paper studies how ethnic share of cabinet positions changes with natural resources. The empirical strategy exploits (1) resource discoveries in an ethnic homeland that has no history of discovery as an exogenous source of variation, and (2) fluctuations in commodity prices that are exogenous to the ethnic groups.

3.3.1 Effects of Natural Resource Discovery

We use the following econometric model to identify the effect of resource discoveries on ethnic power share:

$$Power_{j,c,t} = \alpha_j + \beta_t + \eta_{c,t} + \sum_{i=0}^{10} \gamma_i Resource\ Discovery_{j,t-i} + \lambda Leader_{j,c,t} + \epsilon_{j,c,t} \quad (3.1)$$

with $Leader_{j,c,t}$ an indicator function for country c ruler belonging to ethnicity j at year t, capturing rulership co-ethnicity effect on ethnic power sharing. The coefficient on $Leader_{j,c,t}$ implies whether rulers favour their own ethnicity, and λ is expected to be positive and statistically significant. The rationale to control for $Leader_{j,c,t}$ come from the fact that emphasis has been conventionally placed on the ruler's strong co-ethnic preference in ministerial appointments. The effect of $Leader_{j,c,t}$ on power sharing is significantly positive supporting the idea that rulers do indeed favour their co-ethnicity.

We also control for ethnicity fixed effects α_j, year fixed effects β_t and country x year fixed effects $\eta_{c,t}$. Ethnic fixed effects α_j capture ethnic specific time invariant characteristics that may affect ethnic share of cabinet positions (e.g., cultural and historical characteristics affecting ethnic political norms and participation). It could also capture potential systematic differences across ethnicities affecting data recording and reporting. Year fixed effects β_t allows to control for time varying common shocks affecting any general association between ethnic share of cabinet positions and natural resources in a given year (e.g., global shocks affecting the demand for natural resources). Finally, country x year fixed effects $\eta_{c,t}$ control for countrywide time varying characteristics affecting both ethnic ministerial appointment and resource discoveries (e.g., change in power sharing arrangement, and change in exploration investments).

Our main variable of interest $Resource\ Discovery_{j,t-i}$ is a dummy variable equal to 1 if natural resource discovery has been made in year $t-i$ in a particular ethnic group-year and 0 if no discovery has been made and missing for every year post-discovery years. We exploit random variation in the timing of natural resource discoveries to minimise the potential reverse causality challenges. Our approach is similar with the one adopted by Smith (2015). Smith uses the first natural resource discoveries in countries that were not previously resource rich as a plausibly exogenous source of variation. We therefore restrict $Resource\ Discovery_{j,t-i}$ to *first discoveries*, that is to discoveries in ethnic boundaries that never had any natural resource discovery before. It is coded to take the value $i \in \{1(1)10\}$ for a particular ethnic group-year if that group had discovery in i year over the past 10 years window.

As explained in chapter 2, restricting $Resource\ Discovery_{j,t-i}$ to *first discoveries* serves two purposes. First, existing natural resource extracting activities may affect power sharing arrangement and it is difficult to disentangle this effect from the effect of a new discovery. Second, economic agents including rulers may arguably anticipate repeated discoveries due to the knowledge of past discoveries and geology. In contrast, a discovery and its exact timing is much harder to predict for "virgin" non-mining ethnic homeland. Thus, setting $Resource\ Discovery_{j,t-i} = 1$ for first discoveries is the cleanest treatment group. In fact, the coefficient γ estimate at *t=0* tests whether there is a significant level difference between ethnicities with no resources discovery and ethnicities in which a discovery has just been made. Overall, the coefficients γ measure the difference in share of cabinet positions i years after a discovery.

The proportion dependent variable $Power_{j,c,t}$ indicates ethnic j share of cabinet positions, in country c in year t based on FRT15. This is our main dependent variable. Alternatively, we have dependent variable as a binary response, which is an indicator whether ethnicity j, in country c, access cabinet positions in year t. We convert the FRT15 proportion variable into a 0/1 variable. We also use the categorical variable of power access in EPR dataset. The EPR dataset provides information on ethnic access to the executive state power. It is a dummy variable equal to 1 if an ethnicity is represented by at least one elite and 0 if no elite represents an ethnicity. We, therefore, use both proportion variable and dummy variable as the measure of political power.

3.3.2 Effects of Commodity Prices

Similarly, we identify the effect of ethnic specific commodity price indices on ethnic share of cabinet positions by estimating the following model:

$$Power_{j,c,t} = \alpha_j + \beta_t + \eta_{c,t} + \gamma Commodity\ Price_{j,t} + \lambda Leader_{j,c,t} + \epsilon_{j,c,t} \qquad (3.2)$$

Our main variable of interest $Commodity\ Price_{j,t}$ represents lagged ethnic specific commodity price indices.[4] We combine time invariant production of various agricultural and mineral commodities with time varying data on global commodity prices. We construct price index for every ethnicities in our sample as follows:

$$Ethnic\ Commodity\ Price\ Index_{j,t} = \sum_{i=1}^{34} \omega_{i,j} P_{i,t} \qquad (3.3)$$

where $\omega_{i,j}$ is ethnic j's share of agricultural or mineral commodity i in the ethnic group's total production of commodity in 2000 (or in the year closest to 2000) and $P_{i,t}$ is the annual price series for commodity i, which we extract from IMF Commodity Prices, Unites States Geological Survey historical commodity prices, and Bazzi and Blattman (2014). All prices are normalised to initial sample period as the base year. The mineral production come from IntierraRMG (SNL Metals and Mining), and the agricultural production come from Spatial Production Allocation Model (SPAM). All the mineral and agricultural production data are matched to the ethnic homeland using their location coordinates from IntierraRMG and SPAM. Our sample covers 21 mineral commodities and 13 agricultural crops. Details and summary statistics are provided in the Appendix.

[4] Ethnic specific commodity price index is a simple moving average which are lagging (as opposed to predictive indicators). It is based on historical global commodity prices and its past impact on the economy have already occurred. In practice, its past impact helps agents including rulers to form an opinion on future potential. This is an example of adaptive expectations where agents form their future expectations based on what has happened in the past.

3.4 Results and Discussion

3.4.1 Main Results

Table 3.1 presents the estimates of the effect of resource discoveries on the distribution of cabinet positions across diverse ethnicities in Africa. In column (1), we link ethnic share of cabinet positions in year *t* to resource discoveries over the 10 previous years. In column (4), we change the proportional outcome variable into an indicator of ministerial appointment using the FRT15 dataset.

The estimate of γ in column (1) is significantly positive within 2-6 years of resource discoveries. Two years post discovery, ethnicity that discovered resources receive 0.7 = 25 x 0.028 more ministerial appointments compared to ethnicity with no resource discovery. We calculate the number by multiplying the average cabinet sizes by the coefficient in column (1). Six years post discovery, ethnicity with discovery significantly receive 2 more ministerial appointments.

The negative γ estimate at *t=0* implies that there is a significant pre-existing level difference between ethnicity which has discovered no natural resources and ethnicity in which a discovery has just been made. At the time of discovery, on average, ethnicities that just discovered resources have a significant lower cabinet shares. Consistent with our argument, positive effect is observed two years after a discovery (indicating increasing ethnic cabinet position shares, or increasing likelihood of representation). This positive effect could indeed reflect both the initial differences and the effects of resource discovery. Previously unrepresented ethnicities have now higher cabinet shares, or political representation after discovering natural resources. Hence, we argue that the positive effect due to the natural resource discovery is larger.

We also present the effect of ethnic share of resource discoveries in the country and cumulative resource discoveries in ethnic homeland. This is based on the notion that rulers allocate cabinet appointments based on historical level of discoveries. We find that cabinet allocations appear to be closely associated with the ethnic share of discoveries and cumulative discoveries. In column (2), the coefficient on the ethnic share of discovery within a country is positive and statistically significant, indicating that higher share of discoveries in the country is associated with more ministerial appointments. In column (3), ethnic group cumulative discoveries has also significant effect on ethnic share of cabinet positions.

Table 3.1: Natural Resource Discoveries and Distribution of Cabinet Positions

Dependent Variable:	Share of Ministerial Appointments			Indicator of Ministerial Appointments		
	(1)	(2)	(3)	(4)	(5)	(6)
Resource Discovery, *t*	-0.033***			-0.613***		
	(0.007)			(0.080)		
Resource Discovery, *t-2*	0.029**			0.289***		
	(0.012)			(0.075)		
Resource Discovery, *t-4*	0.066*			0.270***		
	(0.040)			(0.062)		
Resource Discovery, *t-6*	0.087***			0.286***		
	(0.017)			(0.054)		
Resource Discovery, *t-8*	-0.012			0.179***		
	(0.010)			(0.055)		
Resource Discovery, *t-10*	-0.064			-0.263		
	(0.040)			(0.392)		
Share of Resource Discoveries		0.041***			0.060*	
		(0.006)			(0.031)	
Cumulative Resource Discoveries			0.021***			0.058***
			(0.002)			(0.006)
Leader Group	0.080***	0.158***	0.156***	0.266***	0.426***	0.421***
	(0.004)	(0.005)	(0.005)	(0.020)	(0.009)	(0.009)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,303	6,732	6,732	6,303	6,732	6,732

Notes: This table reports the effect of natural resource discoveries on the distribution of ministerial cabinet positions. For convenience, we report coefficients every second year. Dependent variable in columns (1)-(3) denote the share of all cabinet positions held by ethnicity, and in columns (4)-(6) it denotes an indicator of whether any ministerial level positions held by ethnicity. We control for ruler's co-ethnicity effect by including Leader Group, indicating whether the ruler come from the same ethnicity. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

In column (4) in Table 3.1, the outcome variable denotes an indicator of whether any ministerial level positions held by ethnicity. The estimate of γ is positive and statistically significant within 2-8 years of resource discoveries. This imply that an ethnicity in which a discovery has been made is significantly more likely to be appointed as cabinet minister than ethnicity with no resource discoveries. On average, 2 years post discovery, an ethnicity which discovered natural resource is 28.9% more likely to be appointed as cabinet minister than ethnicity with no resource discovery. The coefficients on the ethnic discovery shares and cumulative discoveries are also positive and statistically significant.

Our empirical result is qualitatively in line with a forward looking behaviour, implying the effects of an anticipated resource revenue on the allocation of cabinet appointments. We argue that the announced resource discoveries plausibly change the *windfall revenue expectations* of the rulers, and hence affects the way the power sharing operate, provided that the resource discovery is credible in generating revenue. It is understandable that patronage distribution is a function of actual revenue, yet we observe rulers allocate cabinet positions across the elites of the various ethnicities before resource production starts. The effect is observed 2 years post discovery, whereas the delay between a discovery and production is on average 4 to 6 years (Arezki et al., 2017). For rulers, the future is in mind and they are indeed a forward looking agent.

Table 3.2 reports result on the effect of ethnic specific commodity price indices on the distribution of cabinet positions. In columns (1)-(4), we link ethnic share of cabinet positions in year t to the contemporaneous commodity price indices and average commodity prices over the 10 previous years, controlling for year fixed effects, ethnic fixed effects and countrywide fixed effects (we present the coefficient at the preceding 3, 5 and 10 years).

Table 3.2: Commodity Prices and Distribution of Cabinet Positions

Dependent Variable:	Share of Ministerial Appointments				Indicator of Ministerial Appointments			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Commodity Price, *t*	0.003**				0.015*			
	(0.001)				(0.008)			
Average Price, *3 Years*		0.005***				0.022**		
		(0.002)				(0.009)		
Average Price, *5 Years*			0.006***				0.028***	
			(0.002)				(0.010)	
Average Price, *10 Years*				0.009***				0.031**
				(0.001)				(0.012)
Leader Group	0.087***	0.087***	0.089***	0.089***	0.254***	0.235***	0.225***	0.218***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.019)	(0.019)	(0.020)	(0.022)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,536	6,251	6,001	5,238	6,536	6,251	6,001	5,238

Notes: This table reports the effect of ethnic specific commodity price indices on the distribution of cabinet positions. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

The estimates show that ethnic share of cabinet positions is higher when the ethnic price indices increases. The significant effect at t imply that a 10% increase in ethnic specific commodity price index is associated with an increase in 0.77 ministerial appointments (this number is the estimate in Table 3.2 column

(1) multiplied by 10 and again multiplied by the average cabinet size). The significant effects of average ethnic commodity prices over the preceding 3, 5 and 10 years imply that a 10% increase in ethnic group's commodity price indices is associated with an increase in 1.17, 1.57 and 2.2 ministerial appointments, respectively. The effect of commodity prices remains strong when we change the proportional cabinet shares into a dummy variable. The result is reported in columns (5)-(8) in Table 3.2.

In Table B.7 in the appendix, we look at the link between ethnic power sharing and ethnic commodity prices using the EPR dataset. The political power is measured as dummy variable, which is similar with the dependent variable in columns (4)-(6) in Table 3.1. It captures ethnic group's access to the executive state power (dummy variable equal to 1 if an ethnicity is represented and 0 if not represented). The effect of commodity price on power sharing is consistent with the main results reported using FRT15 dataset in Table 3.1.

In summary, the allocation of cabinet appointments based on resource discoveries and commodity prices rejects clearly the claim that cabinet positions being allocated exclusively based on population sizes. Besides to ethnic population sizes (Francois et al., 2015), rulers could also appoint elites from different ethnicities based on natural resource discoveries and commodity price indices.

In the following section we investigate the potential mechanisms explaining the association between natural resources and ethnic share of cabinet positions.

3.4.2 Why Do Natural Resources Matter for Power Sharing?

In the following sections, we discuss the economic and political factors that plausibly explain the patterns shown in the data. More specifically, we test three potential mechanisms linking natural resources to ethnic power sharing coalitions. First, we emphasise on the rulers' pursuit of stability or co-optation by expanding state cabinet sizes in the shadow of resource discoveries and rising commodity prices. Second, we emphasise on the potential enhancement of *de facto* political power of excluded ethnicities. Finally, we emphasise on the ways in which natural resources promote social actors' contentious collective action to demand inclusive power sharing coalitions. Our finding supports the idea that rising resource discoveries and commodity prices provide rulers with more revenues to expand the cabinet sizes; hence they build broader multi-ethnic coalitions.

3.4.2.3 Natural Resources and Cabinet Expansion

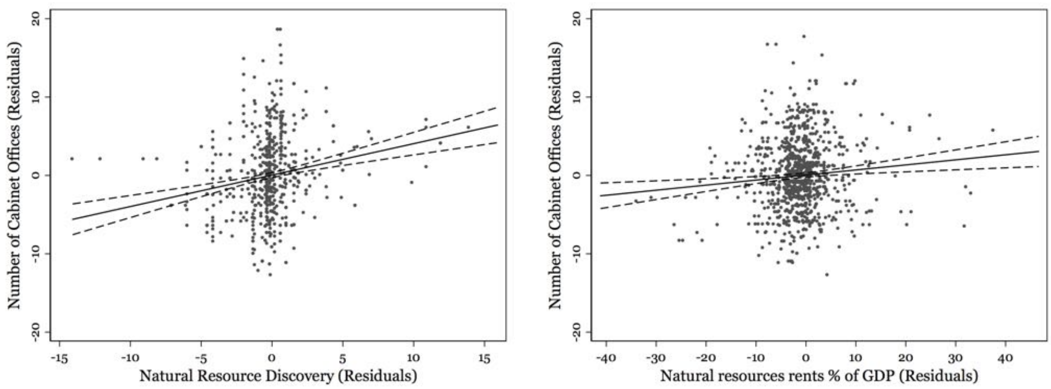
Several empirical evidence link natural resources with the behaviour of rulers in power (Caselli and Cunningham, 2009; Robinson et al., 2006). Given the slow economic growth in the region, Africa's rulers typically use state resources to expand cabinet sizes and co-opt powerful elites from diverse ethnicities that control ethnic or regional support bases that are distinct from the ruler's birth region. And, elites are allocated enough patronage by the ruler in exchange for their loyalty and that of their followers (Francois et al., 2015). The political patronage is just more than the ministerial wage.[5] This ensures that the ruler dissuades revolution attempts by outsiders (excluded ethnicities), or coup attempts by insiders (Francois et al., 2015). Moreover, Arriola (2009) documents that cabinet expansion as a political patronage increases rulers' survival and stability in Africa.

To examine the evidence in favour of this mechanism, we rely on FRT15 dataset to construct the size of cabinet (the number of cabinet offices), and then combine the information with natural resources at the country level. We also utilise information on cabinet sizes by Arriola (2009). We undertake simple linear regression and non-parametric analysis at the country level.

Figure 3.3 visualises the association of state cabinet sizes with resource discoveries and natural resources rents as a percent of GDP at the country level. There is positive association between cabinet sizes and natural resources conditional on country fixed effects. The other important observation is the increasing number of ethnicities involved in the central executives in Africa. On average, the number of ethnicities involved in the centre politics almost doubled during our sample period. The cabinet offices were about 10 in 1960s and increased to about 19 cabinets in 2000s.

[5]This is based on the practice of *Prebendalism* which states that appointed officials in non-democracies use state revenues to enrich themselves, and benefit their supporters and members of their ethnic group. This guarantees electoral support or general popular support for the ruler.

Figure 3.3: Natural Resources and Cabinet Sizes



(a) **(b)**

Notes: The graph shows the twoway linear prediction plots of the association between natural resources and cabinet sizes. Number of cabinet sizes (residuals) stands for residual variation in cabinet sizes after subtracting country-specific means. Resource discovery (residuals) stands for residual variation in natural resource discovery after subtracting country-specific means. Natural resources rents (residuals) stands for residual variation on total natural resources rents (% of GDP) after subtracting country-specific means.

The regressions reported in Table 3.3 also show the positive association between cabinet sizes and natural resources. Columns (1)-(4) show that cabinet size across African countries can be significantly attributed to natural resources, as measured by discoveries and rents as the share of GDP. Inclusion of other key variables, such as rulers years in office, civil war, GDP growth, aid, population and ethnic fractionalisation, do not affect the significance of resource discoveries. Higher natural resource is significantly related to a larger cabinet. The result imply that rulers of countries with abundant natural resources are able to mobilise greater resources to expand their patronage coalitions.

Therefore, our finding supports the idea that natural resources lead to larger multi-ethnic coalitions in Africa. Natural resource discoveries and rising commodity prices provide a new financing opportunity that helps to expand investment in cabinet sizes. The cabinet office are then allocated to political elites representing different ethnicities. The result is consistent with the finding of Robinson et al. (2006) that rulers distribute resource windfall as patronage to influence political systems. This is a windfall revenue imperative that imply multi-ethnic coalition as a top-down process driven by revenue-hungry leaders.

Table 3.3: Natural Resources, Cabinet Sizes and Military Expenditure

Dep Var:	State Cabinet Sizes				Military Expenditure (% of GDP)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Resource	0.4013***	0.5323***			-0.0334***	-0.0538**		
Discovery	(0.060)	(0.066)			(0.011)	(0.025)		
Ruler Years		0.0586**		-0.0042		0.0090		0.0124
in Power		(0.025)		(0.024)		(0.015)		(0.011)
Ongoing Civil		0.8447*		0.5072		0.9179***		0.6884***
War		(0.503)		(0.415)		(0.321)		(0.263)
Lagged GDP		0.0377		0.0546**		-0.0207		-0.0132
Growth		(0.023)		(0.022)		(0.028)		(0.020)
Lagged		0.6236***		0.7746***		-0.0320		0.0975
Population		(0.200)		(0.160)		(0.146)		(0.074)
Lagged Aid		0.0230***		0.0266***		-0.0052		-0.0006
Per Capita		(0.006)		(0.004)		(0.004)		(0.002)
Fractionalisation		0.7602		0.3059		-0.2639		-0.8913**
		(0.892)		(0.665)		(0.490)		(0.365)
Resource Rent			0.0645***	0.0296			0.0057	0.0011
			(0.024)	(0.024)			(0.008)	(0.014)
Observations	813	667	982	823	603	276	849	378

Notes: This table reports the association between natural resources, cabinet sizes and military expenditure at the country level. Two main explanatory variables: resource discovery and resources rents (% of GDP). Standard errors are clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Our finding do not support the idea that winner-take-all form of politics by excluding other ethnicities. The literature supports that idea that rising windfall revenue improve counter-insurgency, or military capacity of rulers in power. And hence, such militarily strong rulers share power and spoils with their loyal co-ethnics through the politics of ethnic exclusion. However, our result clearly contradicts the finding that natural resources (discoveries and commodity prices) increase military spending in non-democracies (including African countries) (Cotet and Tsui, 2013; Bazzi and Blattman, 2014). We do not observe a significant positive association between natural resources and military expenditure in Africa. The results are reported in columns (4)-(8) in Table 3.3.

In the following sections we provide evidence that natural resources do not incentivise excluded ethnicities to engage in armed violence to capture the state and reform power sharing arrangement. Moreover, we find mixed evidence whether natural resources incentivise social actors to engage in non-violence movement to secure inclusive power sharing coalitions. Our evidence indicate that power sharing arrangement across diverse ethnicities in Africa is all about the behaviour of rulers and the associated windfall revenue imperative.

3.4.2.1 Natural Resources and *de facto* Political Power

Does natural resource abundance enhance the *de facto* political power of outsider ethnicities to challenge the incumbent for power sharing? We investigate the association between natural resources and *de facto* political power of ethnicities. The concept of *de facto* political power imply the potential violence threat by excluded ethnicities that may lead to major reforms of the way existing power sharing function (Acemoglu et al., 2005). If the political power is exclusively at the hands of a single autocratic ruler, or a small group (ethnically determined), the excluded ethnicities challenge the incumbent. The literature documents that the likelihood of such violence depends on resource windfalls.[6]

The effect of natural resources on *de facto* political power is easy to comprehend: the association focuses on ethnic violence, arguing if resources are concentrated in a particular region of a country, it may incentivises excluded ethnicities to engage in violence (Humphreys, 2005; Morelli and Rohner, 2015). In Africa, ethnic violence are more likely to challenge states that exclude large portions of the population on the basis of ethnicity (Wimmer et al., 2009). Such armed violence can potentially alter the existing power sharing arrangement.

To examine the evidence in favour of this argument, we rely on Ethnic Armed Conflict Dataset (EACD) linked to the EPR dataset. As we show in columns (2) and (3) in Table 3.4, there is no significant association between resource discoveries and *de facto* political power, as reflected in the outbreak and intensity of ethnic violence. All coefficient remain negative.

Similarly, we do not observe significant association between ethnic specific commodity price indices and the outbreak of ethnic violence. The results are reported in Table 3.5. These results suggest that resource discoveries and commodity prices do not enhance *de facto* political power of excluded ethnicities.

[6]Note that there are several dissimilarities in the identification of the association between natural resources and violence, hence the findings are mixed. Cotet and Tsui (2013) and Lei and Michaels (2014) present contradicting cross-country evidence on the effect of natural resources on political violence. Lei and Michaels (2014) attribute the contradiction to dissimilarity in the implementation of their paper including methodological and measurement issues. Similarly, Arezki et al. (2015a) and Berman et al. (2014) present contradicting subnational evidence on the effect of natural resources on armed violence. Arezki et al. (2015a) use natural resource discoveries as plausibly exogenous source of variation, whereas Berman et al. (2014) rely on production data and commodity prices.

And hence, *de facto* political power is not a significant mechanism explaining the association between natural resources and ethnic share of cabinet positions .

Table 3.4: Resource Discoveries, Political Violence and Collective Action

Dependent Variable:	Collective Action	Ethnic Violence	
	(1)	(2)	(3)
Resource Discovery, *t*	0.241	-0.009	-0.006
	(0.177)	(0.010)	(0.007)
Resource Discovery, *t-2*	-0.097**	-0.011	-0.002
	(0.042)	(0.010)	(0.006)
Resource Discovery, *t-4*	-0.098**	-0.019	-0.012
	(0.041)	(0.014)	(0.011)
Resource Discovery, *t-6*	-0.117***	-0.014	-0.009
	(0.043)	(0.011)	(0.008)
Resource Discovery, *t-8*	-0.121***	0.134	0.139
	(0.043)	(0.133)	(0.133)
Resource Discovery, *t-10*	-0.141***	-0.007	-0.002
	(0.041)	(0.008)	(0.005)
Year Fixed Effects	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes
Observations	7,670	7,670	7,670

Notes: This table reports the effect of natural resource discoveries on the outbreak of ethnic political violence and collective contentious action. In column (1), the outcome variable represents an indicator of protest events and various other collective contentious political events, including riots and strikes. In column (2), the outcome variable represents the year in which a new ethnic armed violence starts. In column (3), the outcome variable represents an indicator of the year in which high intensity ethnic armed violence starts. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.4.2.2 Natural Resources and Collective Contentious Action

The literature also emphasise the importance of the link between natural resources and social actors collective action. This is a bottom-up ethnic coalition project that is not readily explained by rulers' pursuit of windfall revenue nor opposition groups' *de facto* political power. We test the hypothesis that natural resources can impel social actors to press for inclusive ethnic coalitions. The argument is simple: natural resources can transmit clear incentives for social actors by improving capacities for organising popular collective action to secure distributional political advantage (Saylor, 2014). Such collective actions can be manifested as protest events and various other social movements, including riots and strikes. This may create circumstances under which rulers are inclined to fulfil inclusive coalition requests.

To examine the evidence in favour of this mechanism, we use the Social Conflict Analysis Database (SCAD) that contains information on protests, riots, strikes, and other social movements in Africa. We find mixed evidence. In Table 3.4, we report that ethnicities with natural resource discoveries are associated with less likelihood of the outbreak of collective contentious action. On the other hand, however, we find significant positive association between ethnic commodity prices and the outbreak of collective contentious action. The regression coefficients of ethnic commodity prices is reported in Table 3.5.

Table 3.5: Commodity Prices, Political Violence and Collective Action

Dependent Variable:	Collective Action				Ethnic Violence			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Commodity Price, *t*	0.036***				0.004			
	(0.011)				(0.003)			
Average Price, *3 Years*		0.001**				0.0002		
		(0.000)				(0.000)		
Average Price, *5 Years*			0.038***				0.006	
			(0.012)				(0.004)	
Average Price, *10 Years*				0.043***				-0.001
				(0.014)				(0.001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,016	7,515	7,181	6,346	6,902	6,589	6,334	5,640

Notes: This table reports the effect of ethnic specific commodity price indices on the outbreak of ethnic political violence and collective contentious action. In columns (1)-(4), the outcome variable represents protest events and various other collective contentious political actions, including riots and strikes. In columns (5)-(8), the outcome variable represents the year in which a new ethnic violence starts. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Our result for ethnic specific commodity prices echoes the finding of Berman et al. (2014). Exploiting variations in the global mineral prices, Berman et al. (2014) find a positive impact of mining on the probability of low-level violence (riots, protests) in African countries at grid level. Our results with large-scale resource discoveries, however, provide no evidence that general findings of Berman et al. (2014) hold in Africa at ethnicity level. The mixed result is not a new phenomenon, as studies have often reported mixed results. It would perhaps cast a doubt on the association between natural resources and organised collective action to secure distributional political advantage.

Not all natural resources impact social actors equally, and its potential for patronage is different. Revenues from resource discoveries (usually capital-intensive) accrue mainly to the state, hence do not directly affect social actors collective capacity (Bazzi and Blattman, 2014). In contrast, commodity booms do affect social actors' capacity directly as taxation is typically limited on agricultural and some mineral commodities. Thus, both resource discoveries and commodity booms potentially play different roles to affect political patronage. However, we cannot make firm conclusion given the mixed statistical evidence.

3.4.3 Other Related Results

3.4.3.1 Heterogeneous Effects of Commodity Prices

Is there a great deal of heterogeneity in the political potential of agricultural commodities and mineral commodities? As a traditional sector, agriculture was often seen to contribute passively to political economy. However, mineral sector is at the centre of political foundations of resource curse in most developing countries. Thus, one may expect the two types of commodities may have different impacts on the distribution of cabinet positions across diverse ethnicities in Africa.

In Tables 3.6, we find that the significant effect of commodity prices on cabinet appointment is not affected by the type of commodities. Therefore, given the widespread popular support for rulers in rural Africa, our statistical evidence supports a significant role for agricultural booms in African power sharing coalitions. Increase in agricultural prices can have the scale and growth-linkages potential to influence aggregate growth and thus the political patronage allocation.

Table 3.6: Heterogeneous Effects of Commodity Prices

Dependent Variable:	Share of Ministerial Appointments			
	(1)	(2)	(3)	(4)
Panel A: Effects of Mineral Commodity Prices				
Mineral Price, *t*	0.0029			
	(0.002)			
Average Mineral Price, *3 Years*		0.0042**		
		(0.002)		
Average Mineral Price, *5 Years*			0.0053**	
			(0.002)	
Average Mineral Price, *10 Years*				0.0072***
				(0.002)
Leader Group	0.0966***	0.1040***	0.1083***	0.1202***
	(0.010)	(0.011)	(0.012)	(0.015)
Observations	1,145	1,088	1,041	906
Panel B: Effects of Agricultural Commodity Prices				
Agricultural Price, *t*	0.0062			
	(0.004)			
Average Agri Price, *3 Years*		0.0137***		
		(0.004)		
Average Agri Price, *5 Years*			0.0165***	
			(0.005)	
Average Agri Price, *10 Years*				0.0243***
				(0.006)
Leader Group	0.0866***	0.0869***	0.0877***	0.0880***
	(0.004)	(0.004)	(0.005)	(0.004)
Observations	6,536	6,251	6,001	5,238
Year Fixed Effects	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the effect of ethnic specific mineral and agricultural price indices on the distribution of cabinet positions. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.4.3.2 Natural Resources and Prominence of Single Ethnicity

How about the effect of natural resources on the prominence of single ethnicity? Some scholars characterise African states as monopolisation or dominance of political power by few elites, with political arrangements ranging from authoritarian systems to quasi-democracies. In the EPR dataset, *power monopolisation* denotes elites of an ethnicity who monopolise the executive branch of government by excluding elites of all other ethnicities. Similarly, *power dominance* denotes elites hold key position in the executives, and also include limited elites from all other ethnicities.

We find significant negative association between natural resource discoveries and ethnic power monopolisation. Likewise, we observe statistically insignificant negative relation between resource discoveries and dominance power in the national level executives. This contradicts clearly the conventional wisdom that political power in Africa is monopolised, or dominated by few elites.

We also estimate the effect of ethnic specific commodity price indices on power monopoly and dominance, and find mixed result. The mixed coefficients do not harm the interpretation of our finding. We observe negative relation with power monopoly, whereas significant positive relationship with power dominance. This is not surprising given that indicator of dominance of the national level executive power also include other politically relevant ethnicities, for which we observe increased representation in the shadow of resource discoveries and commodity price rises. Regression table is reported in Table B.8 in the Appendix.

3.4.3.3 Natural Resources and Other Ethnic Power Configurations

Leaders in Africa conventionally face opposition from ethnicities that pose different threats to their control over the country. These may include *centre-seeking*, *autonomy-seeking* and *independence-seeking* threats. For this reason, people may expect that natural resources lead to different risk of ethnic violence conditional on ethnic political agenda (threats to the ruler). We present evidence regarding the anticipated heterogeneous effects of natural resources on different ethnic political power configurations.

EPR dataset allows us to estimate the effect of natural resources on ethnic exclusion from central government, ethnic domination of regional government, and ethnic domination of a breakaway region (separatism movement). We find that resource discoveries and ethnic commodity prices have no significant relationship with ethnic exclusion, regional autonomy, and domination of a breakaway region. All regression tables are reported in Tables B.9 and B.10 in the

Appendix. This finding supports the idea that power sharing coalitions (ethnically determined) have been widely used in Africa as a strategy to avoid violence (LeVan, 2011). This may be purported as power shift in the favour of rulers in power, as the conventional wisdom holds that conflict over natural resources shifts relative power in the ruler's favour (Bell and Wolford, 2014).

3.4.3.4 Natural Resources and Window-Dressing Power Sharing

Is power distribution in Africa a window-dressing appointments? We check the types of cabinet positions distributed across ethnicities and investigate whether ethnicities are allocated low (symbolic) cabinet positions. We distinguish between top and low cabinet positions, and test their relation with natural resources. Based on Francois et al. (2015), we experiment different categorisations of cabinet positions into top and low. For example, we categorise the Defence, Finance, Economy, Foreign Affairs, Trade, Education, etc. as top ministerial appointments. The low ministerial appointments may include Environment, Civil Service, Cultural Affairs, Social Service, Youth and Sport, etc. We believe that Economic and Finance ministerial positions, and expansive cabinet positions, such as Transportation and Education, are associated with rent distribution to ethnicities represented by elites at the executives.

We estimate the effect of resource discoveries and commodity prices on the distribution of top and low cabinet positions. The effect is significantly positive, which imply that the allocation of cabinet positions is not a window-dressing politics. Leaders bring in elites into top political positions, which are real power to impact rent distribution. The result is reported in Table B.11 in the Appendix.

3.4.4 Multi-Ethnic Coalitions and Distributive Politics

Do ministerial appointments come with real power to impact distributive politics? We test the effect of ministerial appointments on rent distribution. We rely on satellite data on night lights intensity as a measure of rent distribution, because no rent distribution data are widely available at the ethnicity level. The results are reported in Table 3.7. We find that ethnicities that share the ethnicity of the head of cabinet positions receive larger economic benefit, as reflected in intense night lights. In contrast, excluded ethnicities do not enjoy higher intensity of night lights. On average, ethnicities that have no access to state cabinet positions are associated with about 42% less night lights distribution.

Table 3.7: Power Sharing and Distributive Politics

Dependent Variable:	Natural Logarithm of Night Lights Density			
	(1)	(2)	(3)	(4)
Ministerial Appointment	7.7066***	1.5453***	1.2461***	
	(0.092)	(0.202)	(0.197)	
Exclusion from Power				-0.4170***
				(0.144)
Year Fixed Effects	No	Yes	Yes	Yes
Ethnic Fixed Effects	No	Yes	Yes	Yes
Country x Year Fixed Effects	No	No	Yes	Yes
Observations	3,220	3,220	3,220	3,220

Notes: This table reports the effect of ministerial appointments on rent distribution. The dependent variable, which measure rent redistribution to ethnic groups, is based on satellite data on night lights. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Our evidence is consistent with other studies that document ethnic power sharing coalitions in Africa signals significant rent re-distribution. The rent distribution is often reflected in the form of public goods expenditure in school, transport and other public goods provision. For example, Hodler and Raschky (2014) show that regional favouritism is most prevalent in countries such as in Africa, where they document the birth region of the current political ruler is associated with intense luminosity distribution. Kramon and Posner (2016b) find co-ethnics of the president, or co-ethnics of the minister of education is associated with more schooling than children from other ethnicities in Kenya. Similarly, Burgess et al. (2015) find that districts that share the ethnicity of the president receive higher expenditure for paved roads.[7]

[7]Note that the result of Burgess et al. (2015) indicate ethnic ministerial appointments does not translate into enhanced road investment in the districts that share the ethnicity of these co-ethnic ministers. They observe increased road investment only in the districts that share the ethnicity of president, which they interpret as the president retains the power to distribute road investment in Kenya. Night lights potentially represent a range of public investment including public constructions other than paved roads.

3.5 Robustness and Sensitivity Analysis

We now check the robustness of our results to common econometric issues. The main coefficient estimates reported in this paper are based on linear regressions. However, linear regression may not be appropriate due to limited frequency in which power sharing happens in relation to natural resource discoveries and rising ethnic specific commodity price indices. Hence, analysing rare events like cabinet reshuffling requires specialised statistical techniques, or different approach to the data frequency. We, therefore, use a poisson regression method, and the main results remain unchanged. The results are reported in Table B.12 in the Appendix. The outcome variable for the poisson regression is a nonnegative count variable, which indicates the number of times the cabinet reshuffling incidence have happened.

Our main dependent variable is proportional variable, reflecting ethnic share of cabinet positions. And in practice, the distribution of proportion variable is bounded between 0 and 1; hence one may expect that the relationship may not be linear, and the variance tends to decrease when the mean gets closer to one of the boundaries (Papke and Wooldridge, 1996; Baum, 2008). The percentiles distribution of our sample indicate that the smallest cabinet share value is 0 and the largest is 0.57. The frequency distribution shows a marked spike at the zero, which is about 39% of country-year observations. The observed zeros here are structural zeros, which means ethnic groups receive no cabinet positions because of many reasons. Consequently, linear OLS estimator may tend to be less desirable. Fortunately, the predicted values from the OLS model fall within the range of 0 to 1 without outcome variable transformation. However, we still model the distribution of the dependent variable using generalised linear model (fractional logit option). The results remain unaffected and reported in Table B.13 in the Appendix.

In addition to the exogenous variations in natural resource discoveries and global commodity prices, the identification strategy in this paper rests on the fixed effects regression analysis. We control for ethnic specific characteristics, year dummies and countrywide time varying characteristics. This would help to better account for change in natural resource discoveries and ethnic specific commodity price indices affecting ethnic cabinet share. An alternative way to probe the robustness of our identification strategy is to include linear ethnic specific parametric time trends among the regressors. The rationale of controlling for ethnic specific time trends is that ethnic groups may influence the set of political procedures that determines power sharing at different times, giving rise to a differences-in-differences type of identification. This approach works very well as we have sufficient sample periods. The main regression coefficient estimates remain unaltered. The results are reported in Table B.14 in the Appendix.

Furthermore, this paper may not capture all the mechanisms depicting how ethnicities, or perhaps powerful elites use natural resources as a political leverage to get to power. There are several potential outcomes, such as building new opposition parties, new electoral coalitions, and breakaway from the ruling party in the shadow of resource discoveries and rising commodity prices. Unfortunately, we have no ethnic level dataset to test further.

3.6 Conclusion

This paper has empirically examined the association between resource resources and power sharing coalitions in Africa. The paper employs ethnic ministerial appointments to the cabinet as a measure of power sharing coalitions. Within 2-8 years of resource discoveries, ethnicities that discovered resources are significantly more likely to be appointed as cabinet minister than ethnicities with no resource discoveries. Similarly, increase in ethnic specific commodity price index is associated with an increase in ministerial appointments. We find that ethnic groups that discovered natural resources receive about 2 more ministerial appointments compared ethnicity with natural resource discovery.

We also explored the economic factors which may explain the patterns shown in the data. Our evidence contradicts the theory that resource discoveries and rising commodity prices incentivise state capture via political violence, but supports the idea that natural resources raise the value of being in power, and provide rulers with more finance which they can use to expand cabinet sizes and distribute across politically relevant ethnicities. We also show that resource discoveries and commodity price indices are not significantly associated with ethnic exclusion from central government, ethnic domination of regional government, nor ethnic engagement in separatist movement.

The welfare implication of our finding in this chapter is as follows: we find evidence that ethnicities that share the same ethnicity with head of cabinet positions receive larger rent distribution, as reflected in night lights intensity. On average, ethnicities that have no access to state cabinet positions are associated with about 42% less night lights distribution. The story is different for excluded ethnicities, as they receive less economic opportunity. Our result is consistent with other studies that document ethnic power sharing in Africa signals significant rent distribution. The rent distribution is often reflected in the form of public goods expenditure in school, transport and other public goods provision.

CHAPTER 4

Resource Discovery and Local Armed Conflict

4.1 Introduction

Armed conflict has been part of human history since time immemorial. Eighteenth century political economist Thomas Malthus in his paper entitled *An Essay on the Principle of Population* noted that faced with resource scarcity, armed conflict is a key strategy for humans in their struggle for existence. Charles Darwin was also inspired by Malthus' work when he professed that conflict and competition over scarce resources are germane to the evolutionary strategies of species in their quest for survival in the natural world. Even though armed conflict is integral to the process of allocation of scarce resources, the interrelationship between the two is not very well understood. Provocative theories on the relative power of greed and grievances abound, the true causes of conflict in the resource rich regions of Africa remains largely unknown.

Until recently, research on the interrelationship between natural resources and intrastate civil conflict stood on the periphery of the economics discipline.[1] The past decade however witnessed a surge in research on conflict. Indeed, a large body of macro cross-country literature documents positive association between natural resources and conflict.[2] The emphasis is on the role of economic motives as opposed to social motives in triggering conflict. For example, access to an oil rig or a mine could provide lucrative financial opportunities to rebel

[1]Note that *conflict* here implies *intra-state conflict*. We do not analyse the link between resources and interstate wars. For a recent study on oil and interstate wars see Caselli et al. (2015).

[2]See Blattman and Miguel (2010) and Nillesen and Bulte (2014) for a survey of this literature.

rulers to build and sustain rebel organisations which would encourage armed conflict. This could override atypical social motives such as inequality, political repression, and ethno-religious divisions.

Establishing causality has been the key motivation in this literature. Chilling examples of conflict in Angola, Congo, Rwanda, Sudan and other resource rich regions of Africa often tempt scholars to argue that resources cause conflict. Yet establishing causality has remained illusory largely due to the obvious limitations associated with cross-country studies. Furthermore, lack of useful data for Africa limits the scope for adequately examining the causal link.

In this chapter we aim to systematically explore the effect of oil and mineral discoveries on intra-state armed conflict onset, intensity, and incidence in Africa at the grid level corresponding to a spatial resolution of 0.5 x 0.5 degrees latitude and longitude. Using detailed geocoded data on resource (oil and mineral) discoveries and armed conflict, we are able to construct a quasi-natural experiment to establish causality. In other words, we are able to test whether resource discovery as an exogenous news shock has any bearing over conflict onset, intensity, and incidence at the local level in Africa. We also discuss the plausibility of channels through which natural resource discovery shocks affect the intra-state armed conflict. We use three different datasets containing the geographical location of conflict events in Africa: the PRIO-GRID conflict dataset, the Armed Conflict Location and Event Dataset (ACLED) and the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED). These datasets cover different time periods and countries. The three datasets allow us to use alternative definitions of armed conflict: onset, incidence and intensity.

This work has some distinctive characteristics in the resource-conflict literature. First, the study uses a novel geocoded dataset of resource discovery at the grid level. In particular, the new dataset is able to distinguish between minerals and oil discoveries.[3] Note that two existing cross-country studies Cotet and Tsui (2013) and Lei and Michaels (2014) use national level oilfield discovery data only and not minerals. Second, the study presents results on the effect of resource dis-

[3]The dataset includes the commodities copper, diamond, fluorite, gold, graphite, lead, manganese, mineral sands, nickel, niobium, PGE, phosphate, platinum, potash, rare earths, silver, uranium, zinc, zircon, oil and gas. The Appendix for Chapter 2 (Tables B.4 and B.5) presents additional descriptive statistics on primary commodities in the dataset.

covery on conflict using grid level data. This is a departure from the existing grid level studies of natural resources and conflict which tend to exclusively focus on the use of global commodity prices as a source of exogenous variation to address potential endogeneity issues (Berman et al., 2014). Third, we use 3 different grid level datasets on conflict in Africa and find consistent new results. Fourth, we investigate the potential heterogenous effects of natural resource discovery on armed conflict by the size of discovery, type of discovery, and time-varying proximity to the discovery. Therefore, we are able to present new results. Finally, our study is able to cover all African countries (including both North Africa and sub-Saharan African (SSA) countries) at the grid level. Hence we are able to significantly improve the external validity of the findings.

The popular discourse both within the academy and the press is that competition over resource wealth in Africa is the root cause of armed conflict. Several cross-national studies support this view (Collier and Hoeffler, 1998, 2004; Humphreys, 2005). Fearon (2005) and Brunnschweiler and Bulte (2009) however challenge this view. The positive association between natural resources and conflict is not borne out in our grid level geocoded data. Contrary to some of the cross-country results, we find that oilfield and mineral discoveries significantly reduce the likelihood of intra-state armed conflict onset post resource discovery in a simple pooled cross-section set up with a sample of 48 African countries observed over the period 1950 to 2008. The effect remains negative but statistically insignificant or weakly significant in most specifications when we control for high dimension fixed effects (time-varying common shocks, grid fixed effects, grid-specific time trends, and country x year fixed effects). We observe little or no heterogeneity in the relationship across resource types (minerals or oil), size of discovery (giant or major), proximity to discovery locations and national borders, pre and post end of the cold war, and quality of national political institutions measured by Polity2 score.

We also analyse the effect of resource discovery on conflict incidence and intensity using the same panel of all African countries covering the period 1989 to 2012. The smaller sample size here is due to the truncated temporal coverage of conflict data from ACLED (1997-2012) and UCDP GED (1989-2010). Even though the negative effect of resource discovery on conflict incidence and intensity remains in a pooled cross-section set up, the trajectory of the coefficient appears to be somewhat different once we control for grid fixed effects.

Resource discovery in one grid could trigger conflict elsewhere in the neighbouring grid, region or country. Therefore, a grid level analysis may not be fully informative here. Hence, we estimate the model using higher grid resolution, region-year and country-year as units of analysis. Although determining the optimal level of aggregation is not straightforward, our aggregation procedure is twofold: systematic grouping (region and country level) and random grouping (higher level grid demarcation). It is worthwhile noting that a key limitation with higher level aggregation is the phenomenon known as ecological fallacy (Maystadt et al., 2013). The association between resource discoveries and armed conflict may differ in magnitude and signs across different levels of aggregation.

We undertake the following three steps. First, we aggregate the conflict events and resource discoveries at higher grids-cells (1x1 degrees latitude and longitude, which is equivalent to 111x111 square kilometres at the equator) and estimate the main model. The effect of discovery on conflict onset remains statistically insignificant and negative in most cases. Second, we estimate the relationship at the region level. We find resource discovery significantly reduces conflict onset after controlling for year fixed effects, region fixed effects, region-specific time trend and country x year fixed effects. Third, we report the country level results and our result is comparable to recent cross-country studies by Cotet and Tsui (2013) and Lei and Michaels (2014). Unlike these studies which solely focus on the effects of oilfield discovery, we are able to consider both oil and minerals. We find that oil and mineral discoveries have no discernible effect on conflict onset at the national level after controlling for fixed effects and country specific trends. Estimating the model separately for oil and minerals do not alter our results. The country level results confirm the findings of Cotet and Tsui (2013). It is worthwhile noting that we do not find any evidence of the ecological inference fallacy here.

We also perform numerous robustness tests and sensitivity analysis using different alternatives and samples to carefully validate our results. First, in order to address the potential temporal correlation of oilfield and mineral discoveries, we control for past discoveries in all specifications and exclude grid-year observations within a decade of past oilfield or mineral discoveries. Second, we restrict our sample to observations where at least one oilfield or mineral discovery was made during the sample period in order to address the concern that observations with oilfield and mineral discoveries are different from others in ways that we cannot measure and control for directly (Lei and Michaels, 2014). Third, we restrict our sample to grids in which at least one conflict event occurred over the sample period. Berman and Couttenier (2015) refer to such grids as high-conflict-risk grids. Finally, we also apply buffer zone analysis in order to address the potential concern that oilfield and mineral discoveries could take up large geographies and hence influence the surrounding geographies of armed conflict. The results remain unchanged and even gets stronger in some cases.

An important aspect here is to explain the plausible economic factors which may explain the impact of natural resource discoveries on the intra-state armed conflict. Most empirical studies of natural resources and armed conflict are motivated by various rival mechanisms, which makes the impact of natural resource on armed conflict somewhat ambiguous (Besley and Persson, 2011). The most widely reported economic factor linking resources to conflict is the opportunity cost phenomenon. According to the opportunity cost mechanism, the returns from non-fighting activity could potentially increase in the event of resource booms, thereby reducing the likelihood of armed conflict. Another mechanism is the 'State Prize' phenomenon, which implies that natural resources may increase the prize value of state capture and in turn increase the incentive for armed conflict. The 'State Prize' mechanism asserts that natural resource discoveries matter because local rebels may engage in direct armed conflict against the state to benefit from natural resources, and/or to secede from the state.

Furthermore, natural resource discoveries might increase state's counter insurgency capacity, which could then be used to strengthen the military and other security infrastructure and thereby reducing the likelihood of armed conflict. More recently, studies indicate that 'political patronage' might serves as an important mechanism explaining the association between resources and armed conflict. Resource discoveries may generate political incentives for incumbents to distribute political patronage more widely to survive longer in power, and the distribution of patronage to the elites and citizens ensures that the incumbent dissuades a militant subset of the society from attempting armed rebellion. Patronage distribution may take the form of public sector employment offers, ethnic brokerage, or personal networks that connect the co-opted elites in the centre to local citizens.

Using the novel satellite data on night lights (Henderson et al., 2012), our evidence appears to be favouring the theories of opportunity cost and political patronage. Resource discovery could impact on the local living standards and influence the opportunity cost of conflict. We use natural logarithm of night lights density as a measure of local living standards. We find that resource discovery improves luminosity at the grid level which in turn reduces armed conflict onset. This is purely economic mechanism. Another plausible mechanism would be the distribution of political patronage by the state. We also find support for this mechanism.[4] This is based on the finding in Chapter 3, and we also report graphical illustration in Figure C.5 in the Appendix. We argue that multi-ethnic distribution of ministerial appointments by the ruler reduces the probability of armed conflict.

Our identification strategy relies on the exogenous variation in the discovery dates of oilfield and mineral deposits. Our dataset allows us to distinguish between giant and major discoveries. Even though it is possible to identify the area where minerals or oil are likely to be found using geological data, it is not possible to accurately predict the timing of discoveries. Therefore, the discovery dates of giant and major reserves are exogenous. One might argue that politicians and government could manipulate the announcement of the precise timing of discovery. Our data is immune to such possibility as the discovery dates are independently verified and documented using multiple sources. More discussion on this follows in Section 4.2.

[4]Note that Bazzi and Blattman (2014) also find support in favour of the income theory of conflict. Cotet and Tsui (2013) find resource discoveries increase military spending (in nondemocratic countries) using cross-country data. Both cross-national evidences supports the idea that rising windfalls improve counter-insurgency capacity and reduce individual incentives to fight in armed conflicts.

How random is resource discovery? Resource discovery could be a product of exploration effort and the latter could be influenced by pre-existing conflict. This could potentially contaminate the identification strategy if the dependent variable is either conflict incidence or conflict intensity both of which are measures of pre-existing conflict. However, this would not be a challenge if the dependent variable is conflict onset (our main measure) which records the start of a new conflict in areas which did not have conflict before. Therefore it is unlikely that current conflict onset would predict past exploration efforts in a grid that did not have any history of conflict. Furthermore, the timing of natural resource discovery appears to be largely uncorrelated with the grid's average economic and political performance in the past years after controlling for grid fixed effects. This is suggestive that resource discovery is largely orthogonal and the conditional estimates that we present for conflict incidence and intensity are not contaminated. Nevertheless, we also present IV estimates with commodity price as an instrument for resource discovery.

Administrative boundary demarcation could be a potential source of endogeneity. For instance, administrative demarcations in a country could be determined by political, geographic and demographic characteristics of the area. This could in turn be correlated with both local conflict dynamics and resource extraction contaminating the coefficient estimate. This is unlikely to be a concern here as our main unit of analysis is a grid cell. The grid level data by construction is independent of political and geographic characteristics and therefore is exogenous to conflict and resource discovery. Nevertheless, we also check the effect of resource discovery on conflict at the region and country levels.

Another source of bias could be the fact that mines and oil rigs are often military targets in a conflict giving rise to a positive association between the two variables without any causal link. Again, this is unlikely to be a concern here as we are finding negative or no association between discovery and conflict.

Our paper is broadly related to the resource curse literature. Auty (2001), Gylfason (2001) and Sachs and Warner (2001) note that resource rich countries on average grow much slower than resource poor countries. Subsequent studies have argued that natural resources may lower the economic performance because they strengthen powerful groups, weaken legal frameworks, and foster rent-seeking activities (Tornell and Lane, 1999; Besley, 2007). Others have argued whether natural resources are a curse or a blessing depends on country-specific circumstances: institutional quality (Mehlum et al., 2006; Robinson et al., 2006; Bhattacharyya and Hodler, 2010, 2014b; Bhattacharyya and Collier, 2014), natural resource type (Isham et al., 2005a) and ethnic fractionalisation (Hodler, 2006).

More specifically, our paper is also related to the literature documenting the effect of natural resources and income on conflict. Recent theoretical studies argue that the likelihood of conflict is related to three key variables (Besley and Persson, 2009, 2011). The prize for the winner in a conflict is increasing in natural resources rents. Therefore resources increase the likelihood of conflict. Higher wages in contrast increases the opportunity cost of fighting and hence reduces the likelihood of conflict. Weak institutions and lack of state capacity to raise revenue compromises inclusivity of political institutions and hence increases the likelihood of conflict. In a nuanced general equilibrium model, Dal Bó and Dal Bó (2011) show that resource boom in the form of a favourable price or technology shock diminish wages and reduce the opportunity cost of conflict.

In spite of the apparent theoretical clarity, estimating the causal relationship between natural resources and conflict has been challenging. Several macro cross-national studies Collier and Hoeffler (1998, 2004); Humphreys (2005) and Brückner and Ciccone (2010) report robust positive association between resource dependence and conflict.[5] However, Fearon (2005) point out that these results cannot be interpreted as causal as they could be driven by omitted variables and endogeneity. Furthermore, Fearon and Laitin (2003) identify weak institutions as the main cause of conflict rather than natural resources.

Contemporary cross-national studies have used instrumental variables and exogenous news shocks to address endogeneity concerns and identify the effect. Miguel et al. (2004) use rainfall shocks as an instrument for economic shocks and find that negative economic shocks trigger conflict. Cotet and Tsui (2013) and Lei and Michaels (2014), both use oilfield discovery as an exogenous shock to identify

[5] Hegre and Sambanis (2006) and Sambanis (2004) find that the effect of resource dependence on conflict onset is not robust. More recently, Bazzi and Blattman (2014) revisit the question and find no robust association between commodity price shocks and civil war.

the effect of oil on conflict. The former reports no effect while the latter reports positive effect. Brunnschweiler and Bulte (2009) examine the effect of resource wealth and find that the same in fact reduce the risk of conflict. The overall direction of the cross-country evidence could be summed up as conflicting.

Conflict is often localised and cross-national studies by construction fail to capture local effects. Yet disaggregated local level studies of natural resources and conflict are rare with the exception of the following few studies. Angrist and Kugler (2008) study the effects of upsurge in coca prices and cultivation on civil conflict in Colombia. Maystadt et al. (2013) study the Democratic Republic of the Congo and find that mineral concessions have no effect on conflict at the lowest administrative unit, but significant effect at the higher administrative units. More recently, Berman and Couttenier (2015) study how external income shocks affect the probability of conflict events in SSA by working with a full grid of 0.5 x 0.5 degrees latitude and longitude.

Using a similar approach, Berman et al. (2014) study Africa at the grid level corresponding to a spatial resolution of 0.5 x 0.5 degrees latitude and longitude and covering the period 1997 to 2010. Using data from the ACLED, they find evidence that mineral price shifts trigger low-level as well as organised conflict incidents in Africa. Note that ACLED offers data since 1997 which truncates the sample. In contrast we are able to use a much larger sample of georeferenced data covering the period 1950 to 2008. Nevertheless, we also use the ACLED dataset to check robustness of our results. We are able to exploit giant and major resource (oilfield and minerals) discovery as exogenous news shock to identify the effects of natural resources on conflict which is not covered in the Berman et al. (2014) study. The different results reported by us and Berman et al. (2014) could be explained by the heterogeneous effects of discovery and production on conflict as the prospect of future production affects conflict onset and incidence less than actual production (Humphreys, 2005).

The remainder of the chapter is structured as follows: Section 4.2 describes the data and descriptive statistics. Section 4.3 discusses the empirical strategy to identify the effects of natural resource discovery shocks. Section 4.4 presents evidence and discusses the causal mechanism.This section examines the effect of discovery on conflict onset, conflict incidence, and conflict intensity separately. It also reports any potential heterogeneous effect across resource types (oilfield and minerals), proximity to discovery and national border, pre- and post-cold war conclusion, size of discovery (giant and major), and quality of political institutions. Section 4.5 deals with robustness. Section 4.6 concludes.

4.2 Data Sources and Measurement

Our main objective is to study the effect of resource discovery shocks on the risk and intensity of intra-state armed conflict in Africa at the grid level. Therefore, we divide the whole continent of Africa into a spatial resolution of 0.5 x 0.5 degrees latitude and longitude, which approximately amounts to 55 x 55 square kilometres at the equator.[6] In order to check robustness of our results, we also analyse the relationship at higher levels of aggregation. These results are reported in the appendix. We have data on the specific geographic location of armed conflict events, mineral and oilfield discoveries, and local economic activities measured by night lights. Our grid is matched with the standardized PRIO-GRID project (Tollefsen et al., 2012), which allows us to merge our resource discovery dataset with the conflict dataset. Table C.1 in the Appendix reports summary statistics.[7] Figure 4.1 presents the grid level map of Africa.

4.2.1 Natural Resource Discovery Dataset

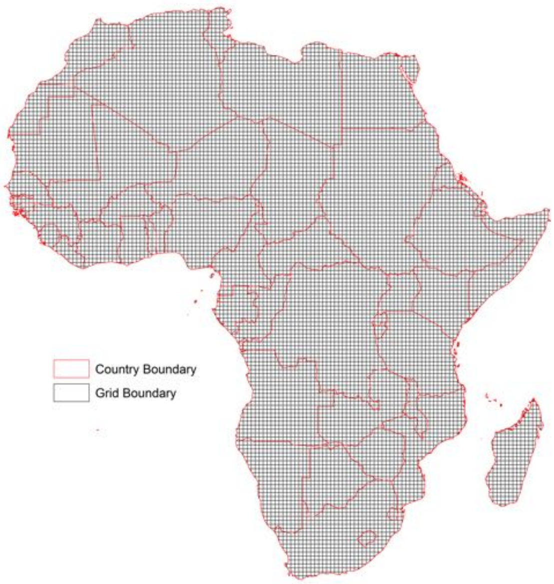
We use two datasets containing the geographical location of natural resource discoveries in Africa: mineral deposits (MinEx Consulting, 2014) and giant oilfield discovery Horn (2011).[8] MinEx reports 263 discoveries of 19 minerals over the period 1950 to 2012. They also report the size of the discoveries: major and giant. MinEx codes a mineral deposit as giant if it has the capacity to generate at least

[6]This structure has been used by several recent studies. See for example Alesina et al. (ming), Michalopoulos and Papaioannou (2013a), Berman et al. (2014), Besley and Reynal-Querol (2014) and Berman and Couttenier (2015).

[7]We also check for stationarity of the variables used in the model using Levin-Lin-Chu and Harris-Tzavalis variety of unit root tests. Both tests account for bias emanating from cross-sectional association. We find all variables to be stationary.

[8]Mike Horn identifies whether the field contains oil and/or gas, but in the rest of our paper we refer to them as oilfield discoveries. Mike Horn's dataset contains information on the estimated ultimate recoverable reserves (URR) (Arezki et al., 2015b).

Figure 4.1: Grid Level Boundary Map of Africa

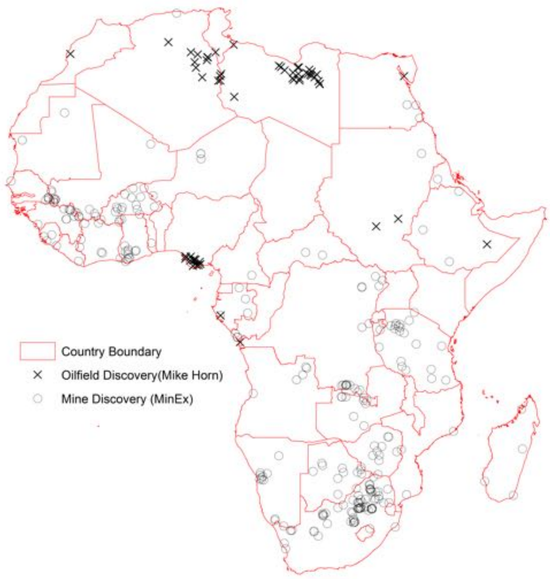


Notes: This boundary map is the grid level subnational division of Africa. The grid has a spatial resolution of 0.5 x 0.5 degrees latitude and longitudes latitude and longitude (i.e. around 55 x 55 square kilometres at the equator), dividing the whole continent into equally sized cells.

USD 0.5 billion of annual revenue for 20 years or more accounting for fluctuations in commodity prices. A major mineral deposit is defined as one that could generate an annual revenue stream of at least USD 50 million but not as long life as a giant reserve. Horn (2011) reports 59 onshore giant oilfield (including condensate) discoveries in Africa over the period 1955 to 2010. Mike Horn codes oilfield as giant if it has ultimate recoverable reserves (URR) of at least 500 million barrels of oil equivalent. Based on this information from both datasets, we construct an indicator whether a grid has discovered at least one giant or major natural resource (oil and/or minerals) deposit in a given year. Figure 4.2 presents a map of oilfield and mineral discovery locations.

We observe that countries are heterogeneous in terms of the number of discoveries (see Figures C.1 and C.2 in the Appendix for the distributions of natural resource discoveries within countries). For example, Botswana, Burkina Faso, DRC, Ghana, Mali, Namibia, South Africa, Tanzania and Zimbabwe individually represent more than 4% of the total mineral discoveries in the continent while other countries feature a lot less on the mineral discovery league table. In the oilfield discovery dataset, Libya and Nigeria accounts for 45.8% and 23.7% of the total African oilfield discoveries respectively. We also observe that 47.9% of the

Figure 4.2: Oilfield and Mineral Discovery Locations



Notes: The map shows the location of mineral deposit and oilfield discoveries in Africa over the period 1950-2012.

mineral discoveries are gold whereas 78% of the hydrocarbon discoveries are oil.

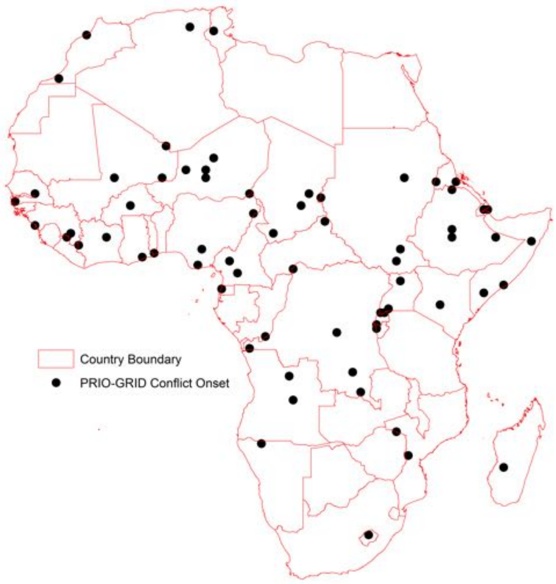
4.2.2 Intra-State Armed Conflict Dataset

We use three geocoded datasets of conflict events in Africa: PRIO-GRID conflict dataset, Armed Conflict Location and Event Dataset (ACLED) and Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED). These datasets cover different time periods. The PRIO-GRID (Version 1.01) presents a long time series, 1946-2008 while the ACLED and the UCDP GED (Version 1.5) covers the time period 1997-2012 and 1989-2010 respectively. The conflict events recorded in these datasets are obtained from various sources including press reports, case studies, historical archives, and country-expert statements.

The temporal PRIO-GRID is a vector grid network with 0.5 x 0.5 degrees. It contains cell-specific information on the onset and incidence of conflict, represented by a conflict ID variable that corresponds to the standard UCDP/PRIO datasets (Tollefsen et al., 2012). Note that UCDP/PRIO is the most widely used conflict datasets in the cross-country literature, including recent studies by Cotet and Tsui (2013), Bazzi and Blattman (2014) and Lei and Michaels (2014).

Studies show that historical conflict systematically predicts contemporary

Figure 4.3: PRIO-GRID Armed Conflict Onset Locations

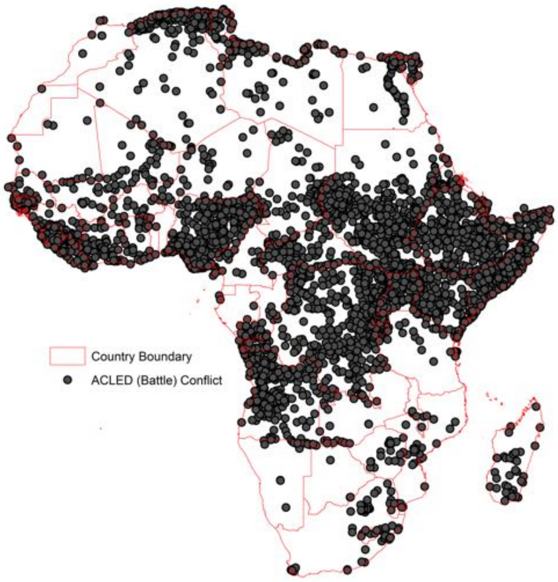


Notes: The map shows the location of PRIO-GRID armed conflict onset locations in Africa over the period 1946-2008.

conflict in post-colonial Africa (Besley and Reynal-Querol, 2014). Hence, historical legacy of conflict within a grid could contaminate the potential causal relationship between resource discovery and conflict. Indeed causality could run in the opposite direction as mining companies could avoid exploration in locations with a history of conflict. For this reason, we are only interested in the onset variable from the conflict attribute table in PRIO-GRID. The PRIO-GRID onset is a dummy variable identifying the grid hosting the initial battle location for each new intrastate armed conflict (Tollefsen et al., 2012). Note that by definition these grids host the start of a new conflict and therefore they never had a conflict before. It takes the value 1 for the first year of an outbreak with minimum 25 fatalities and 0 for all other years. According to UCDP/PRIO, an armed conflict is defined as 'a contested incompatibility between a government and oppositions that result in at least 25 battle deaths in a year' (Gleditsch et al., 2002).

We also use alternative definitions of conflict onset using ACLED and UCDP GED. ACLED codes violent political activity within all African states, including dyadic interactions between rebels and governments, riots and protests within and outside a civil conflict, and violence perpetrated against civilians. However, it does not specify a battle related fatalities threshold and conflict events may not adhere to the standard UCDP/PRIO definitions. Hence we focus on the ACLED's

Figure 4.4: ACLED Armed Conflict Locations



Notes: The map shows the location of ACLED battle related armed conflict locations in Africa over the period 1997-2012.

battle related conflict definition which was also used by others in the literature.[9] Note that ACLED defines a battle as 'a violent interaction between two politically organised armed groups at a particular time and location within the context of a armed conflict or civil conflict' (Raleigh et al., 2010).

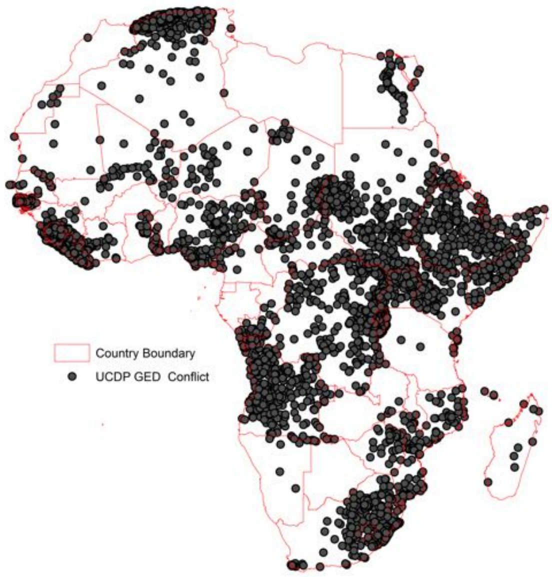
The UCDP GED dataset contains armed conflict events for all actors that surpass the 25 deaths threshold per year (Sundberg and Melander, 2013). This makes it comparable to the country-level data commonly used in the cross-country literature. We construct our additional armed conflict onset variable from the UCDP GED dataset based on the widely accepted definition of 25 battle-related fatalities threshold per year.

We use the Bazzi and Blattman (2014) conflict onset definition to code onset using the ACLED and UCDP GED datasets. Note that this definition of onset is the most widely used in the cross-country literature. It codes onset as 1 for the first year of outbreak with 25 or more fatalities. All peace years are coded as 0 and the years of ongoing conflict are coded as missing.

All three conflict datasets report the precise geographical location of conflict. Hence we are able to merge the PRIO-GRID's armed conflict onset to our

[9] In some studies ACLED's battle related armed conflict is referred to as organised violence. See for example Berman et al. (2014).

Figure 4.5: UCDP GED Armed Conflict Locations



Notes: The map shows the location of UCDP GED armed conflict locations in Africa over the period 1989-2010.

spatial-temporal grid structure. For ACLED and UCDP GED, we aggregate the conflict event data by year and grid. Our unit of analysis therefore is a grid-year. Figures 4.3-4.5 presents maps of armed conflict onset locations from the PRIO-GRID, ACLED, and UCDP GED datasets respectively.

The literature acknowledges that conflict datasets could over-represent certain subnational regions or conflict types (Berman and Couttenier, 2015). In particular, we observe the following three broad trends. First, the number of grids with intra-state armed conflict varies across the three datasets. Second, conflict across countries within African continent is heterogeneously distributed and this distribution varies across datasets. Third, the distribution of conflict affected grids within a country also varies across datasets. We document these trends in the Appendix (see Figures C.3 and C.4 and Tables C.2, C.3 and C.4 in the Appendix for details). In spite of these differences, it is important to appreciate that these datasets have been constructed under different rules. Therefore, any definitional or otherwise traits in them are likely to be idiosyncratic. Since we are finding consistent results across three different datasets, it is unlikely that these results are driven by measurement error. Furthermore, our very demanding high dimensional fixed effects approach also make it unlikely that the results are driven by measurement error and data quality issues.

4.2.3 Night Lights Data: Proxy for Local Economic Performance

Note that we do not have measures of income for Africa at the grid level. We use satellite data on night lights or luminosity density observed over the period 1992 to 2012 as our proxy for income. We calculate luminosity density by dividing the sum of all night lights pixel values within a grid by the grid area. We source the night lights data from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS). The satellite images of the earth are captured between 20:30 to 22:00 local time, and the satellites circle the earth 14 times per day. The data we use here is the cleaned luminosity after filtering for cloud coverage, other ephemeral lights, and background noise. The measure comes on a scale from 0 to 63 (digital number) calculated for every 1 square kilometre, where a higher value imply greater night lights intensity.

The distribution of night lights across grids is not normal. We have a significant volume of observations that takes the value zero. To account for this, we follow Michalopoulos and Papaioannou (2013a) and Hodler and Raschky (2014) and define the dependent variable as the natural log of night lights density plus 0.01. It is widely acknowledged that such transformation ensures that all available observations are used and the problem of outliers minimised.

The other challenge with night lights data is measurement error. In particular, issues relating to the difference between true lights emanating into space and what is recorded by a satellite (Henderson et al., 2012). There is also variation in recorded lights data across satellites. Measurement error of this nature is unlikely to be a concern here as it is orthogonal to our models presented in section 4.2. Furthermore, any cross-satellite variation in night lights is already accounted for by the year dummy variable capturing time-varying common shocks.

4.2.4 Other Grid Specific Variables

Resource discovery dates are exogenous and serves as a credible identifier. However, there is no consensus on this issue. Therefore, we also adopt an instrumental variables (IV) approach to check robustness. We construct global commodity price index for each of the grids in our sample following (Brückner and Ciccone, 2010). We source the exogenous price in international commodity markets from the International Monetary Fund (IMF) and UN Conference on Trade and Development (UNCTAD). This data runs back to 1960 and covers all commodities.

The robustness section includes measures of the distance between grid's centroid and the closest national border. We source this data from PRIO-GRID attribute table. We also use regional GDP per capita, ethnic size or total population, and ethnic political representation and exclusion from executive state power. All of these variables are sourced from PRIO-GRID. Note that the PRIO-GRID itself relies on other datasets such as the geographically based economic data (G-Econ) for regional GDP (Nordhaus et al., 2006) and the Ethnic Power Relations (EPR) dataset for ethnic political variables (Wucherpfennig et al., 2011).

Our democracy variable is the Polity2 score. It is based on parameters such as executive constraints, competitiveness of political participation, and openness and competitiveness of executive recruitment (Marshall et al., 2014).

4.3 Empirical Strategy

4.3.1 Resource Discovery and Local Armed Conflict

We use a panel dataset covering more than 10000 grids from 48 African countries.[10] The grids are constructed using ArcGIS. To analyse the local effects of resource discovery on conflict, we estimate the following model:

$$Conflict_{g,t+j} = \alpha_g + \beta_t + \mu_{g,t} + \eta_{i,t} + \gamma_1 Discovery_{g,t} + \gamma_2 Past\ Discovery_{g,t} + \epsilon_{g,t} \quad (4.1)$$

where $Conflict_{g,t+j}$ is the outcome variable that captures conflict onset, conflict incidence, and conflict intensity in grid g at year t. The variable $Discovery_{g,t}$ is an indicator of resource discovery in grid g at year t. $Past\ Discovery_{g,t}$ is the number of years with resource discoveries in the last ten years (from t-10 to t-1). Note that $Past\ Discovery_{g,t}$ accounts for the history of discovery news shock in that grid. It

[10] Due to data limitations, our sample period varies from specification to specification depending on the conflict dataset: PRIO-GRID (1950-2008), ACLED (1997-2012) and UCDP GED (1989-2010). In most specifications, the panel is unbalanced. Appendix C presents a list of countries included in the sample.

is coded to take the value $N \in \{1(1)10\}$ for a particular grid-year if that grid had N discovery years over the past 10 years. The 10 year window is based on Lei and Michaels (2014). Our results are not sensitive to the inclusion or exclusion of past discoveries and or alternative definitions of past discoveries. We estimate this model for different leads j, where in most cases $j \in \{0, 2, 4, 6, 8, 10\}$.

As discussed earlier, our main outcome variable is conflict onset from PRIO-GRID. It is a rare event with 84 instances of battle events. This definition of onset could be viewed as overly restrictive even though it does very well in addressing endogeneity issues. Therefore we also use the Bazzi and Blattman (2014) definition of onset using ACLED and UCDP GED datasets. There are 3473 onset events for ACLED, and 3272 onset events for UCDP GED.

We also estimate the effect of resource discovery on conflict incidence and intensity. The results are reported in the Appendix. Conflict incidence is a dummy variable which takes the value 1 for grid-year when there is an internal conflict with more than 25 fatalities. Conflict intensity is measured by the number of conflict events observed in a grid-year. Even though widely used in some circles, both of these measures are criticised because of the lack of uniformity in their definitions (Sambanis, 2004). Fearon (2011) and Ciccone (2011) argue that both conflict incidence and intensity are aggregate measures of onset and persistence. Conflict onset and its continuation are disparate outcome variables potentially driven by widely different factors. Hence, there is very little logic in combining the two and assuming that discovery would affect them in the same way. Following some notable recent studies (Ciccone, 2011; Cotet and Tsui, 2013) we use the terms armed conflict and civil conflict interchangeably.

Our main coefficient of interest here is γ_1 which presents the effect of resource discovery on conflict. If African conflicts are natural resource driven then we would expect γ_1 to be significantly positive. Any indication otherwise would serve as a refutation of the view that resource triggers conflict in Africa.

In all specifications, we control for high dimensional fixed effects: grid fixed effects α_g, year dummies β_t, grid-specific time trend $\mu_{g,t}$ and countrywide time-varying characteristics $\eta_{i,t}$. Grid fixed effects account for geological characteristics, altitude and ruggedness, proximity to the ports and cities, and ethnic characteristics. It also captures potential time invariant systematic differences across grids affecting conflict data recording and reporting. Year fixed effects account for global shocks such as a spike in minerals or oil price. Grid-specific time trend accounts for external shocks such as a grid-specific weather event. The country x year fixed effects account for factors such as defense burden or military expenditure as a share of GDP, national political dynamics including elections, and national regulations regarding resource exploration and property rights.

Our identification strategy is a treatment-control procedure that uses the discovery shock as the treatment and compares it to grids with no discoveries. It relies on the assumptions that the effect of discovery news shock differs with discovery status, and the evolution of conflict is otherwise common in all grids.

In all estimations, we use robust standard errors clustered at the country level. We also use the Driscoll-Kraay standard errors (Driscoll and Kraay, 1998) which is derived from a non-parametric heteroscedasticity and autocorrelation consistent estimator of the variance-covariance matrix.[11] In the robustness section we check that our results are robust to default standard errors, standard errors clustered at different spatial levels including regions, and standard errors that allow for both cross-sectional spatial correlation and serial correlation (or Conley standard errors) (Conley, 1999; Conley and Molinari, 2007).

Is the use of discovery news shock as an identifier appropriate here? First, major and giant resource discoveries signal significant increases in future economic rent and therefore suitably captures the economic motive of a conflict. Second, in all likelihood the timing of giant and major natural resource discovery is exogenous because of its unexpected nature. However, natural resource discoveries in the recent past could raise the likelihood of additional discoveries in the immediate future. This does not appear to be the case within a grid. In Table C.5 in the Appendix we find a positive correlation between past and future discoveries in pooled OLS models (see columns (1), (3), and (5)), but the correlation reverses within a grid when we control for high dimensional fixed effects (see columns (2), (4), and (6)). This is not surprising given that a grid is much

[11]The Driscoll-Kraay standard errors are an extension of the common non-parametric variance-covariance matrix estimation techniques robust to the very general forms of spatial and temporal dependence (Hoechle, 2007; Cameron and Miller, 2015).

smaller than a region or a country. Region and country level results are reported in the long appendix (Tables C.6 and C.7 in the Appendix). The country level result is consistent with Lei and Michaels (2014). In Table C.8 in the Appendix we further check exogeneity of resource discovery by correlating it with economic and political factors (Lei and Michaels, 2014). We observe that a grid's average economic and political performance over the preceding years is not a robust predictor of resource discovery. They also appear to be jointly insignificant with a p-value = 0.4. This is suggestive that resource discoveries are indeed orthogonal. Figure C.5 in the Appendix also supports the exogeneity view as we notice that the timing of discovery is only imperfectly tracked by commodity price but not by African GDP per capita. Third, discovery date is a superior exogenous identifier to production start date as the period between discovery and production start is characterised by significant economic activity which would contaminate the direction of causality.

Exploration effort which leads to successful discoveries could be influenced by pre-existing conflict. This is not an issue when we use PRIO-GRID conflict onset as our dependent variable. However, we also implement the instrumental variable (IV) approach with commodity price as an instrument and we control for high dimension fixed effects. In the absence of grid level exploration expenditure or effort data, we control for past discoveries as a proxy for exploration effort.

4.3.2 Causal Mechanisms

What is the mechanism through which resource discovery affects conflict? The literature offers several competing explanations some of which we reviewed in Chapter 1. Our data allows us to test the income effect thesis which postulates that resource discovery and extraction increases income and therefore increases the opportunity cost of fighting. Higher income also improves state patronage capacity to buy off elites or citizens which reduces the likelihood of conflict.

First, we estimate the following specification to test the link between resource discovery and local income measured by night lights. If discovery improves local income then we would expect θ_1 to be positive and significant.

$$Lights_{g,t+j} = \alpha_g + \beta_t + \mu_{g,t} + \eta_{i,t} + \theta_1 Discovery_{g,t} + \theta_2 Past\ Discovery_{g,t} + \eta_{g,t} \quad (4.2)$$

Second, using the following model we test the link between improved income and conflict onset. If resource discovery affects conflict exclusively via the income channel then we would expect λ_2 to be significant and λ_1 to be insignificant.

$$Conflict_{g,t+j} = \alpha_g + \beta_t + \mu_{g,t} + \eta_{i,t} + \lambda_1 Discovery_{g,t} + \lambda_2 \widehat{Lights}_{g,t+j} + \xi_{g,t} \quad (4.3)$$

Luminosity data has been proven to be a convincing proxy for local economic development in subnational units (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013a; Hodler and Raschky, 2014).[12]

4.4 Results and Discussion

4.4.1 Main Results

We report the main empirical results in Tables 4.1 and 4.2 using the PRIO-GRID conflict onset variable as an outcome variable. Note that the PRIO-GRID onset variable only records the start of a new conflict in areas which did not have a conflict before and therefore it is free of 'exploration effort' induced reverse causality challenge. Table 4.1 reports the standard pooled OLS regressions. Contrary to expectation, the estimate of γ_1 is negative and significant indicating that resource discovery reduces the probability of conflict onset in a between-grid time-series setting. The size of the effect is small: a point estimate shows natural resource discovery reduces the probability of conflict by 0.01 percent within 10 years post discovery. This probability increases to about 0.03 percent when identifying the association using grid fixed effect estimates. The negative effect appears to be stable across resource type (see Panels B and C). It is also persistent over time as it survives 10 years after discovery.

[12] Note that a potential challenge with night lights data is that it could be reflecting changing population density. We therefore control for population density and our result remains robust. We also find no evidence of population surge following a resource discovery at the grid level. This result is independent of grid size, or higher levels of aggregation (region level).

Table 4.1: Resource Discovery and Conflict Onset: Between-Grid Effects

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.00011***	-0.00012***	-0.00012***	-0.00013***	-0.00013***	-0.00014***
	(0.000021)	(0.000021)	(0.000023)	(0.000024)	(0.000025)	(0.000026)
Past Discovery	-0.00011***	-0.00011***	-0.00011***	-0.00012***	-0.00012***	-0.00012***
	(0.000021)	(0.000021)	(0.000022)	(0.000023)	(0.000023)	(0.000024)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.00011***	-0.00012***	-0.00012***	-0.00013***	-0.00013***	-0.00014***
	(0.000021)	(0.000022)	(0.000023)	(0.000023)	(0.000024)	(0.000025)
Past Discovery	-0.00011***	-0.00011***	-0.00011***	-0.00011***	-0.00012***	-0.00012***
	(0.000020)	(0.000020)	(0.000020)	(0.000020)	(0.000022)	(0.000022)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.00011***	-0.00012***	-0.00012***	-0.00013***	-0.00013***	-0.00014***
	(0.000022)	(0.000023)	(0.000024)	(0.000024)	(0.000025)	(0.000026)
Past Discovery	-0.00011***	-0.00011***	-0.00011***	-0.00013***	-0.00012***	-0.00012***
	(0.000021)	(0.000022)	(0.000023)	(0.000024)	(0.000024)	(0.000025)
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605163	579411	553659	527907	502155	476403

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

In Table 4.2 we focus on within grid effects by controlling for high dimension fixed effects. The estimate of γ_1 is negative and insignificant. The individual effects of oilfield and mineral discoveries within a grid remain negative but insignificant (see Panels B and C). The size of the effect is increases (compared to the standard pooled OLS regressions): a point estimate shows natural resource discovery reduces the probability of conflict by 0.03 percent when identifying the association using grid fixed effect estimates. Figure C.6 in the Appendix displays a non-parametric local polynomial regression of resource discovery on conflict onset conditioned on the high dimension fixed effects. Even though not always significant, the figure demonstrate a decline in the likelihood of conflict onset post discovery. Oilfield and mineral discoveries follow a very similar trajectory.

Is the negative and insignificant effect of resource discovery on conflict onset noisy due to the imprecise nature of conflict data? The challenge of attenuation is partially mitigated by the introduction of high dimension fixed effects and in particular country specific characteristics. It is expected that the confounding covariates potentially influencing the estimate of γ_1 is primarily country specific. Nevertheless, in Table 4.3 we also use an instrumental variable (IV) strategy with global commodity price as an instrument. Global commodity price is an exogenous instrument used widely in the conflict literature (Brückner and Ciccone, 2010). The negative and insignificant result remains unchanged.

Table 4.2: Resource Discovery and Conflict Onset: Within-Grid Effects

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.00032*	-0.00028	-0.00031	-0.00034	-0.00037	-0.00039
	(0.00018)	(0.00018)	(0.0019)	(0.00021)	(0.00023)	(0.00025)
Past Discovery	-0.00028*	-0.00031	-0.00033	-0.00036	-0.00039	-0.00041
	(0.00015)	(0.00019)	(0.00021)	(0.00023)	(0.00025)	(0.00027)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.00063	-0.00066	-0.00069	-0.00074	0.00078	-0.00083
	(0.00065)	(0.00068)	(0.00071)	(0.00075)	(0.00079)	(0.00083)
Past Discovery	-0.00060	-0.00063	-0.00066	-0.00071	0.00076	-0.00082
	(0.00059)	(0.00062)	(0.00065)	(0.00069)	(0.00074)	(0.00079)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.00025	-0.00019	-0.00022	-0.00023	-0.00025	-0.00027
	(0.00017)	(0.00013)	(0.00014)	(0.00016)	(0.00018)	(0.00019)
Past Discovery	-0.00020	-0.00022	-0.00023	-0.00025	-0.00027	-0.00027
	(0.00014)	(0.00015)	(0.00016)	(0.00018)	(0.00020)	(0.00021)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605163	579411	553659	527907	502155	476403

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. The dependent variable is armed conflict onset from the PRIO-GRID conflict event dataset. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table 4.3: Resource Discovery and Conflict Onset: 2SLS Estimates

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.016	-0.021	-0.015	-0.019	-0.012	-0.013
	(0.039)	(0.041)	(0.044)	(0.046)	(0.046)	(0.050)
Past Discovery	0.00012	0.00015	0.00006	0.00012	0.00003	0.00005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First-Stage Regression of Discovering Natural Resource (Oilfield + Minerals)						
Grid Commodity Price Index	0.0003***					
	(0.00007)					
F test of excluded instruments	18.33					
(Prob > F)	(0.0001)					
Underidentification of LM statistic	7.04					
(P-val)	(0.008)					
Weak identification F statistic	129.23					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	343294	329282	315270	301258	287246	273234

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. The dependent variable is armed conflict onset from the PRIO-GRID conflict event dataset. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

In Tables 4.4 and 4.5 we use conflict onset from the UCDP GED and ACLED datasets respectively and find that the negative and insignificant result is not unique to PRIO-GRID. This is reassuring and we can be reasonably confident that our result of 'no conflict resource curse' in Africa is not noisy.

Table 4.4: Resource Discovery and Conflict Onset: UCDP-GED Conflict

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.007	0.001	-0.022***	-0.008	-0.009	0.010
	(0.009)	(0.012)	(0.007)	(0.013)	(0.011)	(0.014)
Past Discovery	-0.0005	-0.0002	0.0022	-0.0009	0.0006	-0.0011
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.0044)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.005	-0.028	-0.028	-0.029	-0.016	0.010
	(0.007)	(0.030)	(0.030)	(0.030)	(0.016)	(0.011)
Past Discovery	0.018	0.022	0.022	0.022	0.020	0.009
	(0.020)	(0.023)	(0.023)	(0.023)	(0.021)	(0.009)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.007	0.003	-0.022***	0.011	-0.008	0.002
	(0.010)	(0.013)	(0.007)	(0.014)	(0.013)	(0.012)
Past Discovery	-0.002	-0.002	-0.0005	-0.003	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235246	225236	215226	205216	195206	185196

Notes: The dependent variable is armed conflict onset based on the UCDP GED conflict event dataset. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table 4.5: Resource Discovery and Conflict Onset: ACLED Conflict

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0055	-0.0061	-0.0155*	-0.0197*	-0.0006	0.0194
	(0.0161)	(0.0149)	(0.0094)	(0.0117)	(0.0199)	(0.0227)
Past Discovery	-0.0019	-0.0008	0.0002	0.0002	-0.0015	-0.0032
	(0.0077)	(0.0077)	(0.0082)	(0.0079)	(0.0079)	(0.0067)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.1415**	-0.1085***	-0.0269	-0.0224	0.1433	-0.0015
	(0.0664)	(0.0389)	(0.0311)	(0.0257)	(0.1671)	(0.0205)
Past Discovery	-0.0217	-0.0028	-0.0113	-0.0113	-0.0299	-0.0137
	(0.0289)	(0.0175)	(0.0256)	(0.0259)	(0.0377)	(0.0267)
Panel C: Effect of Discovering Mineral Resources						
Discovery	0.0021	03.04e-06	-0.0148	-0.0193	-0.0130	0.0214
	(0.0148)	(0.0154)	(0.0098)	(0.0126)	(0.0161)	(0.0244)
Past Discovery	-0.0005	-0.0006	0.0011	0.0011	0.0004	-0.0024
	(0.0078)	(0.0081)	(0.0085)	(0.0081)	(0.0079)	(0.0067)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171088	163808	156528	149248	141968	134688

Notes: The dependent variable is armed conflict onset based on the ACLED conflict event dataset. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Factors triggering a conflict could be different from factors motivating the continuation of a conflict. Therefore, we also analyse the effect of discovery on conflict incidence and intensity using data from UCDP GED and ACLED. However, incidence and intensity are not as clean measure of conflict as onset. This is because onset flags the start of a conflict whereas incidence and intensity are aggregate measures of both start and persistence. This confounds causality issues as pre-existing conflict could influence the unobservable exploration effort prior to the actual resource discovery. Nevertheless, we estimate these models and find that the negative and insignificant result remains unaltered. The results of conflict incidence and intensity based on UCDP GED and ACLED data are reported in the appendix Tables C.9, C.10, C.11 and C.12).

The results presented so far suggest that natural resource discovery shocks do not (positively) affect the onset, incidence and intensity of intra-state armed conflict at the grid level. Some may argue that the negative sign of the coefficient estimates within a grid may not be surprising as resource discovery only fuels conflict systematically elsewhere. Resource discovery in one grid could trigger conflict elsewhere in the neighbouring grid, at the region or country level. To test whether this is indeed the case, we estimate the model using higher level grid-year, region-year and country-year as units of analysis. Although determining the optimal level of aggregation is not straightforward, our aggregation procedure is twofold: systematic grouping (region and country level) and random grouping (higher level grid demarcation). A related limitation with higher level aggregation is the phenomenon known as ecological fallacy (Maystadt et al., 2013). The association between resource discoveries and armed conflict may differ in magnitude and may even have a different sign across different levels of analysis.

Here we aggregate the conflict events and resource discoveries at higher grids-cell (1x1 degrees latitude and longitude, which approximately amounts to 111x111 square kilometres at the equator), region level and country level. For the higher level grid, we follow the same approach as the previous main units of interest by aggregating our geocoded conflict data and construct time-varying grid-specific measures of armed conflict in a grid a given year. For region and country level analysis, our main dependent variable is the number of grid-cells covered by conflict events in a given year. We have also try different alternative definitions of conflict at the region and country level. We use the PRIO-GRID, ACLED and UCDP GED datasets. For brevity, we report the results of higher level grid demarcation, region and country level in the Appendix.

We start by considering enlarging our grid units of observation to 1x1 degrees latitude and longitude. Tables C.13, C14 and C.15 in the Appendix report results of higher levels of aggregation, where there is no systematic evidence for an ecological inference fallacy. The effect of discovery on conflict onset remains statistically insignificant and negative in most cases. We control for year fixed effects, grid fixed effects, grid-specific time trends and country x year fixed effects. There is no difference between individual discoveries: oilfield and minerals.

Table C.16 in the Appendix report the region level results. We find resource discovery significantly reduces conflict onset after controlling for year fixed effects, region fixed effects, region-specific time trend and country x year fixed effects. Table C.17 estimates the relationship at the country level. This result is comparable to recent cross-country studies on this issue by Cotet and Tsui (2013) and Lei and Michaels (2014). Unlike these studies which solely focus on the effect of oilfield discovery, our dataset permits us to consider not only oil but also mineral discovery. We find that oil and mineral discovery has no discernible effect on conflict onset at the country level after controlling for year fixed effects, country fixed effects and country x year fixed effects. Estimating the models separately for oilfield and mineral discoveries do not change our results. The country level results confirm the findings of Cotet and Tsui (2013), i.e., natural resource discoveries do not increase the likelihood of conflict. It is worthwhile noting that we do not find any evidence of the ecological inference fallacy here.

4.4.2 Testing the Income Effect Mechanism

In the this section, we discuss the economic and political factors that plausibly explain the patterns shown between resource discovery and armed conflict at the local level in Africa. Theory predicts that natural resources could affect conflict through multiple facors. It is however difficult to establish these causal channels empirically. It is even more difficult for Africa due to the lack of data. Using the novel satellite data on night lights (Henderson et al., 2012), we are at least able to test the income effect mechanism. Resource discovery could impact on the local living standards and influence the opportunity cost of conflict. We use natural logarithm of night lights density as a measure of local living standards. This however restricts our sample to 1992 to 2012. In table 4.6, we find that discovery improves night lights density in a grid after controlling for past discoveries and the high dimension fixed effects. This result is consistent with the findings of (Mamo et al., 2017).[13]

Table 4.6: Resource Discovery and Local Economic Development

Dependent Variable: Natural Logarithm of Night Lights (Luminosity)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Discovery	0.114*	0.172*	0.104*	0.144**	0.191**	0.184**
	(0.063)	(0.088)	(0.054)	(0.065)	(0.079)	(0.083)
Past Discovery	0.078	0.107	0.096	0.088	0.070	0.071
	(0.082)	(0.092)	(0.084)	(0.080)	(0.080)	(0.083)
Population Density	0.172	0.172	0.172	0.172	0.172	0.172
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	215439	206271	197103	187935	178767	169599

Notes: This table reports the effect of discovering at least one natural resource on local economic development in a panel of grid-year observations. The dependent variable is the natural logarithm of luminosity density. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

In Table 4.7 we explore whether the resource discovery driven improvement in living standards has any impact on conflict onset.[14] In columns (1)-(6) we find that indeed higher local living standards (measured by night lights) reduce conflict onset after controlling for population density and high dimensional fixed effects. We test whether the effect of resource discovery works exclusively through improvements in local living standards. The coefficient on discovery is consistently negative and significant in few cases which suggests that there is a direct effect of discovery on conflict over and above the indirect effect via the income channel. The direct effect could be reflective of the changes in expecta-

[13]The effect of resource discoveries on night lights could be driven by the lights emanating from the extractive industries themselves. Therefore, we ignore all lights around an arbitrary 2-5 kilometre radius of an oilfield or mining industry.

[14]Note that we are using UCDP GED conflict events here as the sample period matches more with night lights data. Results are similar with PRIO-GRID and ACLED conflict dataset.

tions. The local population could expect higher future income after a discovery and this could reduce conflict. Our evidence is qualitatively consistent with Bazzi and Blattman (2014) and Berman and Couttenier (2015) who find support for the income shock using cross-country and subnational data respectively.

To what extent the negative and insignificant effect of resource discovery on conflict works via the political patronage and or the military expenditure mechanisms in Africa? It is worthwhile noting that military expenditure represents state capacity towards repression and counterinsurgency. Figure C.7 (a) in the Appendix plots the nonparametric association between resource discovery and the number of cabinet posts. There is a positive relationship indicating increase in patronage and hence a decline in conflict via the patronage mechanism.[15] However, our data do not support the state capacity mechanism as in Figure C.7 (b) in the Appendix we observe military expenditure as a share of GDP to moderately decline with discoveries. This is contrary to the cross-country results of Cotet and Tsui (2013) where they report oil wealth increases defence burden as the state faces more violent challenges.

Table 4.7: Discoveries, Economic Development and Conflict

Dependent Variable: Intrastate Civil Conflict Onset (UCDP-GED Conflict Dataset)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Local Income	-0.0032*	-0.003*	-0.0026*	-0.001	-0.004*	-0.003*
	(0.0017)	(0.0016)	(0.0014)	(0.002)	(0.002)	(0.0017)
Discovery	-0.011	-0.004	-0.020***	0.004	-0.013*	-0.003
	(0.011)	(0.013)	(0.007)	(0.015)	(0.007)	(0.014)
Past Discovery	0.004	-0.005	-0.007	-0.006	-0.003	-0.004
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
Population Density	0.001	0.018	0.048***	0.073***	0.074***	0.061***
	(0.018)	(0.018)	(0.015)	(0.023)	(0.021)	(0.020)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	194921	186627	178333	170039	161745	153451

Notes: This table reports the effect of resource discovery and local economic development on civil conflict in a panel of grid-year observations. The local economic development is natural logarithm of luminosity adjusted for grid surface area. The dependent variable is the onset of civil conflict based on the UCDP GED dataset simple because the sample period matches more with the night lights data. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

[15] This is consistent with the theoretical predictions of Robinson et al. (2006) and empirical evidence of Roessler (2011). Our fining in Chapter 3 also supports such argument.

4.4.3 Further Results

4.4.3.1 Heterogeneous Effects of Discovery Size and Distance

Giant discoveries are significantly larger than major discoveries. Therefore they should have a bigger effect on conflict due to their superior economic value. Furthermore, they also enter production more quickly.[16] Note that 64 percent of all mineral discoveries in our dataset are major while all the oil discoveries are giant. In Table 4.8 we find that our result is not affected by the size of discovery.

Table 4.8: Size of Resource Discovery and Armed Conflict Onset

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Giant Discovery of Natural Resource (Oilfield + Minerals)						
Discovery	-0.00025	-0.00026	-0.00029	-0.00030	-0.00033	-0.00035
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.00025	-0.00027	-0.00029	-0.00031	-0.00034	-0.00036
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Effect of Giant Discovery of Mineral Resources						
Discovery	-0.00002	-0.00002	-0.00002	-0.00002	-0.00001	-0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.00003*	-0.00002*	-0.00002	-0.00002	-0.00002	-0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Effect of Major Mineral Discovery						
Discovery	-0.00038	-0.00032	-0.00036	-0.00039	-0.00042	-0.00045
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.00034	-0.00037	-0.00040	-0.00044	-0.00048	-0.00049
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605163	579411	553659	527907	502155	476403

Notes: The table reports the effect of giant and major discoveries in a panel of grid-year observations. Note that all oil discoveries in the dataset are giant whereas mineral discoveries are giant and major. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Another potential heterogeneity could arise from the proximity of a conflict to a discovered oilfield or mine, and proximity to the border. One would expect armed conflicts to occur in far away locations rather than in close proximity to a discovery. We calculate the time-varying distance to the nearest oilfield or mine discoveries from the centroid of each grid in kilometres, and regress it on conflict onset. Distance does not seem to influence the negative and insignificant association between discovery and conflict onset irrespective of the dataset

[16] Figure 2.5 in chapter two presents Kaplan Meier probability estimates for mine deposits entering production which attests to this point.

(PRIO-GRID, UCDP GED, or ACLED) used to define onset.

Similarly, we calculate the distance to national borders and divide the sample of grids into 4 groups according to their distance to the border: less than 25km, between 25-50km, between 50-100km, and greater than 100km. We estimate equation 4.1 for each of these samples and three different datasets and the negative and insignificant result survives suggesting that proximity to the border (or conflict propensity) is not a factor here. These results are reported in Tables C.18, C.19, C.20, C.21, C.22 and C.23 in the Appendix.

4.4.3.2 The Effects of the Cold War and Institutions

The Cold War had a significant impact on the African political landscape. The Angolan civil war starting in 1975 had major outside involvement in the form of the Soviet Union and Cuba backing the People's Movement for the Liberation of Angola (MPLA) while the United States and the CIA backing the National Union for the Total Independence of Angola (UNITA). The deposition and subsequent execution of Congolese independence ruler and elected Prime Minister Patrice Lumumba in 1961 also shares a similar Cold War history which led to conflict. One could argue that the nature of the association between resource discovery and conflict before and after the end of the cold war in 1989 with the fall of the Berlin Wall could be different.

In Tables C.24 and C.25 in the Appendix, we test whether this is indeed the case by dividing the sample between pre- and post- Cold War. For the 'before end of cold war' sample, the individual effects of oilfield and mineral discoveries display different trends. The coefficient estimates remain negative and insignificant for the minerals but for oil it is positive and significant. However, the effect of discovery on conflict appears to be largely insignificant after end of the cold war.

To what extent institutional quality influence the association between natural resources and conflict (Arezki and Gylfason, 2013)? Representative political institutions could increase legitimacy of the incumbent government and diffuse tensions. Therefore, one would expect democratic institutions to reduce negative consequences of natural resources on conflict. We test this hypothesis in Table

C.26 in the Appendix using Polity2 as a measure of institutional quality. We do not find any effect of institutions on the association between mineral discovery and onset (Panel C). However, we find that oilfield discoveries lead to less onset and that the negative effect is magnified in countries with good institutions.

4.5 Robustness and Sensitivity Analysis

In this section, we present a battery of additional robustness checks to support our findings described above are not sensitive to the use of alternative measurement of variables and samples. First, in order to address the potential temporal correlation of oilfield and mineral discoveries, we control for past discoveries in most of our specifications. To further check the robustness of the results, we have excluded grid-year observations within a decade of past oilfield or mineral discoveries and the effect of resource discovery shocks remain negative. The results for excluding grid-year observations of past discoveries are reported in Tables C.27, C.28 and C.29 in the Appendix.

Second, we restrict our sample to observations where at least one oilfield or mineral discovery was made during the sample period. This would potentially tackle the concern that observations with oilfield and mineral discoveries are different from others in ways that we cannot measure and control for directly (Lei and Michaels, 2014). This were not severe threats to our identification strategy as we mainly exploit high dimensional fixed effects in all the specifications. The results are reported in C.30, C.31 and C.32 in the Appendix.

Third, similarly we restrict our sample to grids in which at least one conflict event occurs over the sample period, where Berman and Couttenier (2015) refer to such grids as high-conflict-risk grids. As we explain in the data section, we observe that the number of conflict events by grid is small, and the vast majority of grids experience no conflict over the entire period. The significance and quantitative effects of resource discovery shocks are much stronger in this case. The results are reported in Tables C.33 and C.34, in the Appendix.

Fourth, we also apply buffer zone analysis because some oilfield or mineral discoveries may cross grid boundaries. We arbitrarily create a bigger zone (with varying Euclidean distance) around the oilfield and mineral discovery geo-coordinates. This will address the potential concern that oilfield and mineral discoveries could take up a large geographies and hence influence the surrounding geographies of conflict. The results are reported in Tables C.35, C.36 and C.37 in the Appendix.

4.6 Conclusions

Africa is often viewed as a prime location for natural resource driven conflict. The volume of research on this topic is sizeable. Yet establishing causality remains a challenge. In this paper we are able to set up a natural experiment to study the effect of natural resources on conflict at the grid level covering the period 1950 to 2008. Note that grids here correspond to a spatial resolution of 0.5 x 0.5 degrees latitude and longitudes (approximately 55 x 55 square kilometres). Using giant and major resource discovery dates as an exogenous news shock we find no evidence that natural resources trigger conflict in Africa. In particular, discovery significantly reduce the likelihood of conflict onset within 10 years post resource discovery in a pooled cross-section model. The effect becomes insignificant once we control for high dimension fixed effects. This broad pattern in the data holds with both conflict incidence and intensity as dependent variables.

We also explored the economic factors which may explain the patterns shown in the data. Resource discovery appears to influence conflict indirectly via improved local living standards and directly via improved expectations of high future income. We observe that natural resource discovery improves living standards, as proxied satellite data on night lights. The improved living standards in turn is associated with a decline in the likelihood of armed conflict onset within the grids experienced discovery shocks. This is purely economic mechanism, i.e., individuals are not engaging in rebel movement because of resource discoveries affecting their income or overall living standards. Our finding in Chapter 3 also support for another conflict reducing mechanism through the distribution of political patronage by the state. In particular resource discovery appears to increase the number of cabinet ministerial positions.

A common argument is that the association between natural resources and conflict is national rather than local. Therefore, grid level analysis is not the appropriate level of aggregation. Hence, we also test the relationship at higher grid resolution, and regional and national levels. Our main result remains unaffected when we estimate the model at higher levels of aggregation. There is little or no heterogeneity in the association between resource discovery and conflict across resource type, size of discovery, distance to discovery, distance to the national border, pre and post conclusion of cold war, and institutional quality.

Our finding has some important welfare and political implications for resource rich African countries. In spite of her colonial and post-colonial history as a supplier of raw materials, a vast majority of African natural wealth remains untapped (Collier, 2010b). These resources are expected to be exploited over the coming two to three decades amid increasing global demand for raw materials (Humphreys, 2009). The expected steady depletion of natural resources and the favourable commodity prices presents Africa with an opportunity to harness this wealth for improving state capacity (inclusive political power allocations) and living standards for the local communities. Our research suggests that both of these factors could significantly contribute towards the reduction of internal armed conflict in Africa.

CHAPTER 5

Conclusion

In this thesis, we investigated the political economy of natural resources in the context of resource rich developing economies, with a special interest in Africa. The thesis consists of three stand-alone studies and they have distinctive characteristics, and provide different findings about the economic and political effects of natural resources at the subnational level. We use different datasets and exploit subnational variation to uncover the effects of resource abundance.

Our finding in the first study is consistent with most of the findings in the newly emerging literature that has shifted the focus towards exploiting within-country variation. We find that both mineral production and discovery expands economic activity in a panel of 3,635 districts from 42 Sub-Saharan African countries observed over the period 1992 to 2012. The study finds positive effects of mining at the intensive margin, however large effects are associated with mining at the extensive margin. This positive general economic opportunity could be aligned with the different hypothesis linking natural resources to development: backward-linkage (Aragón and Rud, 2013), labour market opportunity (Kotsadam and Tolonen, 2016), public good provision and infrastructure (Caselli and Michaels, 2013; Brollo et al., 2013), and sophisticated (non-farm) forms of economic activity (Fafchamps et al., 2016).

In the second study, we find that resource discoveries and increase in commodity prices are associated with an increase in ethnic ministerial appointments. We show that natural resources raise the value of being in power, and provide rulers with more finance which they can use to expand state cabinet sizes and distribute across politically relevant ethnicities. We do not find evidence of ethnic group exclusion from central government in the shadow of resource discoveries and rising commodity prices. Moreover, we find supporting evidence that ministerial appointment come with real power to influence economic rent distributions. Ethnicities that share the same ethnicity with head of cabinet positions receive larger economic rent, as reflected in the luminosity data. The story is different for unrepresented ethnicities, as they receive less opportunity.

There were little known about the extent to which the natural resources affect the politics of multi-ethnic political patronage system. Our evidence is consistent with the cross-country evidence that African rulers extend their tenure in office and stabilise their regime by expanding their patronage coalition through cabinet appointments (Arriola, 2009). Our finding confirms that rulers do indeed use state resources, which are largely dependent on natural resources, to co-opt different elites (ethnically determined) to maintain political stability.

Our finding in the second study may have different economic and political implications. The first implication of our finding is about the consequence of political power arrangement based on natural resources. It can potentially deepen the challenges of creating and consolidating democracy in Africa through its influence on autocratic nature of political systems or regimes (Jensen and Wantchekon, 2004; Caselli and Tesei, 2016). This can happen by creating perverse political incentives and leading to highly dysfunctional state behaviour (Robinson et al., 2006). Studies document that there is clear association between natural resources and political corruption (Bhattacharyya and Hodler, 2010; Arezki and Gylfason, 2013; Brollo et al., 2013; Ross, 2015; Knutsen et al., 2016). Another implication of our finding is about the link between ethnic favouritism and development. Political power arrangement based on natural resources may breed unfavourable ethnic favouritism, which might not be favourable to sustainable development. It may undermine development by generating mistrust, corruption, and political instability.

In the final study, we find no statistical evidence that resource discoveries trigger intra-state (localised) armed conflict in Africa. Resource discovery appears to influence conflict indirectly via improved local living standards and directly via improved expectations of high future income. We observe statistically significant positive effect of the discovery on living standards, as reflected in luminosity intensity. Consistent with the finding in the first study, the improved living standards in turn is associated with a decline in the likelihood of armed conflict onset within the grids experienced discovery shocks. This is purely economic mechanism whereby individuals are not engaging in rebel movement because of resource discoveries affecting their income. Similarly, as a typical political mechanism, we find support for another conflict reducing mechanism through the distribution of political patronage by the state. In particular resource discovery appears to increase the number of cabinet ministerial positions. This might dissuade a militant subset of the society from attempting armed rebellion against the state.

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APPENDIX A

Paper One Appendix

List of Countries in the Sample

Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Democratic Republic of Congo, Cote d'Ivoire, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Namibia, Niger, Nigeria, Republic of Congo, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe.

Table A.1: Summary Statistics

Variable	Obs	MeaObservations	Std. Dev.	MiObservations	Max
Main Variables					
Ln(0.01+Lights density per sq. km)	76335	-2.36	2.38	-4.61	4.51
Ln(Mineral production)	1802	16.86	3.47	-0.23	27.63
Ln(Min. prod. 1992 commodity prices)	1802	16.96	3.06	1.66	27.57
Mineral production (1=yes)	76335	0.04	0.20	0	1
Mineral discovery	76335	0.00	0.03	0	1
Mineral discovery (permanent switch)	76335	0.01	0.10	0	1
Controls: Population and Geography Variables					
Ln(Population density per sq. km)	76335	3.98	1.61	0.02	10.04
Ln(Altitude in m)	76335	5.88	1.38	0.62	7.91
Ln(Ruggedness)	76335	4.05	1.14	0	6.93
Share of district with fertile soil	76335	18.60	29.45	0	100
Ln(Distance to the coast in km)	76335	5.55	1.39	-4.23	7.45
Ln(Land surface area in sq. km)	76335	7.41	1.72	-0.73	12.79
Controls: Climate Variables					
Ln(Annual average rainfall in mm)	76335	5.12	0.76	0.13	6.38
Share of district with tropical climate	76335	60.19	47.12	0	100
Share of district with temperate climate	76335	14.32	32.64	0	100
Share of district with dry/arid climate	76335	25.28	42.14	0	100
Controls: Urbanization and Political Economy Variables					
Capital city (1=yes)	76335	0.01	0.11	0	1
Ln (Distance to the capital city in km)	76335	5.47	0.97	0.66	7.54
Ethnic FractionalizatioObservations	76335	0.21	0.24	0	0.93
Controls: Infrastructure Variables					
Ln(Paved road density per sq. km (2000))	76335	0.02	0.04	0	0.52
Ln(Railway density per sq. km (2000))	76335	1.01	1.72	0	6.79
Ln(Electric-grid density per sq. km (2000)	76335	0.07	0.17	0	2.25

Notes: This table reports descriptive statistics. All variables are measured at the district level. Discovery is a dummy variable which takes the value 1 for a district year if there is a giant or major discovery for that year and 0 otherwise. The variable discovery (permanent switch) = 1 for the discovery year and every year thereafter. Summary statistics for mineral production is limited to districts with mineral production, hence the smaller number of observations. Log transformation for variable x is conducted using the formula $ln(1+x)$ if x could potentially be equal to 0.

Table A.2: Re-estimation of Table 2.1: Excluding Sparsely Populated Districts

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.032*		-0.011	
	(0.016)		(0.039)	
Ln(Mineral Production in 1992 commodity prices)		0.039*	0.050	
		(0.020)	(0.049)	
Mineral production (1=yes)				0.567***
				(0.131)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,579	1,579	1,579	70,615

Notes: This table is a re-estimation of Table 2.3 in the main text. It shows associations between mining activities and night lights in a panel of district-year observations for the period 1992-2012. In this table, district-year observations are dropped if the population density is less than 4 (i.e. sparsely populated districts are excluded). Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. column 4 uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.3: Re-estimation of Table 2.1: Observation With Zero Lights Intensity

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.021*		-0.065	
	(0.011)		(0.045)	
Ln(Mineral production in 1992 commodity prices)		0.035**	0.102*	
		(0.016)	(0.056)	
Mineral production (1=yes)				0.343***
				(0.087)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,772	1,772	1,772	51,609

Notes: This table is a re-estimation of Table 2.3 in the main text. It shows associations between mining activities and night lights in a panel of district-year observations for the period 1992-2012. In this table, district-year observations are dropped if the sum of light intensity values for the district is zero. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. column 4 uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.4: Re-estimation of Table 2.1: Nights Lights and Population Density

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.024*		-0.061	
	(0.014)		(0.047)	
Ln(Mineral Production in 1992 commodity prices)		0.038**	0.102*	
		(0.018)	(0.057)	
Mineral production (1=yes)				0.554***
				(0.117)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,802	1,802	1,802	76,335

Notes: This table is a re-estimation of Table 2.3 in the main text. It shows associations between mining activities and night lights in a panel of district-year observations for the period 1992-2012. In this table, the dependent variable is light density minus log population density (i.e. log luminosity per capita) based on Cogneau and Dupraz (2014). column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. column 4 uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.5: Re-estimation of Table 2.1: Night Lights and Number of Districts

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.019		-0.089	
	(0.017)		(0.070)	
Ln(Mineral Production in		0.036*	0.128*	
1992 commodity prices)		(0.019)	(0.077)	
Mineral production (1=yes)				0.898***
				(0.204)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,802	1,802	1,802	76,335

Notes: This table is a re-estimation of Table 2.3 in the main text. It shows associations between mining activities and night lights in a panel of district-year observations for the period 1992-2012. In this table, the dependent variable (i.e. sum of nighttime lights density) is weighted by the inverse total number of the districts within a country. column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. column 4 uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.6: Re-estimation of Table 2.1: Grid Level Analysis

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.106***		0.086	
	(0.034)		(0.086)	
Ln(Mineral Production in		0.116***	0.025	
1992 commodity prices)		(0.038)	(0.094)	
Mineral production (1=yes)				0.701***
				(0.096)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	1,200	1,200	1,200	171,633

Notes: In the main analysis we used district level administrative boundaries as units of interest. Administrative boundaries are endogenous by construction, as it is likely to be determined by local geographic and demographic characteristics.This table is a re-estimation of Table 2 in the main text using grid level boundaries corresponding to a spatial resolution of 0.5 x 0.5 degrees latitude and longitude. It shows associations between mining activities and night lights in a panel of district-year observations for the period 1992-2012. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.7: Re-estimation of Table 2.1: Excluding Lights from Mining Industries

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.022		-0.075	
	(0.014)		(0.048)	
Ln(Mineral Production in		0.037**	0.115*	
1992 commodity prices)		(0.018)	(0.058)	
Mineral production (1=yes)				0.466***
				(0.106)
Pop Density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,802	1,802	1,802	76,335

Notes: This table is a re-estimation of Table 2.3 in the main text. It shows associations between mining activities and night lights in a panel of district-year observations for the period 1992-2012. In this table, the dependent variable (i.e. sum of nighttime lights density) excludes lights emanating from the mining industries (i.e deleting pixel values of the light data around 2km radius of mining industries). column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. column 4 uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.8: Re-estimation of Table 2.1: Missing Values in Production Quantities

	Intensive margin		
	(1)	(2)	(3)
Ln(Mineral production value in 1992 USD)	0.040**		-0.083
	(0.018)		(0.065)
Ln(Mineral prod. value in 1992 commodity prices)		0.079**	0.163*
		(0.032)	(0.088)
Pop Density & Rainfall	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
Observations	776	776	776

Notes: In the main analysis we replaced missing values in production quantities by linear interpolation. This may affect estimates of the intensive margin. This table is a re-estimation of Table 2.3 in the main text. It shows associations between mining activities and night lights in a panel of district-year observations for the period 1992-2012. In this table, district-year observations are dropped if production quantity is missing for at least one commodity for one mine in that district. This results in an unbalanced panel and fewer observations. Coefficients in this table are larger and more significant, which can be attributed to selection and measurement error. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). column (1) expresses the mineral production value in 1992 constant USD. column 2 expresses the mineral production value in 1992 constant commodity prices. column 3 includes both those indicators. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.9: Re-estimation of Table 2.3: Excluding Sparsely Populated Districts

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.019	-0.029	-0.040	-0.029
	(0.115)	(0.068)	(0.098)	(0.081)
$j=1$	0.075	0.030	0.088	-0.011
	(0.127)	(0.082)	(0.111)	(0.091)
$j=2$	0.061	0.000	0.063	-0.052
	(0.118)	(0.088)	(0.107)	(0.098)
$j=3$	0.065	0.019	-0.032	0.030
	(0.142)	(0.096)	(0.131)	(0.094)
$j=4$	0.202	0.078	0.070	0.059
	(0.151)	(0.114)	(0.167)	(0.112)
$j=5$	0.244	0.140	0.128	0.110
	(0.161)	(0.119)	(0.174)	(0.115)
$j=6$	0.298*	0.214*	0.296	0.123
	(0.166)	(0.128)	(0.221)	(0.118)
$j=7$	0.318*	0.245*	0.324	0.180
	(0.179)	(0.139)	(0.235)	(0.123)
$j=8$	0.415**	0.433***	0.465*	0.319*
	(0.175)	(0.158)	(0.236)	(0.162)
$j=9$	0.480**	0.447***	0.456*	0.343**
	(0.197)	(0.168)	(0.248)	(0.172)
$j=10$	0.468**	0.460***	0.514**	0.359**
	(0.198)	(0.168)	(0.253)	(0.167)
Pop density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	68,140	68,830	67,914	68,592

Notes: This table is a re-estimation of Table 2.4 in the main text. It reports the effect of mineral resource discoveries on night lights in a panel of district-year observations. In this table, district-year observations are dropped if the population density is less than 4 (i.e. sparsely populated districts are excluded). Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.10: Re-estimation of Table 2.3: Observation With Zero Lights Intensity

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.015	-0.003	-0.007	-0.029
	(0.075)	(0.062)	(0.100)	(0.081)
$j=1$	0.014	0.011	0.104	-0.012
	(0.101)	(0.075)	(0.112)	(0.093)
$j=2$	-0.090	-0.054	0.085	-0.062
	(0.109)	(0.083)	(0.107)	(0.101)
$j=3$	-0.086	-0.059	0.006	0.017
	(0.126)	(0.086)	(0.133)	(0.097)
$j=4$	0.047	0.058	0.111	0.044
	(0.108)	(0.088)	(0.170)	(0.114)
$j=5$	0.073	0.024	0.159	0.090
	(0.124)	(0.093)	(0.175)	(0.118)
$j=6$	0.049	0.073	0.342	0.108
	(0.120)	(0.090)	(0.222)	(0.121)
$j=7$	0.075	0.078	0.372	0.164
	(0.123)	(0.100)	(0.238)	(0.127)
$j=8$	0.104	0.150	0.502**	0.310*
	(0.118)	(0.102)	(0.237)	(0.162)
$j=9$	0.213	0.275**	0.496**	0.340*
	(0.131)	(0.115)	(0.251)	(0.175)
$j=10$	0.170	0.244*	0.551**	0.342**
	(0.138)	(0.126)	(0.260)	(0.171)
Pop density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	49,063	49,620	48,919	49,597

Notes: This table is a re-estimation of Table 2.4 in the main text. It reports the effect of mineral resource discoveries on night lights in a panel of district-year observations. In this table, district-year observations are dropped if the sum of light intensity values for the district is zero. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.11: Re-estimation of Table 2.3: Nights Lights and Population Density

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.024	-0.028	-0.032	-0.024
	(0.106)	(0.063)	(0.098)	(0.081)
$j=1$	0.060	0.024	0.100	-0.005
	(0.118)	(0.075)	(0.111)	(0.091)
$j=2$	0.046	-0.008	0.075	-0.043
	(0.111)	(0.081)	(0.106)	(0.098)
$j=3$	0.048	0.006	-0.015	0.039
	(0.132)	(0.087)	(0.131)	(0.094)
$j=4$	0.174	0.068	0.085	0.070
	(0.141)	(0.104)	(0.167)	(0.111)
$j=5$	0.212	0.114	0.146	0.122
	(0.151)	(0.109)	(0.174)	(0.114)
$j=6$	0.257	0.190	0.314	0.134
	(0.157)	(0.118)	(0.220)	(0.118)
$j=7$	0.277	0.218*	0.342	0.190
	(0.169)	(0.126)	(0.235)	(0.123)
$j=8$	0.363**	0.391***	0.484**	0.331**
	(0.167)	(0.147)	(0.235)	(0.161)
$j=9$	0.427**	0.402***	0.477*	0.355**
	(0.187)	(0.155)	(0.247)	(0.171)
$j=10$	0.430**	0.431***	0.538**	0.373**
	(0.187)	(0.156)	(0.253)	(0.166)
Pop density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	73,428	74,178	73,150	73,828

Notes: This table is a re-estimation of Table 2.4 in the main text. It reports the effect of mineral resource discoveries on night lights in a panel of district-year observations. In this table, the dependent variable is light density minus log population density (i.e. log luminosity per capita) based on Cogneau and Dupraz (2014). In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.12: Re-estimation of Table 2.3: Night Lights and Number of Districts

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.039	-0.051	0.126	-0.095
	(0.235)	(0.135)	(0.306)	(0.167)
$j=1$	0.131	0.043	0.487	-0.107
	(0.279)	(0.191)	(0.309)	(0.218)
$j=2$	0.240	-0.023	0.500	-0.205
	(0.289)	(0.195)	(0.330)	(0.214)
$j=3$	0.042	0.083	0.179	0.155
	(0.315)	(0.192)	(0.328)	(0.199)
$j=4$	0.249	0.008	0.273	-0.006
	(0.318)	(0.226)	(0.404)	(0.223)
$j=5$	0.296	0.173	0.554	0.108
	(0.339)	(0.220)	(0.392)	(0.223)
$j=6$	0.464	0.348	0.692	0.218
	(0.298)	(0.214)	(0.421)	(0.190)
$j=7$	0.445	0.420*	0.747*	0.321
	(0.322)	(0.241)	(0.428)	(0.231)
$j=8$	0.709**	0.677**	0.939**	0.540*
	(0.331)	(0.264)	(0.442)	(0.277)
$j=9$	0.672*	0.529	0.801*	0.417
	(0.380)	(0.326)	(0.485)	(0.366)
$j=10$	0.706*	0.658**	0.950*	0.520
	(0.384)	(0.316)	(0.484)	(0.344)
Pop density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	73,428	74,178	73,150	73,828

Notes: This table is a re-estimation of Table 2.4 in the main text. It reports the effect of mineral resource discoveries on night lights in a panel of district-year observations. In this table, the dependent variable (i.e. sum of nighttime lights density) is weighted by the inverse total number of the districts within a country. In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.13: Re-estimation of Table 2.3: Grid Level Analysis

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	0.160*	0.078	0.088	0.071
	(0.090)	(0.055)	(0.111)	(0.061)
$j=1$	0.234***	0.153**	0.078	0.152**
	(0.088)	(0.065)	(0.097)	(0.074)
$j=2$	0.289***	0.144*	-0.050	0.162**
	(0.108)	(0.075)	(0.129)	(0.082)
$j=3$	0.271**	0.187**	-0.113	0.240***
	(0.109)	(0.079)	(0.123)	(0.092)
$j=4$	0.335***	0.181**	-0.124	0.246**
	(0.126)	(0.091)	(0.131)	(0.101)
$j=5$	0.409***	0.308***	0.157	0.385***
	(0.144)	(0.100)	(0.106)	(0.118)
$j=6$	0.457***	0.323***	0.259*	0.389***
	(0.138)	(0.099)	(0.134)	(0.121)
$j=7$	0.435***	0.385***	0.415***	0.416***
	(0.148)	(0.114)	(0.151)	(0.145)
$j=8$	0.667***	0.654***	0.695***	0.656***
	(0.147)	(0.119)	(0.180)	(0.152)
$j=9$	0.647***	0.681***	0.777***	0.657***
	(0.173)	(0.137)	(0.219)	(0.176)
$j=10$	0.695***	0.742***	0.907***	0.681***
	(0.158)	(0.130)	(0.221)	(0.163)
Pop density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes
Observations	168,244	169,203	167,949	168,861

Notes: In the main analysis we used district level administrative boundaries as units of interest. Administrative boundaries are endogenous by construction, as it is likely to be determined by local geographic and demographic characteristics. This table is a re-estimation of Table 2.4 in the main text using grid level boundaries corresponding to a spatial resolution of 0.5 x 0.5 degrees latitude and longitude. It reports the effect of mineral resource discoveries on night lights in a panel of district-year observations. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j>10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.14: Re-estimation of Table 2.3: Excluding Lights from Mining Industries

Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	0.031	-0.003	0.032	-0.008
	(0.109)	(0.067)	(0.111)	(0.084)
$j=1$	0.102	0.041	0.133	0.013
	(0.121)	(0.078)	(0.119)	(0.095)
$j=2$	0.081	0.007	0.114	-0.030
	(0.117)	(0.082)	(0.105)	(0.102)
$j=3$	0.111	0.022	0.088	0.022
	(0.131)	(0.091)	(0.132)	(0.099)
$j=4$	0.206	0.079	0.146	0.042
	(0.138)	(0.105)	(0.170)	(0.106)
$j=5$	0.249	0.108	0.197	0.102
	(0.160)	(0.112)	(0.193)	(0.116)
$j=6$	0.318*	0.222*	0.384	0.145
	(0.164)	(0.121)	(0.240)	(0.118)
$j=7$	0.288*	0.223*	0.418	0.136
	(0.173)	(0.132)	(0.262)	(0.117)
$j=8$	0.384**	0.386***	0.519**	0.323**
	(0.170)	(0.143)	(0.253)	(0.153)
$j=9$	0.434**	0.396***	0.529*	0.337**
	(0.188)	(0.153)	(0.269)	(0.159)
$j=10$	0.418**	0.409***	0.556**	0.337**
	(0.191)	(0.155)	(0.272)	(0.159)
Pop density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	73,428	74,178	73,150	73,828

Notes: This table is a re-estimation of Table 2.4 in the main text. It reports the effect of mineral resource discoveries on night lights in a panel of district-year observations. In this table, the dependent variable (i.e. sum of nighttime lights density) excludes lights emanating from the mining industries (i.e deleting pixel values of the light data around 2km radius of mining industries). In column (1), the variable of interest $Discovery_{d,t-j}$ is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

APPENDIX B

Paper Two Appendix

List of Countries in the FRT15 Sample

Benin, Cameroon, Cote d'Ivoire, DRC, Gabon, Ghana, Guinea, Liberia, Nigeria, Republic of Congo, Sierra Leone, Tanzania, Togo, Kenya, and Uganda.

List of Countries in the EPR Sample

Algeria, Angola, Benin, Botswana, Burundi, Cameroon, Central African Republic, Chad, DRC, Republic of Congo, Cote d'Ivoire, Egypt, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Togo, Uganda, Zambia, Zimbabwe.

Table B.1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	First Year of Data	Last Year of Data
			FRT15 Dataset				
Share of Cabinet Positions	6732	0.059	0.079	0	0.567	1960	2004
Share of Top Cabinet Positions	6732	0.058	0.110	0	0.800	1960	2004
Share of Low Cabinet Positions	6732	0.058	0.082	0	0.619	1960	2004
Leader's Ethnic Indicator	6732	0.063	0.244	0	1	1960	2004
			EPR Dataset				
Power Representation	8787	0.533	0.499	0	1	1950	2010
Power Monopolisation	8891	0.015	0.123	0	1	1950	2010
Power Dominance	8891	0.057	0.231	0	1	1950	2010
Exclusion from the Power	8787	0.397	0.489	0	1	1950	2010
Regional Autonomy	8891	0.026	0.160	0	1	1950	2010
Separatist Movement	8891	0.001	0.034	0	1	1950	2010
			Natural Resource Discovery and Ethnic Price Indices				
Resource Discovery, *t*	6827	0.003	0.058	0	1	1960	2004
Resource Discovery, *t-2*	6826	0.003	0.058	0	1	1960	2004
Resource Discovery, *t-4*	6826	0.003	0.058	0	1	1960	2004
Resource Discovery, *t-6*	6822	0.003	0.053	0	1	1960	2004
Resource Discovery, *t-8*	6822	0.003	0.053	0	1	1961	2004
Resource Discovery, *t-10*	6819	0.002	0.048	0	1	1962	2004
Share of Discoveries	7245	0.046	0.184	0	1	1960	2004
Cumulative Discoveries	7245	0.145	0.710	0	11	1960	2004
Ln(Average Price, *t*)	7020	5.601	3.243	2.703	16.782	1960	2004
Ln(Average Price, *3 Years*)	6552	5.616	3.253	2.714	16.680	1960	2004
Ln(Average Price, *5 Years*)	6240	5.635	3.255	2.730	16.653	1960	2004
Ln(Average Price, *10 Years*)	5460	5.686	3.260	2.761	16.565	1960	2004
			Ethnic Armed Violence and Collective Action				
Collective Action	8891	0.134	0.341	0	1	1950	2010
New Armed Conflict	8891	0.007	0.085	0	1	1950	2010
High Intensity Conflict	8891	0.004	0.060	0	1	1950	2010

Notes: This table reports summary statistics. All the variables are measured at ethnic level.

Table B.2: List of Countries

Country	Share	Country	Share	Country	Share
		FRT15 Dataset			
Benin	0.62	Gabon	3.11	Nigeria	8.70
Cameroon	8.70	Ghana	8.07	Sierra Leone	4.35
Congo, Dem Rep of	13.66	Guinea	1.86	Tanzania	18.01
Congo, Republic of	1.24	Kenya	7.45	Togo	4.97
Cote d'Ivoire	8.07	Liberia	3.73	Uganda	7.45
		Ethnic Power Relations (EPR) Dataset			
Algeria	1.10	Ethiopia	6.41	Mozambique	1.21
Angola	2.02	Gabon	2.46	Namibia	2.13
Benin	2.29	Gambia	2.07	Niger	3.44
Botswana	0.51	Ghana	3.64	Nigeria	3.44
Burundi	1.10	Guinea	1.79	Rwanda	1.10
Cameroon	3.44	Guinea Bissau	1.66	Senegal	2.87
Central African Republic	1.66	Kenya	4.32	Sierra Leone	1.65
Chad	2.88	Liberia	2.51	South Africa	2.06
Congo, Dem Republic of	7.46	Madagascar	1.15	Sudan	8.04
Congo, Republic of	3.77	Malawi	3.70	Togo	1.15
Cote d'Ivoire	2.87	Mali	1.15	Uganda	4.09
Egypt	1.37	Mauritania	1.72	Zambia	3.70
Eritrea	0.40	Morocco	0.62	Zimbabwe	1.02

Notes: Share: country's share of ethnicities over the sample period.

Table B.3: Ethnic Coalition in Africa

Country	Mean Coalition Size	Min Coalition Size	Max Coalition Size	Ethnic Groups	Mean Proportion
Benin	7.72	4	10	15	51.47
Cameroon	11.93	8	16	21	56.81
Congo, Dem Rep of	15.36	8	21	30	51.19
Congo, Republic of	7.65	5	9	10	76.51
Cote d'Ivoire	10.36	6	13	17	60.96
Gabon	7.02	5	9	10	70.23
Ghana	10.11	6	14	22	45.97
Guinea	6.02	5	8	9	66.92
Kenya	11.23	9	13	16	70.16
Liberia	7.75	2	13	15	51.67
Nigeria	11.60	7	15	17	68.26
Sierra Leone	7.93	5	10	14	56.64
Tanzania	17.53	12	22	37	47.37
Togo	9.07	5	13	20	45.34
Uganda	12.43	9	18	26	47.79

Notes: Mean Coalition Size: mean size of politically relevant ethnicities represented at the centre over the sample period. Min Coalition Size: minimum number of politically relevant ethnicities represented at the centre over the sample period. Max Coalition Size: maximum number of politically relevant ethnicities represented at the centre over the sample period. Ethnic Groups: politically relevant ethnicities. Mean Proportion: mean percentage of politically relevant ethnicities represented at the centre or share ministerial level cabinet positions.

Table B.4: Descriptive Statistics of Primary Commodity

	MinEx Mineral Resource Discovery		
Primary Metal	Share	Largest Country	Country Share
Copper	0.103	DRC	0.482
Diamonds	0.053	Angola and Botswana	0.286
Fluorite	0.004	South Africa	1
Gold	0.479	South Africa	0.222
Graphite	0.004	Tanzania	1
Lead	0.004	South Africa	1
Manganese	0.030	South Africa	0.625
Mineral Sands	0.030	Madagascar, Mozambique, Sierra Leone and South Africa	0.250
Nickel	0.095	South Africa, Tanzania and Zimbabwe	0.160
Niobium	0.008	Gabon and Tanzania	0.500
PGE	0.068	South Africa	0.944
Phosphate	0.004	Rep of Congo	1
Platinum	0.015	South Africa	0.750
Potash	0.008	Rep of Congo	1
Rare Earths	0.011	South Africa	0.667
Silver	0.004	South Africa	1
Uranium	0.053	Namibia	0.500
Zinc	0.019	Namibia and South Africa	0.400
Zircon	0.008	Madagascar and Senegal	0.500
	Mike Horn Oilfield Discovery		
Field Type	Share	Largest Country	Country Share
Oil	0.780	Libya	0.522
Gas	0.220	Algeria	0.538

Notes: Sample Period: 1950-2012. Primary Metal: primary mine deposit discovered. Field Type: the type of deposits-oilfields or natural gas fields. Share: share of primary commodity in the total sample of the discovery. Largest Country: country with the largest share of the primary mine discovered. Country Share: share of the country in the total sample.

Table B.5: Descriptive Statistics of MinEx Mineral Discovery

Country	Discovery	Max Disc	Share	Country	Discovery	Max Disc	Share
Algeria	1	1	0.004	Liberia	3	1	0.012
Angola	5	1	0.019	Madagascar	4	1	0.016
Botswana	11	2	0.043	Mali	13	3	0.050
Burkina Faso	17	3	0.066	Mauritania	2	1	0.008
Burundi	1	1	0.004	Mozambique	3	2	0.012
Cameroon	1	1	0.004	Namibia	12	2	0.047
CAR	2	1	0.008	Niger	4	1	0.016
DRC	19	3	0.074	Rep of Congo	3	1	0.012
Cote d'Ivoire	7	1	0.027	Senegal	6	2	0.023
Egypt	3	1	0.012	Sierra Leone	2	1	0.008
Eritrea	1	1	0.004	South Africa	67	4	0.260
Ethiopia	3	1	0.012	Sudan	1	1	0.004
Gabon	4	1	0.016	Tanzania	21	3	0.081
Ghana	13	2	0.050	Togo	1	1	0.004
Guinea	9	3	0.035	Zambia	7	2	0.027
Lesotho	1	1	0.004	Zimbabwe	10	2	0.039

Notes: Sample Period: 1950-2012. Country: country which discovered mine deposit. Discovery: total number of discovery in the country over the sample period. Max Disc: maximum number of yearly discovery in the country over the sample period. Share: country's share of mineral discovery in the African continent over the sample period.

Table B.6: Descriptive Statistics of Mike Horn Oilfield Discovery

Country	Discovery	Max Disc	Share
Algeria	11	2	0.186
Egypt	1	1	0.017
Ethiopia	1	1	0.017
Gabon	1	1	0.017
Libya	27	5	0.458
Morocco	1	1	0.017
Nigeria	14	4	0.237
Rep of Congo	1	1	0.017
Sudan	2	1	0.034

Notes: Sample Period: 1950-2012. Country: country which discovered oilfield deposit. Discovery: total number of discovery in the country over the sample period. Max Disc: maximum number of yearly discovery in the country over the sample period. Share: country's share of mineral discovery in the African continent over the sample period.

Table B.7: Natural Resources and Chances of Winning the Leadership

Dependent Variable:	Indicator of Winning Leadership Seats				
	(1)	(2)	(3)	(4)	(5)
Resource Discovery, *t*	-0.005				
	(0.005)				
Resource Discovery, *t-2*	-0.014				
	(0.017)				
Resource Discovery, *t-4*	-0.009				
	(0.018)				
Resource Discovery, *t-6*	-0.011				
	(0.017)				
Resource Discovery, *t-8*	-0.029				
	(0.025)				
Resource Discovery, *t-10*	-0.016				
	(0.019)				
Commodity Price, *t*		-0.015***			
		(0.005)			
Average Price, *3 Years*			-0.021***		
			(0.006)		
Average Price, *5 Years*				-0.024***	
				(0.006)	
Average Price, *10 Years*					-0.032***
					(0.008)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	6,303	6,536	6,251	6,001	5,238

Notes: This table reports the effect of natural resource discoveries and commodity price indices on the chances of winning a rulership seat. Dependent variable denote an indicator of ruler coming from an ethnic group. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.8: Natural Resources and Power Monopolisation and Dominance

Dependent Variable:	Indicator of Power Monopolisation					Indicator of Power Dominance				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Resource Discovery, *t*	0.004					0.010				
	(0.008)					(0.008)				
Resource Discovery, *t-2*	-0.006**					-0.005				
	(0.003)					(0.006)				
Resource Discovery, *t-4*	-0.007**					-0.0003				
	(0.003)					(0.007)				
Resource Discovery, *t-6*	-0.007***					-0.004				
	(0.002)					(0.006)				
Resource Discovery, *t-8*	-0.006***					-0.008				
	(0.002)					(0.005)				
Resource Discovery, *t-10*	-0.007***					-0.003				
	(0.002)					(0.004)				
Commodity Price, *t*		-0.002					0.030**			
		(0.003)					(0.012)			
Average Price, *3 Years*			-0.0003***					0.0001		
			(0.000)					(0.000)		
Average Price, *5 Years*				-0.004*					0.034**	
				(0.002)					(0.013)	
Average Price, *10 Years*					-0.003					0.032**
					(0.002)					(0.014)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,670	6,902	6,589	6,334	5,640	7,670	6,902	6,589	6,334	5,640

Notes: This table reports the effect of natural resource discoveries and ethnic specific commodity price indices on the monopolisation and dominance of political power in the executive. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively..

Table B.9: Resource Discoveries and Exclusion, Autonomy and Separatism

Dependent Variable:	Indicator of Exclusion	Indicator of Autonomy	Indicator of Separatism
	(1)	(2)	(3)
Resource Discovery, *t*	-0.108	0.140	0.001
	(0.145)	(0.180)	(0.001)
Resource Discovery, *t-2*	-0.101	0.127	-0.004
	(0.160)	(0.150)	(0.004)
Resource Discovery, *t-4*	-0.077	-0.065	-0.004
	(0.155)	(0.045)	(0.004)
Resource Discovery, *t-6*	0.099	0.095	-0.004
	(0.120)	(0.144)	(0.003)
Resource Discovery, *t-8*	0.045	-0.048	-0.001
	(0.112)	(0.038)	(0.002)
Resource Discovery, *t-10*	0.023	-0.046	0.001
	(0.115)	(0.041)	(0.001)
Year Fixed Effects	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes
Observations	7,584	7,670	7,670

Notes: This table reports the effect of natural resource discoveries on regional autonomy, exclusion from executive power and separatist movement. In column (1), the outcome variable is an indicator of ethnic group's exclusion from central state power. In column (2), the outcome variable is an indicator of regional autonomy-active regional executive organ that operates below the state level but above the local administrative level. In column (3), the outcome variable is an indicator of ethnic group's separatist autonomy. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.10: Commodity Prices and Exclusion, Autonomy and Separatism

Dependent Variable:	Indicator of Exclusion				Indicator of Autonomy				Indicator of Separatism			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Average Price, *t*	0.031*				-0.004				0.002			
	(0.018)				(0.004)				(0.002)			
Average Price, *3 Years*		0.017				-0.003				0.002		
		(0.021)				(0.004)				(0.002)		
Average Price, *5 Years*			0.027				-0.002				0.002	
			(0.021)				(0.003)				(0.002)	
Average Price, *10 Years*				0.041**				-0.004				-0.00003
				(0.019)				(0.003)				(0.0006)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,816	6,503	6,248	5,554	6,902	6,589	6,334	5,640	6,902	6,589	6,334	5,640

Notes: This table reports the effect of ethnic specific commodity price indices on the exclusion of ethnicities, regional autonomy and the separatist autonomy. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.11: Commodity Prices and Allocation of Top and Low Cabinets

Dependent Variable:	Share of Top Ministerial Appointments				Share of Low Ministerial Appointments			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Price, *t*	0.007***				0.005**			
	(0.002)				(0.002)			
Average Price, *3 Years*		0.008***				0.006***		
		(0.003)				(0.002)		
Average Price, *5 Years*			0.010***				0.007***	
			(0.003)				(0.002)	
Average Price, *10 Years*				0.016***				0.009***
				(0.003)				(0.002)
Leader Group	0.175***	0.176***	0.178***	0.169***	0.039***	0.039***	0.042***	0.051***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,536	6,251	6,001	5,238	6,536	6,251	6,001	5,238

Notes: This table reports the effect of ethnic specific commodity price indices on the distribution of cabinet positions. In columns (1)-(4), the dependent variable denote share of top cabinet positions held by an ethnic group. In columns (5)-(8), the dependent variable is low cabinet positions held by an ethnic group. We control for ruler's co-ethnicity effect by including Leader Group, indicating whether the ruler come from the same ethnic group. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.12: Poisson Regression: Resource Discoveries and Commodity Prices

Dependent Variable:	Counting the Number of Ethnic Cabinet Reshuffling				
	(1)	(2)	(3)	(4)	(5)
Resource Discovery, *t*	-14.259***				
	(1.071)				
Resource Discovery, *t-2*	0.769***				
	(0.156)				
Resource Discovery, *t-4*	1.093***				
	(0.156)				
Resource Discovery, *t-6*	1.215***				
	(0.155)				
Resource Discovery, *t-8*	0.758***				
	(0.158)				
Resource Discovery, *t-10*	-1.411***				
	(0.155)				
Leader Group	1.429***	1.477***	1.478***	1.476***	1.453***
	(0.116)	(0.118)	(0.119)	(0.120)	(0.121)
Average Price, *t*		0.055***			
		(0.018)			
Average Price, *3 Years*			0.056***		
			(0.018)		
Average Price, *5 Years*				0.058***	
				(0.019)	
Average Price, *10 Years*					0.059***
					(0.020)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	6,303	6,536	6,251	6,001	5,238

Notes: This table reports the effect of natural resource discoveries and ethnic specific commodity price indices on the distribution of ministerial cabinet positions using poisson regression. We control for ruler's co-ethnicity effect by including Leader Group, indicating whether the ruler come from the same ethnic group. Standard errors are clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.13: GLM Regression: Resource Discoveries and Commodity Prices

Dependent Variable:	Share of Ministerial Appointments				
	(1)	(2)	(3)	(4)	(5)
Resource Discovery, *t*	-9.858***				
	(1.074)				
Resource Discovery, *t-2*	0.829***				
	(0.166)				
Resource Discovery, *t-4*	1.199***				
	(0.165)				
Resource Discovery, *t-6*	1.342***				
	(0.165)				
Resource Discovery, *t-8*	0.817***				
	(0.167)				
Resource Discovery, *t-10*	-1.457***				
	(0.163)				
Leader Group	1.603***	1.672***	1.671***	1.667***	1.638***
	(0.129)	(0.132)	(0.133)	(0.134)	(0.136)
Average Price, *t*		0.061***			
		(0.021)			
Average Price, *3 Years*			0.062***		
			(0.021)		
Average Price, *5 Years*				0.065***	
				(0.022)	
Average Price, *10 Years*					0.066***
					(0.023)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	6,303	6,536	6,251	6,001	5,238

Notes: This table reports the effect of natural resource discoveries and ethnic specific commodity price indices on the distribution of ministerial cabinet positions using fractional logit generalized linear models (GLM). We control for ruler's co-ethnicity effect by including Leader Group, indicating whether the ruler come from the same ethnic group. Standard errors are clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.14: Ethnic Specific Time Trend: Discoveries and Commodity Prices

Dependent Variable:	Share of Ministerial Appointments				
	(1)	(2)	(3)	(4)	(5)
Resource Discovery, *t*	-0.033***				
	(0.001)				
Resource Discovery, *t-2*	0.074*				
	(0.041)				
Resource Discovery, *t-4*	0.112				
	(0.071)				
Resource Discovery, *t-6*	0.128***				
	(0.016)				
Resource Discovery, *t-8*	0.071***				
	(0.001)				
Resource Discovery, *t-10*	-0.026***				
	(0.006)				
Leader Group	0.155***	0.162***	0.161***	0.159***	0.155***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Average Price, *t*		0.004***			
		(0.000)			
Average Price, *3 Years*			0.004***		
			(0.000)		
Average Price, *5 Years*				0.004***	
				(0.000)	
Average Price, *10 Years*					0.004***
					(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Ethnic Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Ethnic Specific Time Trend	Yes	Yes	Yes	Yes	Yes
Observations	6,303	6,536	6,251	6,001	5,238

Notes: This table reports the effect of natural resource discoveries and ethnic specific commodity price indices on the distribution of ministerial cabinet positions using high order fixed effects including ethnic group specific time trend. We control for ruler's co-ethnicity effect by including Leader Group, indicating whether the ruler come from the same ethnic group. Standard errors are adjusted to reflect two-dimensional spatial dependence as modelled in Conley (1999). The spatial correlation is assumed to linearly decrease in distance up to a cutoff of 500km, and ethnic group distances are computed from centroids of the ethnic group polygons. The result remains robust to several distance cutoffs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

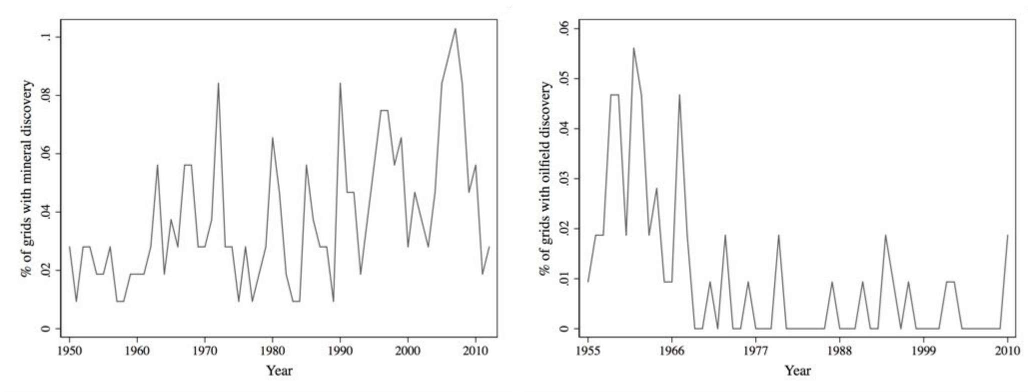
APPENDIX C

Paper Three Appendix

List of Countries in the Sample

Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Comoros, Democratic Republic of Congo, Cote d'Ivorie, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Morocco, Mozambique, Namibia, Niger, Nigeria, Republic of Congo, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe.

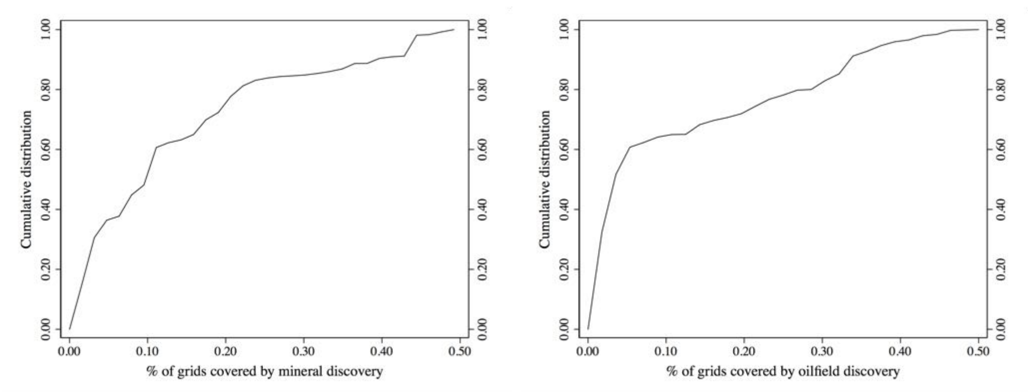
Figure C.1: Percentage of Grids with Discovery



(a) Mineral Discovery **(b)** Oilfield Discovery

Notes: The figures show the percentage of grids discovered minerals or oilfield.

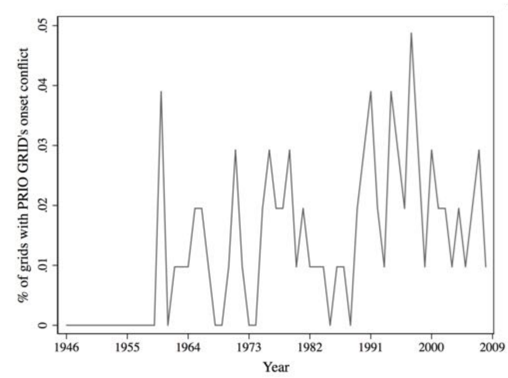
Figure C.2: Distribution of Grids with Discovery



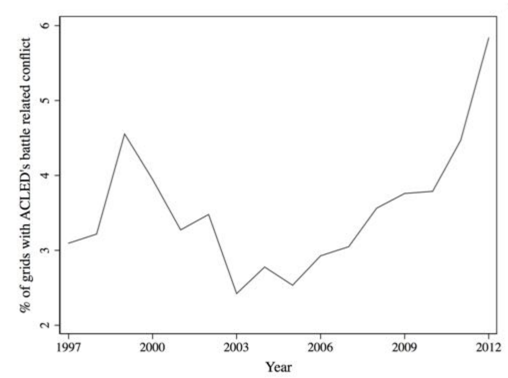
(a) Mineral Discovery **(b)** Oilfield Discovery

Notes: The figures show the distribution of grids discovered minerals or oilfield when the country has discovered.

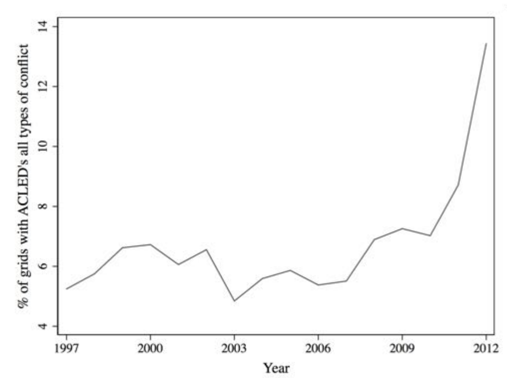
Figure C.3: Comparison of Conflict Datasets-Percentage of Grids in Conflict



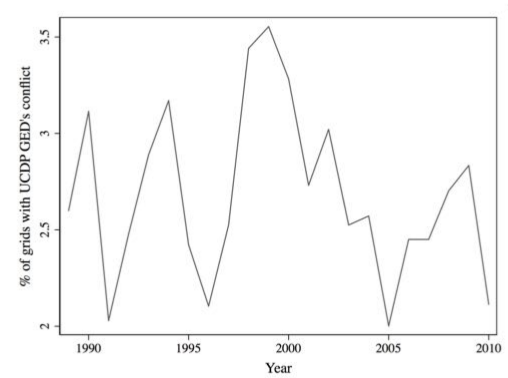
(a) PRIO-GRID Onset Conflict



(b) ACLED Battle related conflict



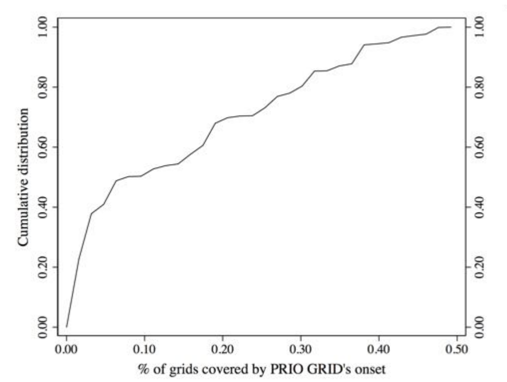
(c) ACLED All conflict



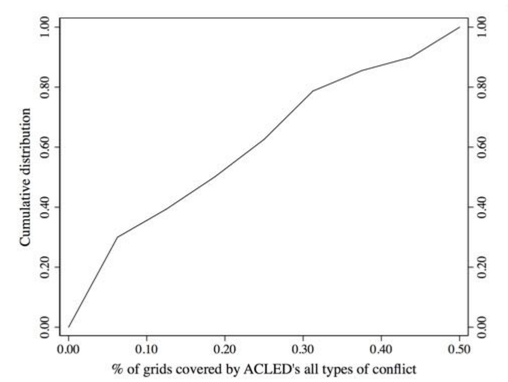
(d) UCDP GED conflict

Notes: The figures show the comparison PRIO-GRID, ACLED and UCDP GED conflict datasets. It represents the percentage of grids in conflict. Note that for ACLED, we show both battle related conflict and all types of conflict.

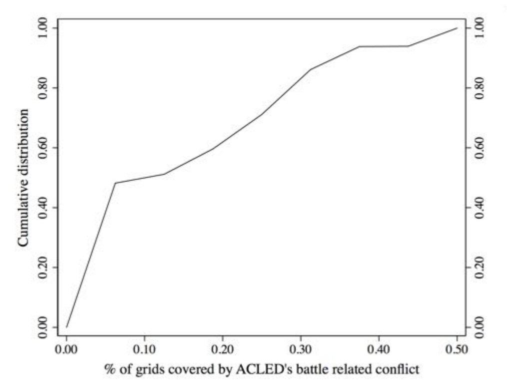
Figure C.4: Comparison of Conflict Datasets-Distribution of Grids in Conflict



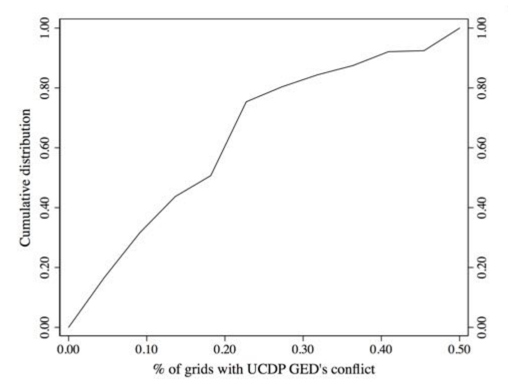
(a) PRIO-GRID Onset Conflict



(b) ACLED All conflict



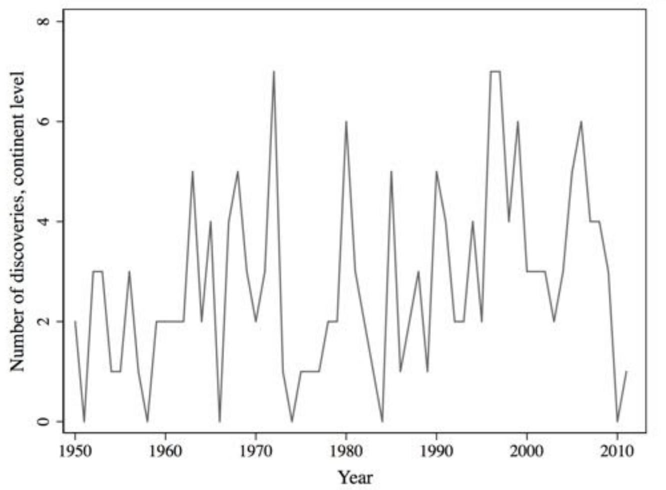
(c) ACLED Battle related conflict



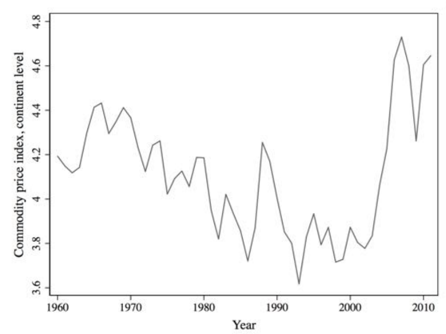
(d) UCDP GED conflict

Notes: The figures show the comparison PRIO-GRID, ACLED and UCDP GED conflict datasets. It represents the distribution of grids in conflict when the country is in armed conflict. Note that for ACLED, we show both battle related conflict and all types of conflict.

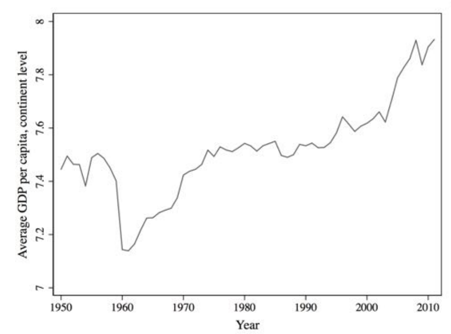
Figure C.5: Discoveries and Other Observables in Africa: Is There Comovement?



A: Natural Resource Discovery



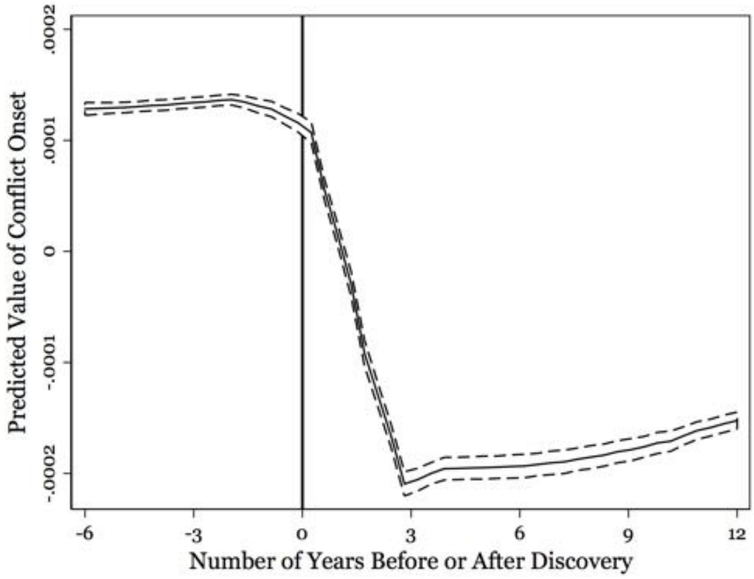
B: Commodity Price Index



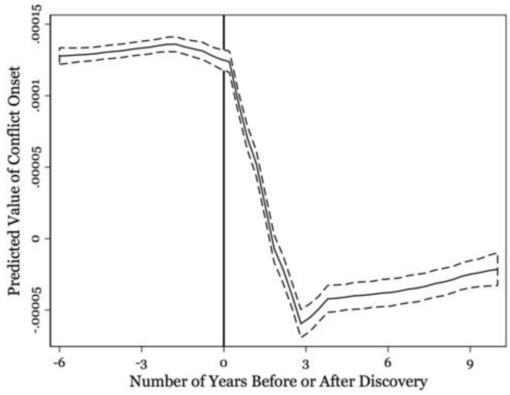
C: GDP Per Capita

Notes: The figure shows the evolution of the annual number of discoveries, average GDP per capita and global commodity price index in Africa.

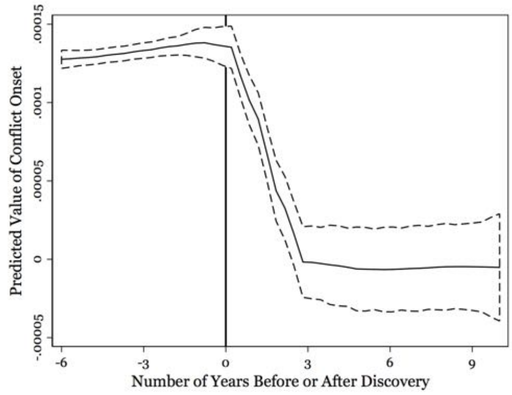
Figure C.6: Resource Discovery and Predicted Value of Conflict Onset



A: Natural Resource: Oilfield and Minerals



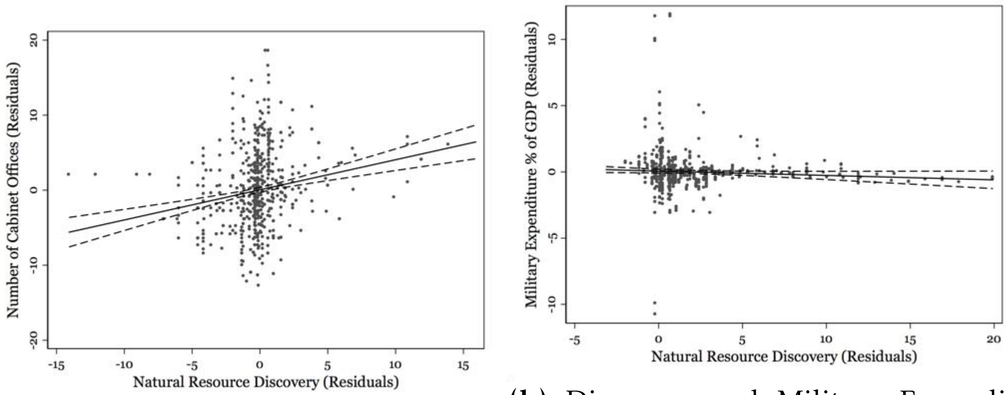
B: Oilfield Discovery



C: Mineral Discovery

Notes: The figure is plotted using a nonparametric local polynomial regression method with an Epanechnikov kernel, and the bar displays a graph of the smoothed values with 95% confidence intervals. The nonparametric regression is conditional on past discovery, year fixed effects, grid fixed effects, grid-specific time trends and country x year fixed effects. We predict the value of civil conflict onset for a given discovery of natural resource in a panel of grid-year observations. The sample period is 1950-2008.

Figure C.7: Discovery, Cabinet Patronage and Military Expenditure



(a) Discovery and Cabinet Sizes

(b) Discovery and Military Expenditures

Notes: The graph shows the association between government cabinet size (the number of cabinet positions), military expenditure and natural resource discovery. It is a non-parametric plot of the residuals with twoway linear prediction plots of government cabinet size and military expenditure as a function of resource discoveries, pooled across all countries. This is country level analysis. We first subtract the country-specific mean from each observation. Number of cabinet sizes (residuals) stands for residual variation in cabinet sizes after subtracting country-specific means. Natural resource discovery (residuals) stands for residual variation in natural resource discovery after subtracting country-specific means. Military expenditure stands for residual variation on military expenditure after subtracting country- specific means.

Table C.1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	First Year	Last Year
Discovery of Oilfield and Mineral Resources					
Resource discovery indicator	646191	0.0004	0.0211	1950	2012
Years with res. disc. (t-10 to t-1)	646191	0.0038	0.0679	1950	2012
Oilfield discovery indicator	646191	0.0001	0.0089	1950	2012
Years with oil disc. (t-10 to t-1)	646191	0.0008	0.0311	1950	2012
Mineral discovery indicator	646191	0.0003	0.0192	1950	2012
Years with min. disc. (t-10 to t-1)	646191	0.0030	0.0604	1950	2012
PRIO-GRID Conflict Dataset					
Conflict onset indicator	646191	0.0001	0.0114	1946	2008
UCDP GED Conflict Dataset					
Conflict onset indicator	232208	0.014	0.118	1989	2010
Conflict incidence indicator	235246	0.027	0.161	1989	2010
Conflict intensity	235246	0.032	0.222	1989	2010
ACLED Conflict Dataset					
Conflict onset indicator	168499	0.021	0.142	1997	2012
Conflict incidence indicator	171088	0.035	0.185	1997	2012
Conflict intensity	171088	0.043	0.262	1997	2012
Democracy Variables					
Polity2	640395	-3.336	3.476	1950	2008
Resource discovery * Polity2	640395	-0.0005	0.105	1950	2008
Oilfield discovery * Polity2	640395	-0.0004	0.053	1950	2008
Mineral discovery * Polity2	640395	-0.0001	0.091	1950	2008
Additional Covariates: Grid Level Characteristics					
Area of the grid cell (sq. km)	646191	7.921	0.436	1946	2008
Distance to the border (km)	632646	4.679	1.137	1946	2008
Distance to national capital (km)	646191	6.242	0.773	1946	2008
Travel time to urban centre (km)	646191	6.210	0.837	1946	2008
Mountainous terrain (% cover)	624771	0.111	0.194	1946	2008
Forest areas (% cover)	433377	2.881	1.478	1946	2008
Average precipitation (mm)	615814	5.976	1.050	1946	2008
Mean temperature (°C)	615814	3.197	0.167	1946	2008
Additional Covariates: Ethnic Level Characteristics					
Ethnic size (share in total pop)	287550	2.908	0.971	1946	2008
Ethnic total population	282165	9.392	1.080	1946	2008
Exclusion from state power	284494	0.477	0.499	1946	2008
Per Capita GDP	281727	1.852	1.894	1946	2008
Political Representation	284494	0.503	0.499	1946	2008
Political Exclusion	284494	0.472	0.499	1946	2008

Notes: This table reports summary statistics for main variables of interest and other grid level additional covariates . See data appendix for variable descriptions and data sources.

Table C.2: Descriptive Statistics at the Country Level-PRIO-GRID

Country	Events	Max Events	Share1	Share2	Country	Events	Max Events	Share1	Share2
Algeria	1	1	0.0001	0.012	Liberia	1	1	0.0001	0.012
Angola	3	1	0.0003	0.036	Madagascar	1	1	0.0003	0.012
Burkina Faso	1	1	0.0001	0.012	Mali	2	1	0.0001	0.024
Cameroon	3	1	0.0003	0.036	Morocco	2	1	0.0003	0.024
CAR	1	1	0.0001	0.012	Namibia	1	1	0.0001	0.012
Chad	3	1	0.0003	0.036	Niger	6	1	0.0003	0.071
Cote d'Ivoire	2	1	0.0002	0.024	Rwanda	2	1	0.0002	0.024
DRC	12	1	0.001	0.143	Nigeria	3	1	0.001	0.036
Equatorial Guinea	3	3	0.0003	0.036	Senegal	1	1	0.0003	0.012
Eritrea	2	1	0.0002	0.024	Somalia	6	1	0.0002	0.071
Ethiopia	5	2	0.0005	0.060	Sudan	5	1	0.0005	0.060
Ghana	3	1	0.0003	0.036	Tanzania	1	1	0.0003	0.012
Guinea	2	1	0.0002	0.024	Tunisia	1	1	0.0002	0.012
Guinea Bissau	5	2	0.0005	0.060	Uganda	1	1	0.0005	0.012
Kenya	1	1	0.0001	0.012	Zambia	1	1	0.0001	0.012
Lesotho	1	1	0.0001	0.012	Zimbabwe	2	1	0.0001	0.024

Notes: Sample Period: 1946-2008. Country: country in which the conflict event took place. Events: total number of events in the country over the sample period. Max Events: maximum number of yearly events in the country over the sample period. Share1: share of grids in the country affected by at least one conflict over the sample period. Share2: country's share of conflict events in the African continent over the sample period.

Table C.3: Descriptive Statistics at the Country Level-ACLED

Country	Events	Max Events	Share1	Share2	Country	Events	Max Events	Share1	Share2
Algeria	1366	274	0.108	0.045	Madagascar	54	23	0.088	0.002
Angola	2178	1215	0.368	0.071	Malawi	5	2	0.143	0.0002
Benin	2	1	0.056	0.0001	Mali	321	165	0.098	0.011
Botswana	3	1	0.015	0.0001	Mauritania	16	5	0.024	0.001
Burkina Faso	23	6	0.207	0.001	Morocco	12	5	0.025	0.0004
Burundi	1479	363	1.000	0.049	Mozambique	46	23	0.032	0.002
Cameroon	77	14	0.157	0.003	Namibia	80	50	0.060	0.003
CAR	481	122	0.284	0.016	Niger	148	34	0.091	0.005
Chad	309	73	0.128	0.010	Nigeria	1785	318	0.534	0.059
Cote d'Ivoire	478	111	0.343	0.016	Rep of Congo	190	70	0.239	0.006
DRC	3847	407	0.361	0.126	Rwanda	144	77	0.750	0.005
Djibouti	18	5	0.500	0.001	Senegal	232	31	0.247	0.008
Egypt	513	343	0.083	0.017	Sierra Leone	838	286	1.000	0.028
Equatorial Guinea	7	4	0.053	0.0002	Somalia	6927	1928	0.612	0.227
Eritrea	234	142	0.357	0.008	South Africa	88	26	0.067	0.003
Ethiopia	1261	179	0.496	0.041	Sudan	1529	336	0.305	0.050
Gabon	3	1	0.033	0.0001	Swaziland	1	1	0.375	0.00003
Ghana	64	11	0.222	0.002	Tanzania	46	11	0.083	0.002
Guinea	171	61	0.233	0.006	Togo	11	4	0.750	0.0004
Guinea-Bissau	110	63	0.471	0.004	Tunisia	110	54	0.352	0.004
Kenya	1023	122	0.556	0.034	Uganda	1734	297	0.813	0.057
Lesotho	26	17	0.250	0.001	Zambia	20	4	0.044	0.001
Liberia	586	194	0.738	0.019	Zimbabwe	59	10	0.103	0.002
Libya	816	505	0.070	0.027					

Notes: Sample Period: 1997-2012. Country: country in which the conflict event took place. Events: total number of events in the country over the sample period. Max Events: maximum number of yearly events in the country over the sample period. Share1: share of grids in the country affected by at least one conflict over the sample period. Share2: country's share of conflict events in the African continent over the sample period.

Table C.4: Descriptive Statistics at the Country Level-UCDP GED

Country	Events	Max Events	Share1	Share2	Country	Events	Max Events	Share1	Share2
Algeria	3591	383	0.128	0.148	Mali	104	41	0.084	0.004
Angola	1912	316	0.438	0.079	Mauritania	20	12	0.021	0.001
Botswana	1	1	0.011	0.0000004	Morocco	10	6	0.019	0.0004
Burundi	1387	193	1.000	0.057	Mozambique	263	131	0.276	0.011
Cameroon	45	8	0.092	0.002	Namibia	24	17	0.050	0.001
CAR	195	52	0.160	0.008	Niger	90	22	0.096	0.004
Chad	298	62	0.133	0.012	Nigeria	428	78	0.296	0.018
Comoros	6	3	0.152	0.0002	Rep of Congo	214	55	1.000	0.009
Cote d'Ivoire	162	47	0.264	0.007	Senegal	282	39	0.233	0.012
DRC	2001	547	0.211	0.083	Rwanda	467	161	1.000	0.019
Djibouti	44	10	0.625	0.002	Sierra Leone	1468	347	0.372	0.061
Egypt	373	117	0.075	0.015	Somalia	1943	316	0.261	0.080
Eritrea	43	13	0.429	0.002	South Africa	2781	576	0.250	0.115
Ethiopia	1351	144	0.499	0.056	Sudan	1766	223	0.750	0.073
Ghana	38	10	0.173	0.002	Swaziland	2	2	0.027	0.0001
Guinea	68	26	0.186	0.003	Tanzania	7	3	0.500	0.0003
Guinea-Bissau	12	9	0.412	0.001	Togo	96	83	0.019	0.004
Kenya	423	119	0.317	0.018	Tunisia	1	1	0.813	0.0000004
Lesotho	5	5	0.438	0.0002	Uganda	1655	251	0.054	0.068
Liberia	545	137	0.905	0.023	Zambia	12	6	0.032	0.001
Madagascar	39	32	0.037	0.002	Zimbabwe	53	40	0.184	0.002

Notes: Sample Period: 1989-2010. Country: country in which the conflict event took place. Events: total number of events in the country over the sample period. Max Events: maximum number of yearly events in the country over the sample period. Share1: share of grids in the country affected by at least one conflict over the sample period. Share2: country's share of conflict events in the African continent over the sample period.

Table C.5: Past Discoveries and Near Future Discoveries: Grid Level

Dependent Variable:	Natural Resource Discovery		Oilfield Discovery		Mineral Discovery	
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	FE
Past Discovery	0.0144***	-0.0073***	0.0111***	-0.0069***	0.0154***	-0.0074***
	(0.003)	(0.0021)	(0.005)	(0.0014)	(0.003)	(0.0026)
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Grid Fixed Effects	No	Yes	No	Yes	No	Yes
Grid-Specific Time Trend	No	Yes	No	Yes	No	Yes
Country x Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	646191	646191	646191	646191	646191	646191

Notes: This table reports whether discoveries in a grid's recent past raise the odds of additional discoveries in its near future. The explanatory variable (past discovery) is the number of years with discoveries from t-10 to t-1. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.6: Past Discoveries and Near Future Discoveries: Region Level

Dependent Variable:	Natural Resource Discovery		Oilfield Discovery		Mineral Discovery	
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	FE
Past Discovery	0.04381***	0.01686**	0.04332***	0.03022***	0.04505***	0.00838
	(0.005)	(0.007)	(0.004)	(0.006)	(0.007)	(0.006)
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Region Fixed Effects	No	Yes	No	Yes	No	Yes
Region-Specific Time Trend	No	Yes	No	Yes	No	Yes
Country x Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	27090	27090	27090	27090	27090	27090
Sample Period	1950-2012	1950-2012	1950-2012	1950-2012	1950-2012	1950-2012

Notes: This table reports whether discoveries in a region's recent past raise the odds of additional discoveries in its near future. The explanatory variable (past discovery) is the number of years with discoveries from t-10 to t-1. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.7: Past Discoveries and Near Future Discoveries: Country Level

Dependent Variable:	Natural Resource Discovery		Oilfield Discovery		Mineral Discovery	
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	FE
Past Discovery	0.0538***	0.0279***	0.0454***	0.0328***	0.0596***	0.0218*
	(0.004)	(0.007)	(0.001)	(0.002)	(0.002)	(0.012)
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Country Fixed Effects	No	Yes	No	Yes	No	Yes
Country x Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	2961	2961	2961	2961	2961	2961
Sample Period	1950-2012	1950-2012	1950-2012	1950-2012	1950-2012	1950-2012

Notes: This table reports whether discoveries in a country's recent past raise the odds of additional discoveries in its near future. The explanatory variable (past discovery) is the number of years with discoveries from t-10 to t-1. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.8: Is Natural Resource Discovery Random?

	Dependent Variable: Indicator of Natural Resource Discovery					
	(1)	(2)	(3)	(4)	(5)	(6)
Per Capita GDP	-0.0003					-0.0002
	(0.0002)					(0.0002)
Population Share		0.0014				0.0014
		(0.0014)				(0.0023)
Population Size			0.0015			0.0005
			(0.0011)			(0.0017)
Political Representation				-0.00014		0.0015
				(0.0005)		(0.0010)
Political Exclusion					0.0005	0.0017
					(0.0003)	(0.0013)
Past Discovery	-0.0121***	-0.0119***	-0.0121***	-0.0122***	-0.0122***	-0.0125***
	(0.0031)	(0.0030)	(0.0031)	(0.0031)	(0.0031)	(0.0032)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	249951	255754	250389	252889	252889	247086

Notes: This table reports whether the timing of natural resource discoveries is correlated with the mean of grid's economic and political variables in the past years. Past discovery is the number of years with discoveries from t-10 to t-1. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.9: Resource Discovery and Conflict Incidence (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Incidence (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.012	-0.010	-0.018	0.007	-0.002	0.009
	(0.015)	(0.014)	(0.013)	(0.016)	(0.016)	(0.015)
Past Discovery	-0.010	-0.008	-0.007	-0.010	-0.009	-0.010
	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)
Panel B: Effect of Discovering Oilfield						
Discovery	0.075	-0.024	-0.024	-0.024	-0.011	0.087
	(0.080)	(0.025)	(0.025)	(0.025)	(0.011)	(0.089)
Past Discovery	0.017	0.015	0.016	0.016	0.014	0.005
	(0.014)	(0.014)	(0.017)	(0.017)	(0.015)	(0.005)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.018	-0.009	-0.018	0.009	-0.001	0.002
	(0.016)	(0.015)	(0.013)	(0.017)	(0.017)	(0.014)
Past Discovery	-0.012	-0.010	-0.009	-0.012	-0.011	-0.011
	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235246	225236	215226	205216	195206	185196

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year Observations. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.10: Resource Discovery and Civil Incidence (ACLED)

Dependent Variable: Intrastate Armed Conflict Incidence (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0197	-0.0137	-0.0015	-0.0272**	0.0054	0.0147
	(0.0241)	(0.0181)	(0.0136)	(0.0109)	(0.0188)	(0.0278)
Past Discovery	-0.008	-0.005	-0.007	-0.005	-0.007	-0.008
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.1873**	-0.1394**	-0.0431	-0.0353	0.1301	0.0033
	(0.0893)	(0.0553)	(0.0476)	(0.0399)	(0.1499)	(0.0231)
Past Discovery	-0.032	-0.008	-0.018	-0.018	-0.036	-0.022
	(0.036)	(0.020)	(0.030)	(0.031)	(0.041)	(0.032)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0105	-0.0063	0.0009	-0.0264**	-0.0049	0.0159
	(0.0227)	(0.0183)	(0.0142)	(0.0117)	(0.0158)	(0.0300)
Past Discovery	-0.007	-0.005	-0.006	-0.003	-0.005	-0.007
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171088	163808	156528	149248	141968	134688

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year Observations. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.11: Resource Discovery and Conflict Intensity (UCDP GED)

Dependent Variable: Intrastate Civil Conflict Intensity (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.035*	-0.014	-0.006	0.005	-0.002	0.004
	(0.018)	(0.020)	(0.025)	(0.018)	(0.016)	(0.017)
Past Discovery	-0.017	-0.014	-0.015	-0.16	-0.015	-0.016
	(0.013)	(0.014)	(0.013)	(0.13)	(0.012)	(0.014)
Panel B: Effect of Discovering Oilfield						
Discovery	0.028	-0.013	-0.012	-0.012	-0.0004	0.043
	(0.115)	(0.013)	(0.013)	(0.013)	(0.002)	(0.045)
Past Discovery	0.002	0.002	0.002	0.002	0.001	-0.003
	(0.006)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.039*	-0.014	-0.005	0.006	-0.002	0.001
	(0.017)	(0.021)	(0.030)	(0.019)	(0.017)	(0.018)
Past Discovery	-0.019	-0.015	-0.016	-0.017	-0.017	-0.0017
	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.015)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235246	225236	215226	205216	195206	185196

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year Observationsz. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.12: Resource Discovery and Conflict Intensity (ACLED)

Dependent Variable: Intrastate Armed Conflict Intensity (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0142	-0.0479*	0.0259	-0.0024	0.0237	-0.0067
	(0.0336)	(0.0277)	(0.0329)	(0.0299)	(0.0282)	(0.0339)
Past Discovery	-0.001	0.006	-0.003	0.000	-0.002	0.001
	(0.018)	(0.019)	(0.017)	(0.016)	(0.017)	(0.018)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.1774**	-0.1416**	-0.0535	-0.0453	0.1859	-0.0066
	(0.0854)	(0.0545)	(0.0497)	(0.0417)	(0.2198)	(0.0244)
Past Discovery	-0.022	0.002	-0.007	-0.007	-0.033	-0.012
	(0.033)	(0.020)	(0.029)	(0.030)	(0.044)	(0.031)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0052	-0.0425	0.0307	0.0010	0.0102	-0.0066
	(0.0336)	(0.0291)	(0.0348)	(0.0322)	(0.0177)	(0.0368)
Past Discovery	0.001	0.006	-0.002	0.001	0.000	0.002
	(0.020)	(0.021)	(0.018)	(0.017)	(0.018)	(0.019)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171088	163808	156528	149248	141968	134688

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year Observations. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.13: Higher Grid Resolution: Discovery and Conflict Onset (PRIO-GRID)

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0009**	0.00003	-0.00004	0.00003	0.00005	-0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.0008*	-0.0008*	-0.0008*	-0.0008*	-0.0009*	-0.0009*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.0017	0.00006	0.00002	0.0002	0.0001	-0.0004
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.0016	-0.0016	-0.0016	-0.0017	-0.00173	-0.0018
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0007**	0.000001	-0.00005	-0.00001	0.00005	0.00013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.0006*	-0.0006*	-0.0006*	-0.0006*	-0.0006*	-0.0006*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	155524	148906	142288	135670	129052	122434

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse at higher levels of aggregation to check whether there is evidence for an ecological inference fallacy. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.14: Higher Grid Resolution: Discovery and Conflict Onset (ACLED)

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.006	0.002	0.014	0.002	-0.001	0.012
	(0.016)	(0.020)	(0.014)	(0.019)	(0.017)	(0.018)
Past Discovery	-0.0009	-0.0009	-0.002	-0.0008	-0.0005	-0.0016
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
Panel B: Effect of Discovering Oilfield						
Discovery	0.09	-0.06**	-0.018	-0.031	0.131	-0.033
	(0.127)	(0.029)	(0.016)	(0.022)	(0.156)	(0.022)
Past Discovery	-0.017	-0.012	-0.019	-0.017	-0.033	-0.017
	(0.024)	(0.022)	(0.025)	(0.025)	(0.039)	(0.025)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.011	0.007	0.015	0.004	-0.01	0.016
	(0.016)	(0.021)	(0.015)	(0.019)	(0.014)	(0.020)
Past Discovery	0.0003	-0.00003	-0.001	0.0004	0.002	-0.0005
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23724	22715	21706	20697	19688	18679

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse at higher levels of aggregation to check whether there is evidence for an ecological inference fallacy. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.15: Higher Grid Resolution: Discovery and Conflict Onset (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	0.037*	-0.013	-0.009	0.009	-0.007	0.008
	(0.021)	(0.014)	(0.017)	(0.015)	(0.019)	(0.015)
Past Discovery	0.00418	0.00401	0.00355	0.00154	0.00303	0.00176
	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.07	-0.07*	-0.015	-0.016	-0.003	0.12
	(0.061)	(0.044)	(0.030)	(0.032)	(0.025)	(0.108)
Past Discovery	-0.004	0.008	0.0002	0.0003	-0.0009	-0.013
	(0.023)	(0.021)	(0.024)	(0.024)	(0.024)	(0.017)
Panel C: Effect of Discovering Mineral Resources						
Discovery	0.04*	-0.009	-0.009	0.011	-0.007	-0.0003
	(0.023)	(0.013)	(0.018)	(0.016)	(0.020)	(0.015)
Past Discovery	0.00478	0.00381	0.00384	0.00169	0.00334	0.00280
	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55820	53445	51070	48695	46320	43945

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse at higher levels of aggregation to check whether there is evidence for an ecological inference fallacy. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.16: Resource Discovery and Conflict Onset: Region Level Analysis

Dependent Variable: Number of Grids Experienced Civil Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0036**	-0.0036**	0.0007	-0.0033**	0.0009	-0.0031**
	(0.002)	(0.002)	(0.003)	(0.001)	(0.004)	(0.001)
Past Discovery	-0.0013*	-0.0010	-0.0015**	-0.0014*	-0.0016**	-0.0015**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.0028	-0.0029	-0.0023	-0.0024	-0.0026	-0.0027
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Past Discovery	-0.0004	-0.0004	-0.0012	-0.0012	-0.0012	-0.0012
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0039**	-0.0039**	0.0012	-0.0036**	0.0015	-0.0032**
	(0.002)	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)
Past Discovery	-0.0019*	-0.0013*	-0.0017*	-0.0015*	-0.0018**	-0.0017**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25370	24508	23646	22784	21922	21060

Notes: This table reports the effect of discovering at least one natural resource in a panel of region-year Observations. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.17: Resource Discovery and Conflict Onset: Country Level Analysis

Dependent Variable: Number of Grids Experienced Civil Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0107	-0.0042	0.0114	-0.0122	0.0032	-0.0060
	(0.009)	(0.015)	(0.017)	(0.008)	(0.011)	(0.010)
Past Discovery	0.0001	-0.0001	-0.0032	-0.0032	-0.0038	-0.0039*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel B: Effect of Discovering Oilfield						
Discovery	0.0185	0.0173	0.0169	-0.0213*	0.0217	-0.0145*
	(0.024)	(0.034)	(0.025)	(0.012)	(0.029)	(0.008)
Past Discovery	0.0001	-0.0005	-0.0022	-0.0024	-0.0047	-0.0039
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0169*	-0.0088	0.0099	-0.0106	-0.0004	-0.0048
	(0.010)	(0.013)	(0.020)	(0.010)	(0.012)	(0.011)
Past Discovery	-0.0007	-0.0003	-0.0045	-0.0041	-0.0037	-0.0039
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2773	2677	2581	2485	2389	2293
Sample Period	1950-2008	1950-2008	1950-2008	1950-2008	1950-2008	1950-2008

Notes: This table reports the effect of discovering at least one natural resource in a panel of country-year Observations. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.18: Proximity to Discovery: Discovery and Conflict Onset (PRIO-GRID)

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Distance from Discovery (km)	-0.00002	-0.00001	-0.00004	-0.00001	-0.00002	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605163	579411	553659	527907	502155	476403

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse a time-varying distance from discovery: do we expect armed conflict occurring far away from oilfield or mines? Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Distance from discovery is time-varying distance of grid's centroid from the nearest discovery field each year.

Table C.19: Proximity to Discovery: Discovery and Conflict Onset (ACLED)

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Distance from Discovery (km)	0.00052	0.00025	0.00164	0.00039	-0.00135	-0.00021
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171088	163808	156528	149248	141968	134688

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse a time-varying distance from discovery: do we expect armed conflict occurring far away from oilfield or mines? Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Distance from discovery is time-varying distance of grid's centroid from the nearest discovery field each year.

Table C.20: Proximity to Discovery: Discovery and Conflict Onset (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Distance from Discovery (km)	-0.0010	-0.0012	-0.0016	-0.0026*	-0.00067	-0.00162
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235246	225236	215226	205216	195206	185196
Sample Period	1989-2010	1989-2010	1989-2010	1989-2010	1989-2010	1989-2010

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse a time-varying distance from discovery: do we expect armed conflict occurring far away from oilfield or mines? Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Distance from discovery is time-varying distance of grid's centroid from the nearest discovery field each year.

Table C.21: Proximity to Border: Discovery and Conflict Onset (PRIO-GRID)

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Distance to the Border, <= 25km						
Discovery	-0.00048	0.00005*	0.00003*	0.00001	-0.00005	-0.00012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	71449	68409	65369	62329	59289	56249
Panel B: Distance to the Border, <= 50km						
Discovery	-0.00084*	0.00006*	0.00002	0.00000	-0.00007	-0.00013**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	132986	127327	121668	116009	110350	104691
Panel C: Distance to the Border, <= 100km						
Discovery	-0.00055	0.00005	0.00002**	-0.00000	-0.00004	-0.00008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	237298	227201	217104	207007	196910	186813
Panel D: Distance to the Border, < 100km						
Discovery	-0.00046	0.00004	0.00002**	0.00001	-0.00003	-0.00010
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	392055	375372	358689	342006	325323	308640
Past Discovery	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse proximity to the borders, as proximity to borders is known to be an indicator for conflict propensity. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.22: Proximity to Border: Discovery and Conflict Onset (ACLED)

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Distance to the Border, <= 25km						
Discovery	-0.031**	-0.011	0.027	0.027	-0.023*	-0.0021
	(0.015)	(0.017)	(0.043)	(0.050)	(0.012)	(0.071)
Observations	18936	18130	17324	16518	15712	14906
Panel B: Distance to the Border, <= 50km						
Discovery	-0.030**	-0.028	0.0015	0.0027	-0.024**	-0.021
	(0.012)	(0.021)	(0.028)	(0.034)	(0.011)	(0.036)
Observations	35269	33768	32267	30766	29265	27764
Panel C: Distance to the Border, <= 100km						
Discovery	-0.007	-0.006	-0.008	-0.008	-0.019**	-0.015
	(0.024)	(0.022)	(0.019)	(0.022)	(0.009)	(0.021)
Observations	63076	60392	57708	55024	52340	49656
Panel D: Distance to the Border, < 100km						
Discovery	-0.017	-0.002	-0.013	-0.012	0.011	0.019
	(0.016)	(0.017)	(0.011)	(0.013)	(0.023)	(0.024)
Past Discovery	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104550	100101	95652	91203	86754	82305

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse proximity to the borders, as proximity to borders is known to be an indicator for conflict propensity. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.23: Proximity to Border: Discovery and Conflict Onset (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Distance to the Border, <= 25km						
Discovery	-0.303*	-0.186	-0.149	0.013	-0.043	-0.29*
	(0.176)	(0.152)	(0.152)	(0.213)	(0.154)	(0.151)
Observations	26642	25508	24374	23240	22106	20972
Panel B: Distance to the Border, <= 50km						
Discovery	-0.166	-0.02	-0.137	-0.022	-0.058	-0.207*
	(0.120)	(0.157)	(0.104)	(0.142)	(0.097)	(0.106)
Observations	49588	47478	45368	43258	41148	39038
Panel C: Distance to the Border, <= 100km						
Discovery	-0.135	0.0012	-0.086	-0.0187	-0.029	-0.119*
	(0.091)	(0.095)	(0.062)	(0.080)	(0.062)	(0.067)
Observations	88484	84719	80954	77189	73424	69659
Panel D: Distance to the Border, < 100km						
Discovery	-0.126*	-0.045	0.083	-0.014	-0.032	-0.015
	(0.065)	(0.065)	(0.169)	(0.059)	(0.043)	(0.061)
Past Discovery	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	146190	139969	133748	127527	121306	115085

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We analyse proximity to the borders, as proximity to borders is known to be an indicator for conflict propensity. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.24: Resource Discovery and Conflict before the End of Cold War

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.00017	-0.00018	-0.00017	-0.00018	-0.00018	-0.00018
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.00018	-0.00019	-0.00018	-0.00019	-0.00019	-0.00019
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Effect of Discovering Oilfield						
Discovery	0.00001**	0.00002**	0.00002**	0.00002**	0.00002*	0.00002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.00025	-0.00025	-0.00025	-0.00025	-0.00025	-0.00025
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.00026	-0.00026	-0.00026	-0.00026	-0.00027	-0.00026
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	451308	430794	410280	389766	369252	348738

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.25: Resource Discovery and Conflict after the End of Cold War

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	0.00001	0.00001	0.00000	0.00001	0.00000	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	0.00002	0.00001	0.00002	0.00002	0.00001	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.00002	-0.00000	0.00001	0.00001	0.00000	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	0.00001	0.00001	0.00004	0.00003	0.00001	0.00002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Effect of Discovering Mineral Resources						
Discovery	0.00001	0.00001	0.00000	0.00001	0.00000	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	0.00002	0.00001	0.00002	0.00002	0.00001	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	194883	174369	153855	133341	112827	92313

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. The dependent variable is civil conflict onset. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.26: Resource Discovery, Democracy and Conflict

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Discovery * Polity2	0.00002	0.00002	0.00002	0.00002	0.00002	0.00003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.0003	-0.0003	-0.0003	-0.0004	-0.0004	-0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.0035***	-0.0037***	-0.0038***	-0.004***	-0.004***	-0.0044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discovery * Polity2	-0.0005***	-0.0005***	-0.0006***	-0.0006***	-0.0006***	-0.0006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.0006	-0.0006	-0.0007	-0.0007	-0.0008	-0.0008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0002	-0.0002*	-0.0002	-0.0002	-0.0003	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discovery * Polity2	0.00004*	0.00004	0.00004	0.00004	0.00005	0.00005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Discovery	-0.0002	-0.0002	-0.0002	-0.0002	-0.0003	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605163	579411	553659	527907	502155	476403

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. The dependent variable is civil conflict onset based on the PRIO-GRID conflict. The Polity2 score ranges from -10 to +10, with higher values indicating stronger country-level democratic institutions. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.27: Excluding Grid-Year Observations of Past Discoveries (PRIO-GRID)

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.00033*	-0.00028*	-0.00030*	-0.00033*	-0.00036*	-0.00038*
	(0.00019)	(0.00016)	(0.00017)	(0.00019)	(0.00021)	(0.00022)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.00039	-0.00042	-0.00044	-0.00048	-0.00052	-0.00055
	(0.00043)	(0.00045)	(0.00047)	(0.00051)	(0.00054)	(0.00056)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.00032	-0.00024	-0.00027	-0.00029	-0.00031	-0.00033
	(0.00022)	(0.00016)	(0.00018)	(0.00019)	(0.00022)	(0.00023)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	602927	582530	562128	541721	521311	500908

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.28: Excluding Grid-Year Observations of Past Discoveries (ACLED)

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.002	-0.018	-0.019**	-0.017	0.002	0.018
	(0.019)	(0.013)	(0.008)	(0.012)	(0.021)	(0.026)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.150*	-0.102*	-0.019	-0.015	0.139	-0.012
	(0.080)	(0.057)	(0.023)	(0.016)	(0.153)	(0.009)
Panel C: Effect of Discovering Mineral Resources						
Discovery	0.007	-0.013	-0.019**	-0.017	-0.011	0.021
	(0.017)	(0.012)	(0.008)	(0.013)	(0.018)	(0.028)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	167617	161748	155879	150010	144141	138272

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.29: Excluding Grid-Year Observations of Past Discoveries (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.009	-0.002	-0.028***	0.006	-0.013	0.010
	(0.011)	(0.012)	(0.008)	(0.016)	(0.014)	(0.015)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.012	-0.018	-0.017	-0.015	-0.001	0.127
	(0.013)	(0.019)	(0.017)	(0.016)	(0.001)	(0.128)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.008	-0.001	-0.029***	0.007	-0.014	0.0001
	(0.011)	(0.013)	(0.009)	(0.017)	(0.014)	(0.013)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231137	223044	214951	206858	198765	190672

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table C.30: Restrict Sample to Grids With At Least One Discovery (PRIO-GRID)

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.00033	-0.00029	-0.00032	-0.00034	-0.00037	-0.00039
	(0.00021)	(0.00020)	(0.00022)	(0.00023)	(0.00025)	(0.00027)
Past Discovery	-0.00029	-0.00032	-0.00034	-0.00037	-0.00039	-0.00041
	(0.00021)	(0.00022)	(0.00024)	(0.00026)	(0.00028)	(0.00029)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.00063	-0.00066	-0.00069	-0.00074	-0.00079	-0.00083
	(0.00062)	(0.00064)	(0.00067)	(0.00072)	(0.00076)	(0.00080)
Past Discovery	-0.00059	-0.00063	-0.00066	-0.00071	-0.00076	-0.00082
	(0.00058)	(0.00061)	(0.00064)	(0.00068)	(0.00073)	(0.00078)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.00026	-0.00021	-0.00022	-0.00024	-0.00025	-0.00027
	(0.00018)	(0.00015)	(0.00016)	(0.00017)	(0.00018)	(0.00019)
Past Discovery	-0.00022	-0.00023	-0.00024	-0.00026	-0.00028	-0.00027
	(0.00016)	(0.00017)	(0.00018)	(0.00019)	(0.00021)	(0.00021)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14679	14213	13747	13281	12815	12349

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.31: Restrict Sample to Grids With At Least One Discovery (ACLED)

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.003	-0.008	-0.016	-0.029***	-0.004	0.043
	(0.016)	(0.017)	(0.012)	(0.007)	(0.024)	(0.035)
Past Discovery	0.004	0.006	0.007	0.007	0.005	0.003
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.160*	-0.122***	-0.058*	-0.058	0.312	-0.017
	(0.080)	(0.025)	(0.034)	(0.034)	(0.345)	(0.028)
Past Discovery	-0.064	-0.016	-0.035	-0.035	-0.065	-0.039
	(0.071)	(0.049)	(0.063)	(0.063)	(0.078)	(0.063)
Panel C: Effect of Discovering Mineral Resources						
Discovery	0.005	-0.002	-0.014	-0.027***	-0.026***	0.046
	(0.014)	(0.018)	(0.012)	(0.006)	(0.007)	(0.036)
Past Discovery	0.007	0.007	0.009	0.009	0.008	0.005
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1456	1408	1360	1312	1264	1216

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.32: Restrict Sample to Grids With At Least One Discovery (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.005	0.001	-0.023***	-0.001	-0.007	0.006
	(0.010)	(0.013)	(0.007)	(0.015)	(0.014)	(0.016)
Past Discovery	0.002	0.002	0.005	0.002	0.003	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.012	-0.025	-0.023	-0.021	-0.005	-0.002
	(0.011)	(0.024)	(0.024)	(0.024)	(0.009)	(0.007)
Past Discovery	0.009	0.013	0.013	0.012	0.011	0.010
	(0.010)	(0.014)	(0.014)	(0.014)	(0.012)	(0.011)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.005	0.003	-0.023***	0.001	-0.007	0.007
	(0.011)	(0.014)	(0.008)	(0.016)	(0.015)	(0.017)
Past Discovery	0.001	0.001	0.004	0.001	0.002	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2684	2596	2508	2420	2332	2244

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.33: High-Conflict-Risk Grids (ACLED)

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0256	-0.0197	-0.0574	-0.0775*	-0.0049	0.0836
	(0.063)	(0.057)	(0.035)	(0.044)	(0.089)	(0.106)
Past Discovery	-0.01933	-0.0138	-0.0115	-0.0099	-0.0163	-0.0230
	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)	(0.031)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.2241***	-0.1444***	-0.0829**	-0.0944**	0.4480	-0.0711**
	(0.073)	(0.022)	(0.035)	(0.036)	(0.397)	(0.035)
Past Discovery	-0.1261	-0.0608	-0.0889	-0.0881	-0.1290	-0.0927
	(0.081)	(0.065)	(0.078)	(0.078)	(0.090)	(0.078)
Panel C: Effect of Discovering Mineral Resources						
Discovery	0.0092	0.0026	-0.0558	-0.0766	-0.0592	0.0908
	(0.065)	(0.063)	(0.038)	(0.047)	(0.076)	(0.112)
Past Discovery	-0.0072	-0.0084	-0.0029	-0.0013	-0.0034	-0.0154
	(0.037)	(0.038)	(0.037)	(0.037)	(0.036)	(0.032)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31096	30036	29012	28023	27068	26145

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We use only the grids in which at least one conflict event occurs over the sample period. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.34: High-Conflict-Risk Grids (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0267	0.0025	-0.0896***	0.0307	-0.0382	0.0479
	(0.039)	(0.047)	(0.024)	(0.052)	(0.048)	(0.061)
Past Discovery	-0.0040	-0.0025	0.0075	-0.0049	0.0007	-0.0058
	(0.018)	(0.022)	(0.020)	(0.018)	(0.018)	(0.019)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.0479***	-0.2261***	-0.2279***	-0.2298***		0.8554***
	(0.008)	(0.004)	(0.007)	(0.011)		(0.026)
Past Discovery	-0.1509***	-0.1767***	-0.1769***	-0.1771***	-0.1532***	-0.0371***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0267	0.0105	-0.0845***	0.0402	-0.0344	0.0099
	(0.040)	(0.046)	(0.023)	(0.052)	(0.049)	(0.054)
Past Discovery	-0.0107	-0.0102	0.0004	-0.0124	-0.0061	-0.00950
	(0.019)	(0.021)	(0.020)	(0.017)	(0.018)	(0.020)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38228	36925	35666	34450	33276	32142

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We use only the grids in which at least one conflict event occurs over the sample period. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.35: Buffer Zone Analysis: Discovery and Conflict Onset (PRIO-GRID)

Dependent Variable: Intrastate Armed Conflict Onset (PRIO-GRID Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0001**	-0.00004	-0.0001	-0.0001	0.001	0.0001
	(0.00005)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0001)
Past Discovery	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001**	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00006)	(0.0001)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.0001	0.00001	-0.00001	0.00003	0.00002	-0.00004
	(0.0002)	(0.00002)	(0.00003)	(0.00003)	(0.00002)	(0.00004)
Past Discovery	-0.0001	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0001**	-0.00005	-0.0001	-0.0001	0.001	-0.0001
	(0.00005)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0001)
Past Discovery	-0.00003	-0.00002	-0.00002	-0.00002	-0.0001**	-0.000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00005)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605163	579411	553659	527907	502155	476403

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We do buffer zone analysis because some oilfield or mine discoveries cross grid boundaries. Numbers in parentheses are robust standard errors clustered at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.36: Buffer Zone Analysis: Discovery and Conflict Onset (ACLED)

Dependent Variable: Intrastate Armed Conflict Onset (ACLED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0064	-0.0028	0.0053	-0.0043	0.0044	0.0005
	(0.007)	(0.007)	(0.007)	(0.005)	(0.007)	(0.006)
Past Discovery	-0.0038	-0.0031	-0.0041	-0.0031	-0.0038	-0.0035
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.054*	-0.045**	-0.013	0.0097	0.029	0.00075
	(0.028)	(0.021)	(0.012)	(0.013)	(0.034)	(0.007)
Past Discovery	-0.0082	-0.00085	-0.0037	-0.0062	-0.0085	-0.0051
	(0.010)	(0.007)	(0.008)	(0.010)	(0.012)	(0.009)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0046	-0.0011	0.0066	-0.0054	0.0021	0.0005
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Past Discovery	-0.0036	-0.0032	-0.0042	-0.0029	-0.0035	-0.0034
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171088	163808	156528	149248	141968	134688

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We do buffer zone analysis because some oilfield or mine discoveries cross grid boundaries. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.

Table C.37: Buffer Zone Analysis: Discovery and Conflict Onset (UCDP GED)

Dependent Variable: Intrastate Armed Conflict Onset (UCDP-GED Conflict)						
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome at:	t	t + 2	t + 4	t + 6	t + 8	t + 10
Panel A: Effect of Discovering Natural Resource (Oilfield + Minerals)						
Discovery	-0.0012	-0.0013	-0.0094**	0.0083	-0.0068	0.0035
	(0.006)	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
Past Discovery	0.0001	0.0003	0.0012	-0.0006	0.0007	-0.0001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel B: Effect of Discovering Oilfield						
Discovery	-0.020	-0.011	-0.012	0.026	-0.0011	0.012
	(0.015)	(0.012)	(0.012)	(0.027)	(0.003)	(0.010)
Past Discovery	0.002	0.004	0.004	0.0002	0.0031	0.0019
	(0.003)	(0.004)	(0.004)	(0.001)	(0.003)	(0.002)
Panel C: Effect of Discovering Mineral Resources						
Discovery	-0.0005	-0.0006	-0.009**	0.007	-0.007	0.003
	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.007)
Past Discovery	-0.00009	0.00001	0.0009	-0.0007	0.0005	-0.0003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Grid-Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235246	225236	215226	205216	195206	185196

Notes: This table reports the effect of discovering at least one natural resource in a panel of grid-year observations. We do buffer zone analysis because some oilfield or mine discoveries cross grid boundaries. Numbers in parentheses are clustered standard errors at the country level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Past discovery is the number of years with discoveries from t-10 to t-1.