Violence, Protection, and the Political Economy of Security Provision in Ongoing Conflicts

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Political Science)
in the University of Michigan
2022

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DEDICATION

While doing fieldwork in DRC, Jean-Paul Zabika helped get me started, keep me safe, and implement the data collections that this dissertation is based on. JP tragically passed away in early 2020. He was the mentor and trusted advisor for so many researchers working in eastern DRC. He was also a dear friend.

This dissertation is dedicated to his memory. I hope it contributes in some small way to the ideals that JP devoted his professional life to: using the tools of social science to promote peace.

ACKNOWLEDGMENTS

I'm from New Jersey. And not just from New Jersey – I'm from the Jersey Shore. I am therefore required to cite Bruce Springsteen lyrics for any major life event. As I try to express my feelings about this dissertation and finishing graduate school, a line from Thunder Road seems especially appropriate: "You ain't a beauty, but hey, you're alright."

The process of conducting the research and writing the papers in this dissertation has been full of stops and starts. Through it all, I was lucky to have a supportive research community at the University of Michigan, my academic home since my sophomore year of college. In particular, I am grateful to my dissertation committee, Christian Davenport, Mai Hassan, Chris Fariss, and Anne Pitcher, who are equal parts mentors and friends. I'm also grateful to a number of faculty members at Michigan who, while not formally on my dissertation committee, were instrumental in my training and provided crucial feedback at various stages: Jim Morrow, Mark Tessler, Justine Davis, Noah Nathan, Mark Dinecco, Iain Osgood, Allen Hicken, Brian Min, Raghnild Nordas, Scott Tyson, Nahomi Ichino, and Martin Murray.

I am at the finish line because of Mai Hassan. Mai took me under her wing after my first year of graduate school when I lost and trying to reinvent my research agenda into something vaguely resembling her work. Since then, Mai has been the best and most patient advisor, co-author, and friend a graduate student can ask for.

Christian Davenport has been my mentor since I took his class as an undergraduate still thinking I would become a lawyer. He has demanded careful work with purpose ever since. Christian's unwavering commitment to using the tools of social science to address the world's most pressing issues – not necessarily the issues that lend themselves to the fanciest research designs – is a model for my own work.

Chris Fariss helped convince me not to quit graduate school. I (think? I) thank him for that. Especially as the dissertation and my job search kicked into high gear, Chris kept me on track, convinced me that what I had was plenty, and helped me see the light at the end of the tunnel. He has always been willing to talk through an idea or an empirical problem, no matter how small or early on in the research process. The research in this dissertation is much better due to his input. And I'm a much more sane person thanks to his friendship.

Anne Pitcher was instrumental in getting my dissertation out of a rut and across the finish line, especially as I started – and then promptly stopped – working in South Africa. She also consistently provided good advice, perspective, and resources as I finished my dissertation. I'm grateful for her friendship and support.

I was lucky to endure the PhD program with friends and colleagues who ensured I was always aware of the absurdity of our career choices. Nick Carney was the colleague most directly responsible for reminding of this and I can't imagine a better friend and roommate to have gone through grad school with. Todd Lehmann and Corina Simonelli's willingness to talk about anything other than political science and Deanna Kolberg's readiness to grab a drink and complain about field work also played a crucial role in my getting to the finish line. Peter Carroll and I wrote our dissertations out loud with each other over tacos at Chelas (and then over Zoom once COVID-19 barred us from getting tacos). Jessica Sun has been my collaborator, office mate, and friend since our first year. I was also lucky to be on this ride with the entire Talibova family – Roya, Ayaz, Ahu, and Araz.

The CPRD group at Michigan is far more than a workshop for me: it has been my home base throughout my time in grad school. A version of each chapter in this dissertation was workshopped at CPRD. I thank the CPRD community, and in particular Meredith Blank, Kiela Crabtree, Hojung Joo, Tim Jones, Rebecca Savelsberg, and Carly Wayne, for their feedback and friendship.

I have also been lucky to benefit from a long-term collaboration with Patrick Vinck and Phuong Pham. Our collaboration has taught me much about how to be a researcher promotes the voices that are often ignored in the processes I write about. The third paper is co-authored with Patrick, Phuong, Anupah Makoond, and Kennedy Bindu and Patrick and Phuong generously allowed me to analyze the survey data for the second paper.

Financially, the research in this dissertation was supported by the Weiser Center for Emerging Democracies, Department of Political Science Director of Graduate Studies Research Fund, the South African Research Initiative Office, International Institute Fellowship Program, the African Studies Center, and the Center for Political Studies' Roy Pierce Award at the University of Michigan.

I put my family through a lot in pursuing this PhD. My mom especially endured sleepless nights as she worried about me in DRC, Kenya, and South Africa. Even when I wasn't doing field work, she worried about my bank account's precarious situation for the past six years. Sorry mom! My siblings Sean, Kelly, and Leigh Anne and my sibling-in-laws, Sarah and Billy, provided emotional support, although the consistent buzzing of the family group chat may have delayed the completion of the dissertation by a few months. The Arnold family took me in with open arms and generously never asked how my dissertation was going. Nala always sensed when I was working too hard and provided emotional support as I wrote the dissertation. She's the best and most injury prone dog there ever was.

I fell in love twice during grad school: first, with the type of field work that this dissertation is based on, and second, with Carolyn. These loves managed to co-exist thanks to Carolyn's patience, understanding, and support. She moved to Ann Arbor so that I could finish this quixotic adventure the right way and has put up with me disappearing for months, working far too many hours, and my side of the Skype call consistently dropping. Despite these unreasonable circumstances, Carolyn is always supportive and full of love. Thankfully – and finally – we can move on to the next step in our lives: married and me having a real job.

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ABSTRACT

This dissertation is a collection of three manuscripts that sequentially unpack the complicated, often contradictory relationship between local political order and security in ongoing conflicts. I unpack these relationships in papers that explain the perspective of armed groups, civilians, and international interveners, respectively.

In the first paper, I examine the consequences of variation in armed group relations for spatial patterns in violence by re-examining the relationship between mines and violence. A large body of research shows that natural resources increase the likelihood of violent competition in resource-rich regions, but at the local level, mines and violence are not correlated. I explain this puzzle by providing a theory of spatial discontinuities in revenue generation in resource-rich conflict zones. Protection rackets and incentives for cooperation limit violence at points of extraction but access to informal taxation opportunities on the transportation network incentivize conflict. Only price shocks upend the armed groups' incentives to cooperate at the mines. My findings explain why natural resources incentivize cooperation locally while still destabilizing the region.

In the second paper, I ask whether protection rackets improve civilian perceptions of their security? I argue that informal, exploitative security arrangements improve civilian perceptions of their security when the community in which they live have recent experience with banditry, which increases local demand for protection, and when the armed actors institute routinized tribute schemes, which while extortive and costly to civilians, provides highly valuable predictability to both the armed actors and civilians in contrast to roving banditry. I empirically evaluate my theory using responses to an original survey in eastern DRCongo, where state absence created privatized local protection rackets, which I pair with fine-grained data on violence and the location and operators of roadblocks. These results demonstrate how local security vacuums can produce exploitative informal institutions that undermine macro state-building projects while paradoxically providing crucial protection to vulnerable civilians.

In the third paper, co-authors and I present and empirically evaluate a theory of civilian perceptions of international peacekeeping missions. We argue that civilians exposed to the mission are more likely to perceive the mission as successful. We find support for our theory leveraging over 16,000 responses to surveys across two waves and two sampling strategies in three provinces of the Democratic Republic of Congo, where one of the world's largest and longest standing peace-

keeping missions, MONUSCO, operates. We show that exposure to MONUSCO is associated with improved perceptions of the mission, and that this relationship is not driven by selection effects. We additionally show that base closures, which abruptly decreased civilian exposure to Blue Helmets locally, are associated with decreased perceptions of the mission. Our findings suggest that missions can improve their relationships by increasing their visibility among host communities.

Combined, the articles in this dissertation represent a research agenda focused on understanding how security provision is provided and manipulated at the local level. It does so by analyzing dynamics from the bottom up and discusses the implications for human security, patterns of violence, and international policy.

CHAPTER 1

Introduction

1.1 Motivation

When the state does not or cannot maintain and enforce political order,[1] how do civilians, armed groups, agents of the state, and the international community interact to stabilize political, economic, and social conditions locally? Even in contexts of state retreat and ongoing violence, informal institutions [70] implemented by a range of state and non-state actors enable predictable interactions and relatively stable conditions locally [125, 109, 149, 2]. How do these arrangements come about and what are their implications for patterns of political violence, civilian security, and peace-building efforts?

This dissertation provides answers to these questions by presenting three research papers that sequentially unpack the complicated – and sometimes contradictory – relationships between the illicit political economy of the conflict that sustains armed groups, civilian perceptions of security, and the efficacy of international interventions to protect civilians in ongoing conflicts.

In the absence of a centralized state providing security and overseeing markets, the means of coercion is the most valuable political and economic asset. In such environments, civilians[2]

[1]The labeling of such contexts is contested. Some reject the idea of a "failed" or "failing" state and prefer "hybrid orders," "limited statehood," "mediated states", or "fragile/weak states" [112, 128]. While such definitional debates are beyond the scope of this dissertation, my focus in this dissertation is on national or sub-national political contexts in which the state chooses not to or lacks the ability to maintain the monopoly on the legitimate use of force and "lacks the ability to implement and enforce rules and decisions" across all or portions of its territory [128]. In addition, I focus on contexts where the state is unable to vertically control large elements of the state apparatus – a core distinction between weak states and failed states. Although the phenomena are closely linked, such conditions should not be conflated with the presence of political violence and conflict, as even states without ongoing conflict have uneven administrative capacity across time and space [23].

[2]Civilians are defined as "those who are not full-time members of an armed group" [86].

prioritize protection from those who wield unaccountable coercive power. But the central dilemma in such contexts is that to obtain protection from such armed actors, civilians must rely on precisely the groups who posed a threat to them in the first place. Armed actors leverage their coercive capacity to further their economic and political interests by participating in illicit economies and by extorting civilians in exchange for protection [53, 111, 10].

In particular, the papers in this dissertation theorize and empirically evaluate the conditions under which *security provision* arises to better understand the origins of local political order in ongoing conflicts, as well as the implications of various mechanisms that sustain security provision arrangements. Security provision occurs when armed actors – including non-state armed groups and state agents such as factions of the military and police – choose to use their coercive power to protect civilian populations from violence that other groups may inflect on them.

While it is the *de jure* responsibility of the state to provide security, agents of the state apparatus – the military and police, for example – are often too weak to deter non-state actors from using violence and are frequently sources of instability and abuse against civilians themselves [37, 38, 39]. "Hybrid governance," [109] in which non-state armed groups or elements of the state privatize their coercive power to provide the essential functions of the state [137], can fill the gap when the state does not fulfill (or actively undermines) such core responsibilities. Similar dynamics have been observed when mafias [53], gangs [98], and rebel groups [106] provide public goods, including security. As a result, security provision is not incompatible with – and indeed, as this dissertation will show, in certain circumstances intimately connected to – other forms of abuse, such as extortion.

The decision for armed actors to provide security is a strategic calculation rooted in the *local political economy of the conflict*. Armed actors face a number of trade-offs providing security to civilian populations. Maintaining territorial control requires navigating a web of connections at the local level. Armed groups must rely on these connections to generate consistent revenue [76] if they intend to continue controlling the territory. If they simply use coercion to extract, the population will undermine the productivity of the territory [144, 115].

When controlling territory, armed groups must thus navigate and sustain connections including (but are not limited to) civilians, the natural environment, economic markets, and other armed groups. Various forms of co-dependence among the actors incentivize armed actors to provide security [83, 92], but these incentivizes and not necessarily consistent over space or time. In certain circumstances, armed groups are incentivized to protect the civilian population and cooperate with other armed actors; in others, they are incentivized to use violence and abuse civilians.

Finally, effective security provision is rooted in *perceptions*. While it is possible to provide protection from external threats without civilians perceiving themselves as more secure, unless provision is translated to perceptions, the informal institutions described in this dissertation are unstable. Likewise, while international interventions may successfully mitigate the highest levels of political violence and civilian targeting [79, 68], civilians must perceive these improvement for them to update their behaviors accordingly.

To understand how these incentives to provide security vary and the observable consequences of security provision when it does occur, I argue that it is crucial first to clarify the mechanisms that connect armed groups to specific areas, such as methods of collecting taxes and tribute, access to natural resources and the labor required to extract them, and the extent to which security providers are visible to the communities they protect.

After establishing what these connective mechanisms look like, each chapter then answers specific questions that unpack the consequences of specific mechanisms of security provision. For example, how specifically do armed groups raise funds to sustain their efforts and how do these efforts vary over space? Does variation in these efforts influence armed group behavior towards civilians and other armed groups? How do civilians in local communities where these processes occur perceive their surroundings and do these informal protection arrangements improve their sense of security? And what role do international interveners play at the local level and how are they perceived by civilians?

In answering these questions, I explain why natural resources shape armed group revenue generating schemes differently over space, thereby creating different spatial incentives for cooperation between rival armed groups and for armed groups to protect civilians (Chapter 2), why different armed group taxation schemes differentially influence civilian perceptions of security (Chapter 3), and how civilians perceive UN peacekeepers who operate in the communities (Chapter 4).

These findings challenge dominant theories of political order in conflict zones and armed group behavior. Conflict is most often theorized as a struggle between rebels and the state for control of the state [49], but in reality most contemporary civil conflicts are much more "complex and ambiguous" [85] political and economic ecosystems. Non-state armed groups often fight one another for control of finite pools of conflict resources more frequently than fighting the state directly [178]. The (implicit) assumption that armed groups are competitively vying for control of the state in a strict insurgency/counter-insurgency struggle misses important spatial variation in how armed groups – including both state and non-state armed groups – interact with each other, the natural environment, and civilians. My research, and in particular Chapters 2 and 3, attempt to highlight the complexity and fluidity of relationships between the various actors in ongoing conflicts, thereby advancing a nascent research agenda on "armed politics" [149, 150].

In addition, I add to literature that seeks to better understand how civilians experience and navigate zones of conflict and violence. A growing body of work shows that, in contrast to common assumptions, civilians are not merely passive observers or wells of information [86] who have violence done to them [82]. Instead, civilians have agency to negotiate with and influence the behavior of armed groups [87, 41]. As Lyall, Blair, and Imai (2013) argue, "civilian attitudes may represent a substantial omitted variable in most statistical accounts of civil war dynamics" (696). I work to advance our understanding of how civilians negotiate with and perceive armed actors by theorizing why civilians evaluate an armed actor in an ongoing zone of violence positively or negatively, including both the state and non-state actors (Chapter 3) as well as international interveners (Chapter 4).

My analysis is rooted in three case studies of the Democratic Republic of Congo (DRC or DRCongo). Focusing on this single case enables an increased focus on internal validity while also speaking to core themes in comparative politics and international relations [118]. I leverage a number of unique characteristics of the political-economy of the conflict in eastern DRCongo to isolate the conditions under armed groups choose to provide and whether civilian perceptions are and are not influenced by security provision locally. These distinctions are crucial to properly understanding core relationships in the political economy of conflict. Existing theory suggests that minerals can distort armed group behavior by making the group reliant on mines and not civilians for financial support [172], for example, but the mechanisms through which armed groups actually collect and use the money to decouple themselves from the population are unclear [107]. In specifying these mechanisms and analyzing their consequences, I demonstrate that there is more fluidity and heterogeneity than commonly assumed in how resources impact armed group incentives towards civilians and other armed groups and show there is variation in how civilians perceive protection arrangements.

In addition to these core theoretical contributions, each paper in the dissertation seeks to make purely descriptive advances to the study of conflict. I aim to stay empirically grounded in lived experiences and local realities by developing our understanding conflict systems from the bottom-up instead of from the top-down. By providing granular details on how political actors are connected and behave at the local level, I add nuance to often reductive portrayals of the relevant actors in contemporary conflicts.

Doing so is substantively important but requires analyzing difficult-to-capture dynamics with existing data. Methodologically, I thus combine a series of micro-level spatial datasets that enable me to capture and evaluate conflict dynamics and perceptions at the local level. The research strategies employed throughout the dissertation are developed inductively [181] based on insights and observations from fieldwork and in-depth case knowledge. Where possible, I pair the observational data presented in these projects with quasi-experimental research designs to approximate casual effects. That said, causal identification is not always possible and experimental treatments are both unethical and impractical with the substantive topics I study. As a general rule, I triangulate among a series of empirical strategies in each project and discuss the limitations of each transparently.

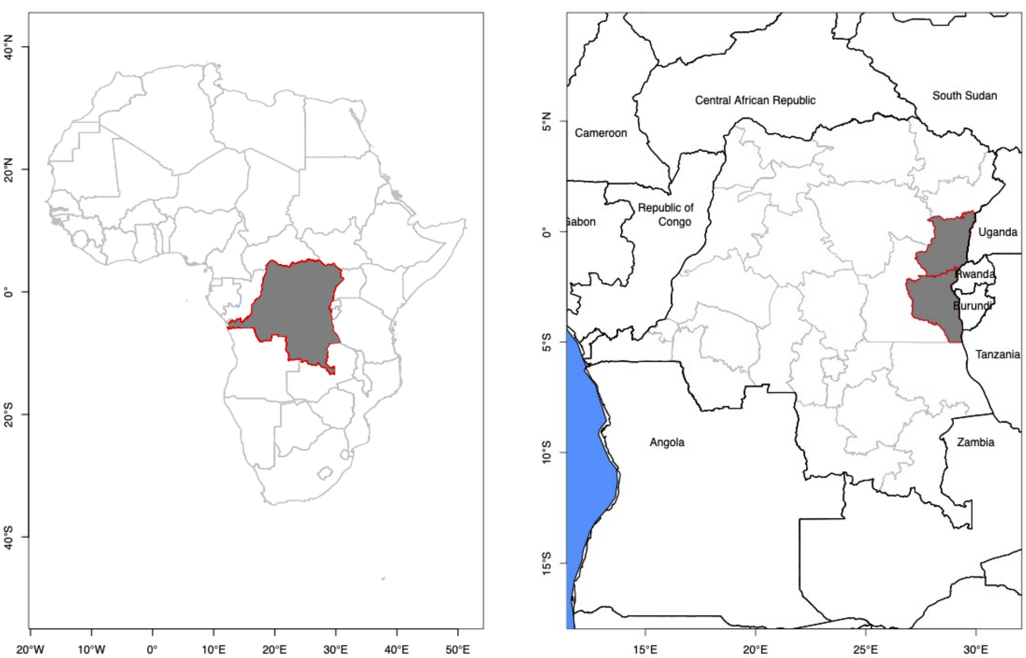
Finally, the projects in this dissertation are a representation of my broader research agenda in several ways. Each paper seeks to make theoretical advances by cutting across disciplinary boundaries between comparative politics, international relations, and public policy. My broader research agenda offers a similarly substantively and methodologically diverse set of projects that probe different elements of local security provision and political violence. For example, in co-authored work with Mai Hassan, I published two papers (in the *Journal of Peace Research* and *Governance*, respectively) on the management of the Kenyan security apparatus at the local level. In these projects, we study who the state trusts with coercive power at the local level under its security provision mandate, thereby politicizing the state [66] and undermining reform efforts [67]. Expanding on my interest in human security, collaborators and I are also advancing a parallel line of research on the consequences of forced displacement. Combined, my work seeks to build a body of evidence that creates new understandings of security provision, conflict dynamics, and political order.

1.2 The Democratic Republic of Congo as a Case

The empirical focus of each of the three papers in this dissertation is the web of ongoing conflicts in the eastern Democratic Republic of Congo (DRC or DRCongo).[3] DRC is the largest country in sub-Saharan Africa, covering roughly the same landmass as Western Europe. Often cited as an example of a "failed state," the Congolese government exerts limited control in the eastern provinces. I display the DRC's national borders in Figure 1.1 and the borders of the Kivu provinces in Figure 1.1b.

Congo is one of the poorest countries in sub-Saharan Africa and thus in the world. In 2018, the World Bank estimated that 73% of the Congolese population – roughly 60 million people – live below the international poverty rate of less than $1.90 a day [180]. DRC ranks 175 out of 189

[3]DRCongo was previously called Zaire. Joseph Mobutu declared himself president in a November 1965 coup, changed his name to Mobutu Sese Seko and the name of the country to Zaire. It was reverted to Democratic Republic of Congo in 1997 after Mobutu was toppled by Laurent-Désiré Kabila, a name it has held since.



(a) The Democratic Republic of Congo (b) North and South Kivu Provinces

Figure 1.1: Area of Analysis

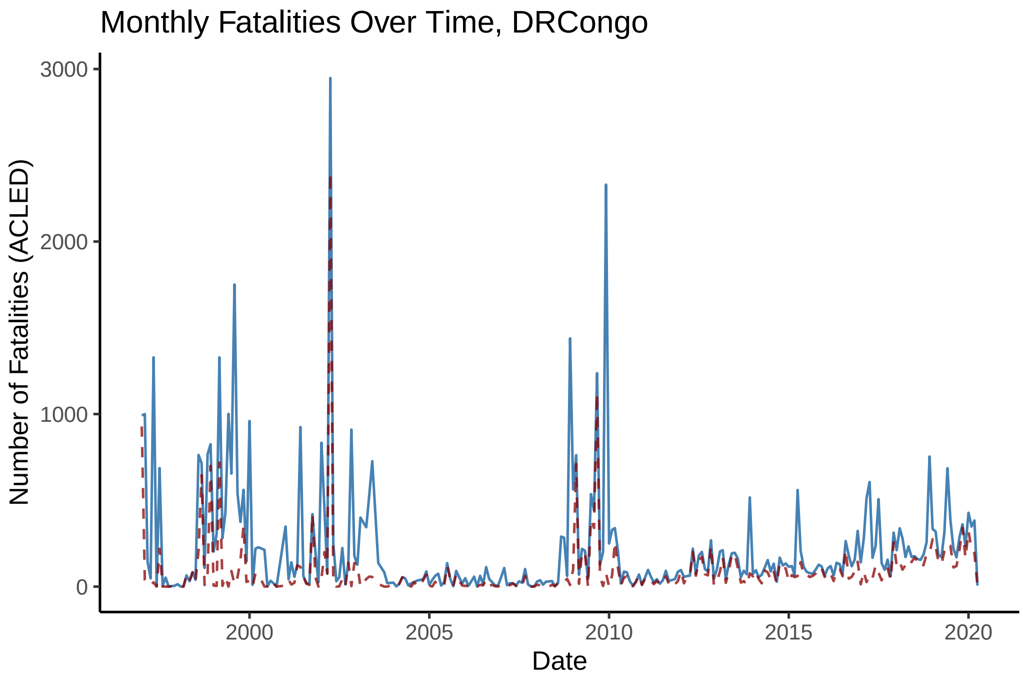
countries on the 2020 Human Development Index [179]. State institutions collapsed under the rule of former President Mobutu, who established a highly kleptocratic system that encouraged state employees to use their power to extract their salaries from civilians since the state would not pay them [183].

Congo is additionally one of the most violent countries in the region and the world, with the Kivus as the main epicenter of the conflicts. I plot monthly fatality in DRC since 1997 in Figure 1.2. Although the violence reached its peak during the First (1997-1997) and Second (1998-2003) Congo wars, these plots show that political violence continues in the Kivu provinces in particular [3].[4] One of the world's most acute and longest running humanitarian crises, more than half the population in eastern DRCongo has never experienced life without some degree of violent conflict [168]. At least 120 different armed groups were actively operating in 2017 in North and South Kivu alone [168] compared to 70 in 2015 [153], highlighting the rapid escalation in armed group proliferation and the inability of the state to control challenges to its monopoly on the use of violence in recent years. I show these provinces in Figure 1.1b. The Kivus are thus not representative of broader trends in Congolese politics. Instead, I focus on the Kivus precisely because they are outliers. The extent, duration, and longevity of its political economy of violence, which allows me to understand how such political economies perpetuate themselves.

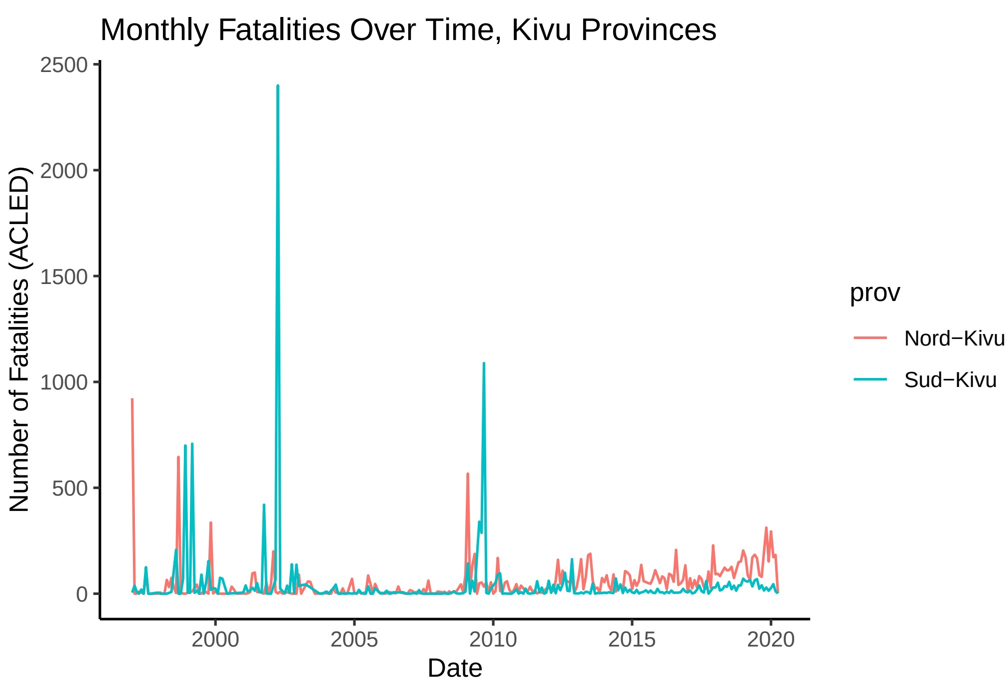
1.3 Plan for the Dissertation

In the remainder of the dissertation, I present three papers which iteratively unpack the local political economy of security provision in eastern Congo before concluding with a general discussion of the implications of my findings. Each individual paper is meant as a stand-alone project, but, as discussed above, they are united thematically, methodologically, and geographically.

[4]These levels of poverty and political instability are driven by a series of political crises dating back to the slave trade and colonialism. The area that became DRCongo was an epicenter of the slave trade and subsequently an especially brutal and extractive Belgian colonial rule [75]. DRC gained independence from Belgium in 1960 but has continued to experience mismanagement and political turmoil in years since. Three autocratic regimes in particular (Mobutu, Kabila, and Kabila Jr) oversaw the hollowing out of the Congolese state in the post-independence era [182, 183].



(a) DRC



(b) Kivus

Figure 1.2: Historical Trends in Violence in DRC and the Kivus (1997-2020, per ACLED)

In Chapter 2, I examine the consequences of variation in armed group relations for spatial patterns in violence by re-examining the relationship between mines and violence. A large body of research shows that natural resources increase the likelihood of violent competition in resource-rich regions, but at the local level, mines and violence are not correlated.

I explain this puzzle by providing a theory of spatial discontinuities in revenue generation in resource-rich conflict zones. Protection rackets and incentives for cooperation limit violence at points of extraction but access to informal taxation opportunities on the transportation network incentivize conflict. Only price shocks upend the armed groups' incentives to cooperate at the mines. My findings explain why natural resources incentivize cooperation locally while still destabilizing the region, unifying several seemingly contradictory findings into a coherent framework.

In Chapter 3, I shift from analyzing armed group behavior to assessing civilian perceptions and ask under what conditions civilians perceive armed groups as improving their security. I argue that informal, exploitative security arrangements improve civilian perceptions of their security when the community in which they live has recent experience with banditry, which increases local demand for protection, and when the armed actors institute routinized tribute schemes, which while extortive and costly to civilians, provides highly valuable predictability to both the armed actors and civilians in contrast to roving banditry.

I empirically evaluate my theory using responses to an original survey in eastern DRCongo that captures civilian perceptions of security and participation in various protection racket tribute schemes. I pair the survey responses with fine-grained data on violence and the location and operators of roadblocks. These results demonstrate how local security vacuums can produce exploitative informal institutions that undermine macro state-building projects while paradoxically providing crucial protection to vulnerable civilians.

In Chapter 4, which is a co-authored paper with Patrick Vinck, Anupah Makoond, Kennedy Bindu, and Phuong Pham, I analyze the dynamics of an international intervention into an ongoing conflict, focusing on civilian perceptions of the United Nations Peacekeeping mission in the Democratic Republic of Congo, MONUSCO. We argue that civilians exposed to the mission are more likely to perceive the mission as successful.

We find support for our theory leveraging over 16,000 responses to surveys across two waves and two sampling strategies in three provinces of the Democratic Republic of Congo, where one of the world's largest and longest standing peacekeeping missions, MONUSCO, operates. We show that exposure to MONUSCO is associated with improved perceptions of the mission, and that this relationship is not driven by selection effects. We additionally show that base closures, which abruptly decreased civilian exposure to Blue Helmets locally, are associated with decreased perceptions of the mission. Our findings suggest that missions can improve their relationships by increasing their visibility among host communities.

Finally, I conclude by tying the findings in the three papers presented in the dissertation together (Chapter 5) and suggesting directions for future research in the Conclusion.

CHAPTER 2

Mines and the Road to Violence: The Geography of Revenue, Cooperation, and Competition in Resource-Rich Conflicts

Abstract

A large body of research shows that natural resources make territory more valuable, increasing the likelihood of violent competition in resource-rich regions. But at the local level, mines and violence are not correlated. I rationalize this puzzle by providing a theory of how different stages in the supply chain that takes minerals to international markets structure incentives towards other armed groups and civilians that vary across space. At points of extraction, protection rackets and cooperation between rival armed groups decrease violence. Only price shocks upend the armed groups' incentives to cooperate at the mines and concentrate violence at the point of extraction. But armed groups fight for less stable, informal taxation opportunities at key nodes transportation network. I find support for my theory analyzing fine-grained geo-spatial data on the control of mines and taxation opportunities on the transportation network in eastern Democratic Republic of Congo, which I pair with a new dataset on violence and exogenous fluctuations in global demand for minerals. My findings explain why the presence of natural resources incentivize cooperation locally while still destabilizing the region, unifying a number of seemingly incongruous findings on the association between resource abundance and violence into a coherent framework.

2.1 Introduction

Conventional wisdom holds that natural resource endowments make territory more valuable [48], increasing the likelihood of violent competition in resource-rich regions [26, 102] as armed groups compete to control and thus profit from them [16, 35].[1] While there exists a large body of research confirming the existence of this relationship at the regional level, the relationship between resource endowments and violence is less clear at the micro-level. The specific mechanisms connecting resource endowments and violence are contested [81] and some have gone as far as to argue that the observed relationship between mines and violence represents an ecological fallacy [108]. In the eastern Democratic Republic of Congo – a paradigmatic example of armed groups using natural resource endowments to fund their activities and fuel violence – only 3% of violent events happen in direct proximity of a mine and less than a quarter of violent events occur within 20km [152].

If resources make territory more valuable, thereby increasing violent competition between armed groups, why are points of extraction not the sites of violent competition themselves? In this paper, I explain why these seemingly contradictory patterns are not mutually exclusive. I rationalize this puzzle by theorizing why resource endowments alter armed group incentives differentially by creating variation in how armed groups raise revenue across space. In particular, I describe why cooperation prevails at points of extraction, dis-incentivizing violence, whereas competition for control of key nodes incentivizes violence on the transportation network. A more nuanced understanding of the role that each stage of the extraction and transportation process plays in armed group revenue generating schemes [107] clarifies why the presence of mines can increase violence in the aggregate but why points of extraction themselves only experience violent competition under specific conditions.

My theory is rooted in the simple but frequently ignored observation to profit from resource endowments, armed groups or other illicit actors must pass those goods through the supply chain to

[1] In this paper, I define armed groups as both state and non-state armed groups who wield coercive power to control territory. Most existing work focuses on a binary competition between the state and rebel groups, but this paper focuses on more complex illicit economies in which both state and non-state armed groups participate. Elements of the state military are often as involved in the minerals trade I describe as non-state groups and thus have similar incentives. Additionally, two or more rebel groups often fight each other in addition to their competition with the state.

international markets [83]. This process requires the goods to travel over space, a process that creates multiple revenue generating opportunities for actors operating throughout the region. These revenue generating opportunities shape incentives for armed groups to compete or cooperate with each other as well as to use violence or refrain from using violence against civilians. The resource extraction process and the resulting relationships between the armed group controlling the resource and civilians in the vicinity of its extraction incentivize cooperation and dis-incentivize violence. Exogenous shocks change the incentives armed groups and thus their relationships with civilians and with each other. The transportation process to international markets and the resulting relationships between the armed groups controlling different parts of the country incentivize competition and violence.

To empirically evaluate this theory, I conduct a micro-level study of the Kivu provinces in the eastern Democratic Republic of Congo, where more than 100 armed groups (including factions of the state military) actively participate in and financially benefit from the region's large artisanal mining sector [153]. By looking at local variation within a single case, I can hold macro-level factors constant, such as institutions [104, 129] or international interventions [154], that may mediate the relationship between minerals and violence. Combining fine-grained geospatial information on the mining sector, the transportation network, and violence throughout the Kivus into grid-cells, I create both cross-sectional datasets to analyze aggregate trends and a panel dataset that incorporates exogenous variation in global demand for minerals to explore temporal variation.

Using spatial autoregressive models to capture spatial dependencies in the political economy and violence, I find consistent support for my theory. Grid-cells with mines and their neighbors are not more likely experience violence in aggregate. Indeed, in areas where multiple armed groups are present, mines are negatively correlated with levels of violence between groups. Only rapid changes in the value of controlling the point of extraction concentrate violence in the direct proximity of the mines. Instead, violence is concentrated around key nodes of the road network minerals must pass through to get to international markets. In contrast to the findings at the point of extraction, areas where multiple armed groups compete for taxation opportunities on the transportation network are especially likely to see higher levels of violence.

My theory and findings advance a series of interconnected strands of research in political science, political economy, and political violence. Existing theory suggests that resource endowments distort armed group behavior by making the group reliant on mines and not civilians for financial support [172]. But the mechanisms through which armed groups actually collect and use the revenue from the minerals trade to decouple themselves from the population are unclear [107]. I demonstrate that there is more heterogeneity than commonly assumed in how resources impact armed group incentives towards civilians and other armed groups across space and specify the connection between stages of the supply chain and spatial concentrations in violence and cooperation. In doing so, this paper refines our understandings of the mechanisms that connect resources, revenue, cooperation, and violence.

In doing so, I add to a growing research agenda that highlights the complexity and ambiguity of political order in ongoing conflicts [85, 149]. Civil conflicts have traditionally been studied through a dyadic lens in which a single, unitary rebel group challenges the state using violence [49]. In reality, civil conflicts encapsulate a complex web of actors participating in political economies with a broad variety of political behaviors ranging from violence to cooperation [106, 28, 150, 72, 83]. I add to this work by showing why natural resources can incenvitize behavior on both extremes of the cooperation-conflict continuum within the same region and time.

Finally, I make a purely descriptive empirical contribution: I bring together a sufficiently granular dataset to demonstrate that despite the robust macro-level relationship between mining and violence, localities with mines are not more likely to experience violence. By clarifying these empirical patterns and explaining their connection to armed group revenue generation strategies, I unify a number of strands of theory on minerals-conflict nexus into a single coherent framework. I explain why it can simultaneously be true that the presence of minerals are correlated with higher regional levels of violence [16], that mines are not themselves correlated with violence locally [108, 92], that price shocks increase violent competition to control mines [137], and that armed groups can cooperate in some times and areas while fighting in others [72].

The rest of the paper is broken into 4 sections. In Section 3.2, I first describe the incentives that armed groups have to protect civilians in areas directly surrounding mines, to compete for access to lucrative taxation opportunities on trade routes, and to tacitly collude to keep mines productive. I then explain how these incentives structure the spatial distribution of the violence in resource-abundant conflict zones. In Section 4.3, I motivate my case selection and present background information on the artisanal mining sector in eastern Congo. In Section 2.4, I describe my data and methodological approach before presenting my results in Section 3.6. Finally, in Section 2.6, I conclude with a discussion of my findings and their policy implications.

2.2 The Geography of Revenue, Cooperation, and Violence in Resource-Rich Conflicts

In this section, I outline why different stages in the process that takes minerals from the point of extraction to international markets differentially structure incentives towards other armed groups and local civilians, thereby influencing the spatial distribution of cooperation and violence between groups and with civilians. I summarize the incentives and their empirical implications in Table 2.1.

My theory has a number of important scope conditions. First, I explain patterns of violence in ongoing multi-party conflicts with illicit economies, not the role that illicit economies or minerals play in starting conflicts in the first place.[2] Second, I assume an institutionally weak context where natural resources are illicitly extracted, taxed, and transported to international markets. I do not explain spatial variation in violence in more industrialized conflict zones, for example. Finally, I explain dynamics in conflict zones where multiple armed actors operate and seek generate revenue, not in binary civil wars where a rebel group fights the state for control. Although civil conflicts are traditionally studied in such a binary framework, the empirical reality of most contemporary civil conflicts is more accurately represented by the more complex context I describe [86, 178].

[2]A large body of research examines the role that resource abundance plays in conflict initiation. See Ross (2006) for a summary of this work.

A diverse set of conflict economies fit within these scope conditions. For example, UNITA rebels and state army officers were reported to have a gentleman's agreement to exploit diamonds on each bank of the river in the Cuango Valley in Angola's civil war [96]. The incentives and patterns I describe are not simply restricted to natural resources: illicit drug trafficking creates similar spatial variation in incentives for cooperation and conflict. Consistent with my theory, Idler (2020) describes how spatial variation in cocaine supply chains create incentives for cooperation at production sites while creating incentives for conflict at strategic trafficking nodes in Colombia. Additionally, Meehan (2015) illustrates that in Myanmar belligerents often forge stable arrangements related to the illicit opium trade.

2.2.1 Protection and Cooperation at Points of Extraction

2.2.1.1 Protection Rackets at Extraction Sites

Armed groups require revenue to sustain their fight and to provide public goods to their constituencies [106]. When a group controls territory, they typically generate revenue by taxing the population living in the territory they administer [99]. Existing theory posits that controlling territory with natural resource endowments can distort the need for taxation as the main form of revenue and decouple armed groups from civilians [173]. In first stage of the supply chain, though, armed groups must cultivate or extract the natural resource. To do so, armed groups rely on civilian labor pools.[3]

Reliance on civilian labor provides communities around the point of extraction leverage over armed groups operating in their area. While armed groups can use coercion and force labor, an overly coercive approach risks the labor pool fleeing, working more slowly, or otherwise undermining the productivity of the area [144]. Moreover, if armed groups confiscate all the produced resources, civilians would not have an incentive to continue producing [115]. As a result, armed groups must negotiate with and provide benefits to civilians in the area directly around the re-

[3]Most armed groups do not have access to the capital necessary to industrialize their extraction. When they do, they trade protection to the companies that do the mining in exchange for taxes.

sources they seek to extract. Given the pervasive insecurity in ongoing conflict zones, armed groups trade on their coercive capacity by providing security [10] in exchange for civilian labor and taxes.

When this exchange occurs, the armed group and the population surrounding the resources become intertwined in a protection racket [53, 147]. Armed groups that control points of extraction must provide protection from rival armed groups and minimize the unnecessary use of force against populations that live in the areas directly around points of extraction. To benefit from these arrangements, armed groups build extensive administrative and oversight capacities [137], creating co-dependence between armed groups and civilians and increasing armed group time horizons [11], thereby stabilizes armed group incentives.

At the same time, as with other "markets for extortion," the supply of violence is necessary to create demand for security provision [111]. To ensure the sustainability of demand for their protection and civilian willingness to comply with the armed groups' racketeering behavior, armed groups both provide security and ensure the continued need for their security provision services by using limited violence on the periphery of their protection rackets [92]. Armed groups thus have cross-cutting incentives to both limit violence at the point of extraction while also using limited violence on the periphery to keep civilians reliant on their security provision. Combined, these incentives make produce levels of violence observationally similar to the modal locality within the conflict zone.

H1a In aggregate, the site of extraction is not correlated with violence between armed groups or against civilians.

2.2.1.2 Cooperation Between Armed Groups at Points of Extraction

Despite the strength of the incentives for stable protection rackets at sites of extraction, competing armed groups may have incentives to challenge a rival group's control of production. Especially when pursuing political goals with expansionary aims, armed groups presumably want to undercut rival revenue streams while expanding their own. But in reality, armed groups do not operate under such a zero-sum logic. Instead, belligerents often cooperate in some areas while fighting in others in ongoing conflicts [149]. Natural resource endowments can incentivize such behavior.

Natural resources are associated with longer, more fragmented conflicts [102, 131]. As the length of the conflict extends and the sustainability of revenue generating schemes becomes more important to armed groups, they come to recognize the need to co-exist and cooperate over multiple periods [7]. In such scenarios, armed groups accept that taking a portion of the profit is a worthwhile alternative to fighting for – and potentially losing – monopolistic control. Such a tradeoff requires accepting that other groups also take a portion of the profit from the point of extraction.

If they trust the other group to continue cooperating with them over time, such a trade-off is worthwhile. As armed groups actually cooperate, however, the credibility of their commitments becomes challenged. Illicit resource extraction and conflict economies typically occur in relatively anarchic environments in which "cheating and deception are endemic" [8]. Armed groups must thus find ways to signal the credibility of their commitments to each other without formal institutions.

A "commercial equilibrium" [132] can fill this role and dis-incentivize reneging. Armed groups benefit from stable markets and predictability, which competition and violence at the point of extraction undermines. Rival armed groups instead have a shared interest in maintaining steady extraction, which requires consistent cooperation between the armed groups that operate locally. This cooperation can range from unspoken agreements to not attack each other to outright collusion and profit splitting. Through this shared incentive, the commercial equilibrium produces interest convergence among groups [83] and decreases the attractiveness of expansionary, monopolizing behavior.[4]

As a result, otherwise competitive armed groups refrain from fighting at the points of extraction under normal market conditions. Multiple armed groups – such as a non-state armed group and members of the state security apparatus – can instead share control and profits from a single

[4]Similar patterns of cooperation between rivals are observed in a variety of fields, from international business where rival firms or companies can cooperate when advantageous [103, 184] to evolutionary biology where songbirds can form temporary coalitions with territorial intruders [62].

point of extraction. These arrangements render control over natural resources not indivisible, but rather mutually beneficial, enabling for the formation of long-term relationships and relative stability at the points of extraction [149, 72]. This is even the case in areas where multiple armed groups converge, precisely the contexts existing theory suggests should be most violence. Instead, the overarching incentive between groups at points of extraction under *status quo* conditions is cooperation.

H1b The site of extraction is negatively correlated with violence between groups in areas where multiple armed groups operate.

Stage of the Mineral Trade	Incentive		Violence Expected
	Civilians	Armed Groups	
Site of Extraction	Protection	Cooperation	$-$
Key Transit Nodes	Predation	Conflict	$+$

Table 2.1: Summary of Theory and Cross-Sectional Empirical Expectations

2.2.1.3 The Sustainability of Cooperation

Even though armed groups face strong incentives to refrain from violence and to cooperate at the site of extraction, external influences may interrupt the stability of these incentives. The credibility of commitments to cooperate between groups vary over time based on the value of monopolizing production. As described in Section 2.2.1.2, in status quo periods, cooperation agreements between groups to maintain production allow them to overcome commitment problems. As groups cooperate over time, their commitments become stronger and the relationship more predictable.

But armed groups consistently recalibrate their posture towards other armed groups accordingly. Fluctuations in the global market for the resources shifts over time based on time-varying demand for local minerals, which shifts the value of the resources. Armed groups follow these fluctuations closely as they prioritize controlling resources that enable them to generate more revenue [16].

Changing economic trends can create uncertainty about the incentives other groups have to sustain their commitments to cooperate. When prices swing dramatically, armed group incentives to refrain from fighting at the point of extraction come under strain. Due to the increased value of controlling the mine itself, previously cooperative armed groups may attack each other in direct proximity of the mine to establish a monopoly, set up administrative systems, and benefit financially from monopolizing taxation [137]. Such price shocks also decrease the incentive for armed groups to protect civilians who operate the mines, as armed groups know that the shock is likely short lived and therefore work to extract as much as possible while prices are elevated.

H2 Violence increases at the point of extraction when the value of control fluctuates rapidly due to a price shock.

2.2.2 Transportation, Taxation, and Violence

After resources are extracted, they must be transported on the road network to international markets. Like other illicit markets, once minerals leave the point of extraction, the minerals trade is regulated through a set of informal institutions that determine the costs, quantity, and types of goods that can pass through certain nodes of the transportation network [52].[5] Armed groups and state agents leverage these informal institutions to generate revenue through illicit but widely accepted taxation [139].

This process creates addition revenue generating opportunities for armed groups even if they do not control points of extraction by enabling them to tax the transport of resources at strategic points of the road network. For example, state security forces[6] – which often rely on such illicit taxation opportunities to supplement their own salaries in weak states – and multiple non-state armed groups can control different stretches of the transportation network. If a resource must pass along roads that transverse more than one group's territorial control to reach international markets, it can be taxed by each group.

[5] Similarly, this transportation phase is the most susceptible to looting in oil supply chains [114].

[6] Roads are typically assumed to extend state control [71], but multiple armed groups can control different segments of the road network and use that control to generate revenue and project violence.

The fact that multiple armed groups can benefit from the minerals trade across the transport network may appear similar to the dynamics that create common cause among groups at points of extraction. But two main differences undermine incentives for cooperation on the road network in ways that they do not at the points of extraction.

First, given the relatively limited road network in most situations where illicit economies thrive, the most valuable portions of the road network are especially attractive to control. Such valuable portions of the road network include key intersections where multiple extraction-to-market routes converge and large roads leading to international markets [83], as these are the portions of the road network that the transportation process cannot avoid.

Because of their centrality to the transportation network, controlling such a stretch of road is beneficial for not only the minerals trade and revenue generation, but also for projecting violence [185]. It is therefore both militarily and economically beneficial to control these trafficking nodes. The military value of key road junctures makes them unlikely to be divisible between rival groups over the long-term. As a result, groups more frequently compete to establish monopolistic control over such junctures.

Second, relationships between civilian populations and armed groups are weaker along the transportation network than at the site of extraction. Armed groups who control territory around these junctures can generate large amounts of revenue with a limited spatial footprint and without much demand for labor. Instead, in such contexts armed groups rely on broader "economies of violence" to generate revenue, for example using complementary tactics such as the exploitation of other natural resources (agriculture or timber, for example), pillaging livestock, and looting [95]. When armed groups do not rely on civilian labor for the vast majority of their income, these alternative revenue streams can incentivize more predatory behavior to civilians [173].

In areas directly around the point of extraction, the resource exploitation process provide sufficiently predictable income for stable protection rackets and credible commitments between armed groups to emerge. In contrast, relatively unstable revenue generating opportunities on the road network and more predatory arrangements between communities and armed groups weakens protection prerogatives. Competition between groups is more acute in such areas, as they compete for a limited set of especially strategic junctures. As a result, the transportation process incentivizes higher levels of violence on the road network than at sites of extraction.

H3 The transportation network is correlated with higher levels of violence, especially in areas where multiple armed groups compete for access and at key nodes that minerals must pass through to get to international markets.

2.3 The Mining-Conflict Nexus in the Kivus

I empirically evaluate my theory through a micro case study of two provinces in eastern Democratic Republic of Congo: North Kivu and South Kivu. The Kivus are frequently cited as the prototypical case of "conflict minerals," where armed groups fund their violent activities through the minerals trade. In this section, I provide background information on the nexus of the mining sector, armed group revenue generating schemes, and violence in the Kivus.

Artisanal mining, – or mining done manually with relatively simple tools (i.e. shovels, hammers, and picks) in contrast to industrial, mechanized mining – dominates the economy throughout the Kivus. After former President Mobutu liberalized the mining sector in the 1980s, artisanal mining replaced colonial-era industrial mining companies. As a result, thousands of informal artisanal mines extract a diverse set of minerals in the Kivus today. The most commonly mined minerals in the Kivus are the "3TGs"[7]: cassiterite (for tin),[8] wolframite (for tungsten),[9] coltan (for tantalum),[10] and gold ore. Figure 2.1 displays the spatial distribution minerals and mines in the Kivus in greater detail.

Despite the importance of the mining sector to the economy in the Kivus, Congo is a price taker for each of these minerals. The Enough Project estimates that DRC produces 15-20% of the global

[7]Cobalt is another commonly cited example of a mineral often linked to the violence in DRCongo, but its is not mined in North or South Kivu and is therefore outside the scope of this paper.

[8]Cassiterite is the chief ore needed to produce tin.

[9]Wolframite is an important source of the element tungsten.

[10]Columbite-tantalite ("coltan" is the colloquial Congolese term) is the metal ore from which the element tantalum is extracted.

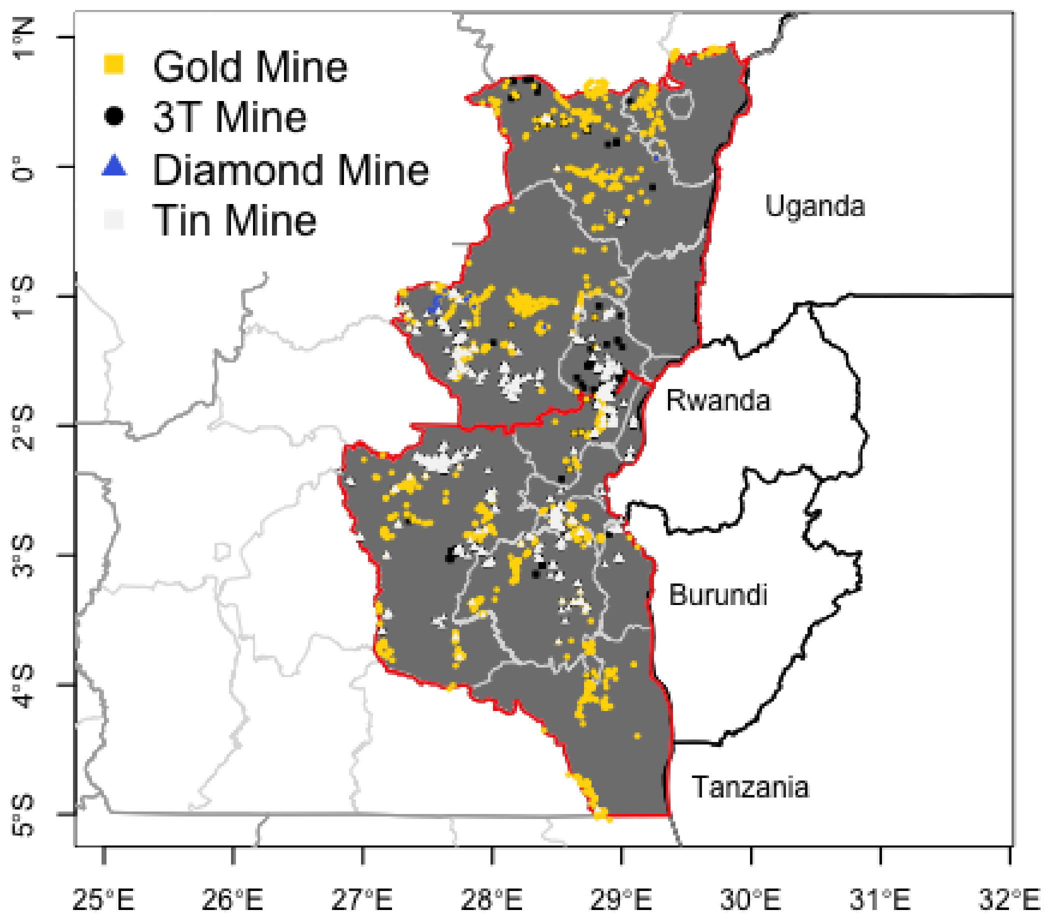


Figure 2.1: Area of Interest. *Territoire* boundaries are shaded in light gray. Geolocations of artisanal mines are plotted and colored by type of mineral. Neighboring country borders are in black and labeled with the country name. Axes represent the latitude and longitude.

supply of tantalum, 6-8% of tin, and 2-4% for tungsten. They further estimates that DRC produces less than 1% of the global gold supply, but gold and tin generate the most local revenue [117].

The operation of these mines are embedded in a complex web of ongoing violent conflicts in the Kivus. At least 120 different armed groups were actively operating in North and South Kivu alone as of 2017 [168]. It is generally accepted that although the mines are not the cause of the conflicts in the Kivus [5], they do help fund armed groups and perpetuate the violence.[11]

Many of the armed groups who are participants in the conflict, including elements of the state military (FARDC), seek to control mines and use revenue from the minerals trade to financially support their military efforts. 98.08% of mines have some level of armed group presence at or around the mine and 78.97% of mines have direct interference (such as illicit taxation or forced labor) by armed groups according to Shouten, Matthysen, and Spittaels (2019). Contrary to many depictions, though, the importance of minerals to the violent actors is not simply a story of minerals supporting rebel groups: 38.45% of mines have FARDC presence and elements of the state military frequently supplement their (lack of) pay by participating in the mineral trade.

Controlling mines is not the only way that armed actors participate in and benefit from the mineral trade, however. The minerals must be transported along the road network to trading sites, where they are then flown to end-destinations to be sold in international markets.[12] The goods are taxed multiple times on the way to these markets by multiple armed groups at roadblocks (*péage route*) [141].

2.4 Data and Research Design

I combine a series of spatial data to evaluate the relationship between the presence of mines, the transportation network, and intensity of violence locally. These datasets are collected independently of each other but overlap in their temporal scope, enabling me to construct a granular picture of the political-economy of the conflicts in the Kivus. I construct both cross-sectional datasets and time series datasets to analyze different components of my theory.

[11]There are many explanations for the conflicts – and indeed, each explanation is contested – but the most commonly cited triggers are some combination of the weakness and inefficiency of state, spillover effects from the Rwandan genocide, ethnic polarization, and domestic and foreign competition for access to the abundant natural resource wealth.

[12]Most of the gold mined in the Kivus goes to East Asia or the Middle East and most metals go to China due to US sanctions (in particular Section 1502 of the Dodd-Frank Act), which regulated the importation of Congolese minerals to the United States by levying fines on companies that cannot ensure the purchase of the minerals do not support armed groups (an effectively impossible standard in eastern DRC [146]).

2.4.1 Grid-cell Construction

To create my units of analysis, I impose a grid over North and South Kivu. Using a grid in this circumstance has a number of advantages over, for example, using administrative unit boundaries, which are drawn at least in part based on ethnic boundaries and therefore endogenous to the violence I analyze.[13] Additionally, constructing small units enables me to capture variation that might otherwise be unobservable within larger administrative boundaries.[14]

The grid-cells are 100 km^2 area[15] hexagonal cells, with 10 km diameters.[16] Using 10km diameter grid cells as the unit of analysis captures variation in local political economies at the granularity at which my theory operates while also respecting the levels at which I trust the accuracy of my data. I aggregate all measures to the grid cell level so that any individual error is unlikely to substantively influence the results.

There are trade-offs in using different geometries to construct grid cells: Square cells are the most commonly used grid structure and the easiest to manage computationally, but I opt to use hexagons as they reduce edge effects by giving the lowest perimeter-to-area ratio of any regular tessellation of the plane [17]. To ensure the modifiable areal unit problem (MAUP) [51] is not driving any results, I replicate my analysis using square grid cells and alternative sized grid cells in the Appendix.[17]

I create two datasets based these grid-cells. First, I create a cross-sectional dataset by aggregating all variables across my temporal scope to the grid-cell level. The dataset is comprised of 1,113 unique hexagonal grid cells, 46.99% of which are in North Kivu, 51.03% in South Kivu, and 1.98% on the provincial border. Then, to account for temporal changes, I create a grid-cell month panel for the period between January 2017 and July 2020, a period of 31 months. By analyzing

[13] Buhaug & Rød (2006) provide further rationale for using grid cells when studying political violence more generally.

[14] Geo-spatial data on sufficiently small administrative boundaries to overcome this challenge are not publicly available for DRCongo.

[15] Cell area decreases at higher latitudes due to the curvature of the earth. Because I am interested in only two provinces and the equator passes through North Kivu, differences in grid cell size due curvature of the Earth is minimal.

[16] I use the formula $A = \frac{\sqrt{3}}{2}d^2$, where A is area and d is diameter, to create hexagons.

[17] Additional details on the grid cells, including information on the differences between the different size and shapes of the cells, is available in the Appendix, Section A.1.

both aggregate and time-varying representations of the violence, I can evaluate both the static and dynamic elements of my theory.

2.4.2 The Minerals Trade in Space

As described in Section 4.3, both the state military and non-state armed groups in eastern DRCongo exploit a large concentration of mines and associated taxation opportunities. I combine information from a number of sources to disaggregate the supply chain that takes these minerals from extraction to international markets. I create a series of measures that indicate the role that specific localities play in the minerals trade. I use these measures as my independent variables, which I summarize in Table **??**.

To measure the presence and control of mines, I use detailed geo-spatial data on the location and control of artisanal mines throughout the Kivus from Schouten, Matthysen & Spittaels (2019). Each observation includes the location of the mine, the mineral(s) mined,[18] whether armed groups are present, and, if so, which group(s) [140].[19] The dataset includes data on 2,328 mines in North and South Kivu, which employ an estimated 382,000 artisanal miners.[20] I aggregate the number of mines within each grid cell.[21] To measure competition for control of the mines locally, I create a binary indicator that notes whether two or more groups control at least one mine within the grid cell or if a mine is controlled by more than one armed group. I alternate between these measures as independent variables when evaluating the direct relationship between points of extraction and violence. As noted in Section 2.2.1.2, I expect local armed group competition is correlated with lower levels of violence between groups.

To measure the indirect relationship between the minerals trade and levels of violence, I also incorporate geo-spatial data on the transportation network and control of roadblocks.[22] I hypothesize

[18] A single mine can produce multiple minerals.

[19] Multiple armed groups can be present at the same mine.

[20] The IPIS mines data is collected by field teams who visit each of the mines throughout eastern Congo at regular intervals.

[21] In the Appendix, I calculate the number of mines per mineral in each grid cell, as different commodities may have cross-cutting implications for the onset of violence [18]. Additionally, I use a binary indicator for the presence at least one mine. Results are consistent when using each of these replacement measures.

[22] Roadblocks, per Schouten, Murairi, & Batundi (2017) are defined as:

that armed groups use violence to compete for strategic nodes of the transportation network.

First, using descriptive network analysis, I create a measure of the centrality of different nodes to the road network. In particular, I calculate the eigenvector centrality of each vertex on the road network to capture the influence of each node in the network. A high eigenvector score means that a node is connected to many nodes who themselves have high scores. Practically, the eigenvector centrality measure captures the importance of the node to the process that takes the minerals from the mines to international markets. I expect the more central the node, the more likely it is to experience violence. I capture the highest centrality value within each grid-cell.

Second, I use information on roadblocks, which are a key source of (illicit) funding for FARDC and non-state armed groups throughout eastern Congo. The coordinates of roadblock is identified and includes information on who controls each roadblock [141, 138]. There are more than 940 roadblocks in North and South Kivu, a staggering number given the limited road network in these provinces. Schouten, Murairi, & Batundi (2017) calculate that there is a roadblock for every 18km of road on average in North and South Kivu. Using the same definition for a competitive environment for the mines, I create an indicator variable for local competition for taxation opportunities along the transportation network.

Finally, to measure the changes in the incentives that armed groups have to control mines [137], I capture the global prices of the commodities that are mined locally. Congo is a price taker for each, so I use global prices for each mineral as exogenous variation in the incentives armed groups have to control mines. In Figure 2.3, I plot monthly variation over 10 years in global prices for the most frequently mined minerals in eastern Congo and shade the period of analysis in gray.

> "A roadblock (or checkpoint) is an obligatory passage point erected by an entity that exercises *de jure* or *de facto* authority over a given road crossing. In addition, the roadblock constitutes a principal inscription of politico-military might in the physical landscape. As a mechanism of taxation, it is light and effective, and deployed by all kinds of "entrepreneurs of imposition" – whether civilian or military, state or rebel. The roadblock itself can take the shape of a barrier, or more discreetly, an improvised roadside chair or grass hut. The roadblock can also be referred to as a "post" because it is a place where agents from within a certain hierarchy have been deployed" (12).

Further information on the data generating process and coding decisions for the roadblocks data are presented in the Appendix.

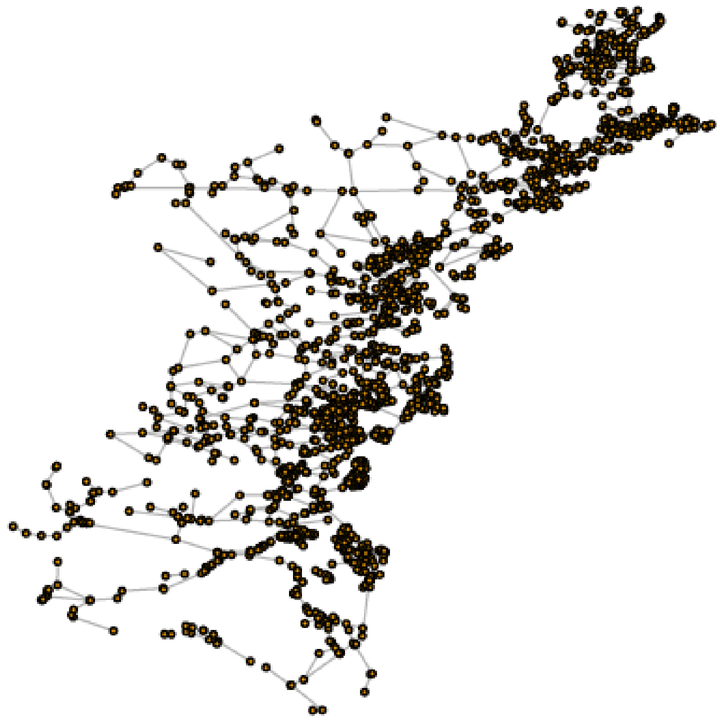


Figure 2.2: Nodes on the Road Network

2.4.3 Measuring Local Violence

Measuring violence in eastern DRCongo is challenging given systematic underreporting of the conflict in media and thus standard event-based datasets [163]. I use new data provided by the Kivu Security Tracker (KST), a Human Rights Watch program that employs a network of researchers throughout North and South Kivu to track and independently verify violent events. Like standard events-based datasets, KST provides information on the location, scale, type, and perpetrators of violence in North and South Kivu.

Events-based data can be biased towards violent events in populated or highly accessible places, which are more visible to news outlets. If violent events near roads are more likely to be reported or if violent events in relatively remote areas – where mines are concentrated – are less likely to be reported, I may observe a potentially spurious baseline correlation with the road network and or miss a correlation between violence with remote locations [170]. KST helps alleviate these concerns by not relying on media based reports of violence, instead relying on a large network of

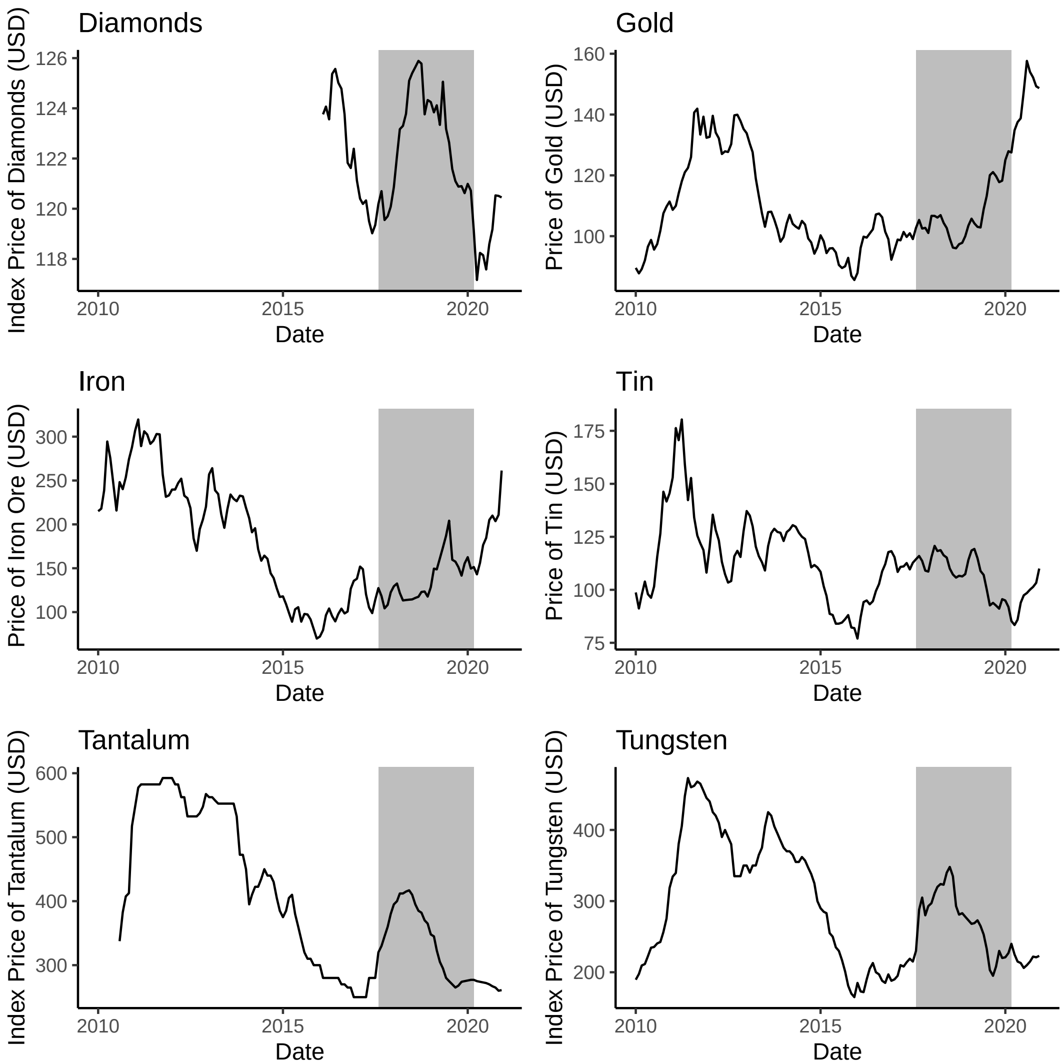


Figure 2.3: Monthly Variation in Prices for Select Minerals. KST Data Coverage in Gray. Data from IMF for gold, iron, and tin. Diamond prices from the Diamond Index. Tungsten and Tantalum data from Bloomberg.

researchers and contacts throughout the provinces. The local expertise, absence of media prerogatives, and representative geographic coverage in the data generating process for KST minimize many of the most acute concerns that are present in more common events based datasets.[23]

As such, I aggregate events to the grid-cell to reduce concerns with reporting bias for individual events. I capture how many Armed Clashes between armed groups occur and how many Looting

[23] Despite these advantages, bias likely remains. As suggested by [36], I run robustness tests in which I only analyze the largest events (top 25%), which are more visible and less likely to be biased according to geography to guard against bias introduced by violent events based data [170, 65]. I also compare KST to other common violent events based datasets in the Appendix, Section A.3.

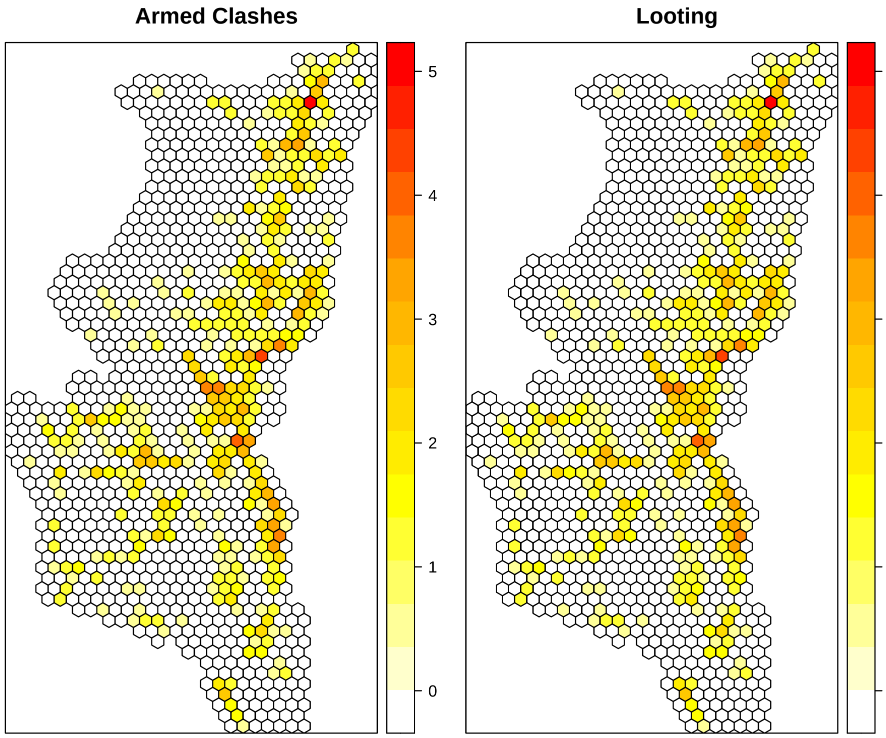


Figure 2.4: Log KST Events Per Grid Cell By Type of Violence

events occur within the cell. Armed clashes are observable manifestations of violent competitions between groups. Looting represents violence against civilians. I analyze these types of violence separately as the target of the violence indicates fundamentally different logics and my theory has divergent hypotheses for the different forms violence. I do the same for the panel data, but aggregate by grid-cell month. I alternate between Armed Clashes and Looting as my outcome variables. I plot the number of events per grid cell in Figure 2.4.

2.5 Models and Findings

My analysis proceeds in two steps. First, I describe correlations in the cross-sectional data. Because both the violence and the mining sector is spatially clustered, I use spatial autoregressive regression models (SARs) for cross-sectional data.[24] I use the more inclusive queens case definition when defining my spatial lag, which is especially appropriate for the hexagonal grid-cell structure. Queen's case defines neighbors as cells sharing either a common edge or a common vertex as contiguous.

Second, I analyze the grid-cell month panel to incorporate spatial-temporal dynamics and to exploit exogenous variation in global market prices. I run two way fix-effects models on the panel data and restrict the sample to grid-cells with mines to show temporal variation within mining communities.

2.5.1 Control Variables

Throughout my empirical analysis, I include a number of control variables to account for the non-random distribution of roads, mines, and taxation opportunities, which in turn may shape patterns of observed violence.

In the cross-sectional analysis, I control for static grid-cell level characteristics. Due to the lack of reliable and available local population or economic statistics in eastern DRC, I mainly rely satellite data to construct control variables. Satellite data has the benefit of providing sufficient granularity to fit the relatively small grid cells I employ and of providing "objective" information that is not impacted by the political calculations, the dynamics of the violence, or the weakness of the Congolese state. In particular, I use the Shuttle Radar Topography Mission (SRTM) dataset to control for the mean altitude within each grid-cell to account for variation in terrain, which may correlate with armed groups' capacity to use violence [49].[25] I use Globcover to capture variation in local land use.[26] From this, I create a binary variable of whether a grid-cell contains any urban centers. I use LandScan 2015 to measure the density of the local population and use the log of the population estimate in the grid-cell as a control for the potential non-mineral based tax base within a grid-cell.[27] In addition to these satellite variables, I use geo-located information on

[24] I re-run models using OLS in the Appendix, Section A.4.

[25] Additional information on the construction of the altitude measure is available in the Appendix, Section A.2.1.

[26] Additional details on the construction of these variables are provided in the Appendix, Section A.2.2.

[27] Additional information on the construction of the local population measures is provided in the Appendix, Section

United Nations peacekeeping bases [29] to account for the deterrent effect peacekeepers can have on violence [79].[28]

In the panel analysis, I control for seasonal patterns in precipitation, which impact the passability of the road network and ground conditions at the mines.[29] I also control for changes in MONUSCO's operational footprint over time, fluctuations in agricultural prices at local markets,[30] and static grid-cell characteristics, such as elevation and urban/rural status.

2.5.2 Cross-Sectional Trends

2.5.2.1 General Associations Between Mines and Violence

In Figure 2.5, I present a correlation matrix to visualize the raw association between the presence of mines within a grid cell and aggregate levels of violence in that grid-cell. As expected, grid cells with mines are not correlated with the observed violence. It is important to note, though, that this lack of correlation also suggests that mines are *not negatively* correlated with observed violence in aggregate, either. Rather, the grid cells with mines have observationally similar levels of violence to grid cells without mines.

Of course, the simple presence of mines does not account for the multiple pathways through which the minerals trade and violence may be related across the full supply chain. And Figure 2.5 does not account for spatial dependencies between grid-cells, which may distort observed relationships. For example, it may be that grid-cells with mines do not experience violence because the violence occurs on the periphery of mines. Likewise, it may be that local competition between armed groups – the proximate cause of violence – only occurs at specific mines. Other mines may be in areas where a specific group maintains a monopoly, so we do not observe violence between groups but may observe violence against civilians.

A.2.3.

[28] The United Nations peacekeeping mission in DRCongo, MONUSCO, has a spatial and operational footprint that evolves over time in response to changing conflict dynamics. More information on the dispersion of bases is presented in the Appendix, Section A.2.4.

[29] I provide additional details on the seasonal precipitation patterns that this measure is based on in the Appendix, Section A.2.5.

[30] I include additional details on the construction of agricultural price measures in the Appendix, Section A.2.6.

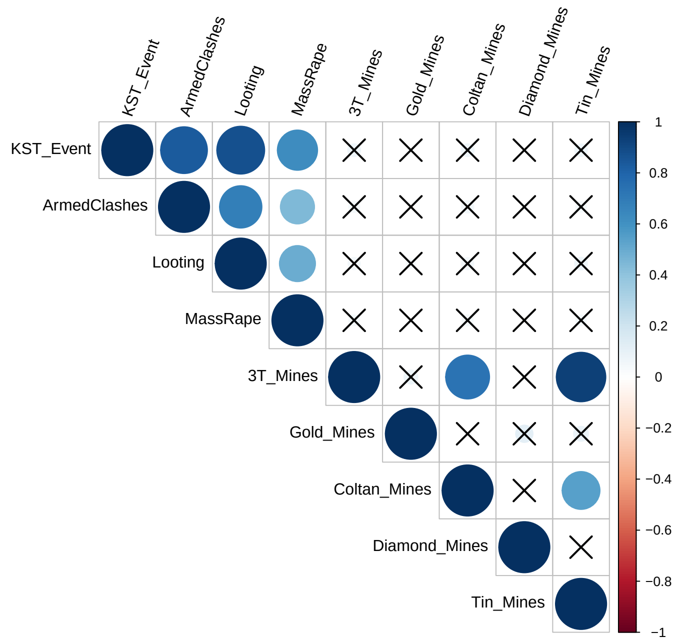


Figure 2.5: Correlation Matrix between Mines and Violent Events. Color intensity and the size of the circle are proportional to the correlation coefficients. Crossed-out cells denote a P value $>$ .05 with α of 95%

2.5.2.2 Points of Extraction Disincentivize Violence

To more systematically examine the relationship between the presence of mines and violence locally, in Table 2.2, I run a series of spatial autoregressive models (SAR) with a spatial lag to account for both direct and indirect effects of the presence of mines. I alternate between two independent variables: the number of mines (Models 1 and 5) and a binary indicator for whether other armed groups operate within the grid-cell (Models 2 and 6). For each independent variable, I examine whether the presence of mines are correlated with Armed Clashes (Models 1 and 2) and Looting (Models 5 and 6).

The results in Table 2.2 show that there is not a systematic relationship between mines and violence in either direction. I show Section A.9 of the Appendix, that this lack of correlation extends to each specific mineral. The loot-ability of mineral (i.e. whether the mineral mined locally is concealable or bulky) is also not correlated with observed levels of violence.[31] Rather, grid cells with mines and grid cells they border are observationally similar to non-mine grid cells in levels of violence.

Despite the lack of statistical significance, Models 2 and 4 warrant further comment. In these models, I use a binary indicator for whether multiple armed groups are operating and controlling mines in the area as the independent variable. Having local competition at the mines is not a isolated incident: multiple armed groups operate in 14.18% of grid cells. Such areas, based on existing theories, are precisely where we would expect the most acute violence between armed groups: valuable territory with local competition.

	Dependent variable:							
	Armed Clashes				Looting			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Mines	-0.009				0.019			
	(0.009)				(0.016)			
Competitive Mines (Binary)		-1.166^{***}				-0.201		
		(0.392)				(0.680)		
Eigenvector Centrality			0.219^{**}				0.621^{***}	
			(0.095)				(0.163)	
Road Block Competition (Binary)				2.988^{***}				3.810^{***}
				(0.539)				(0.936)
Observations	1,033	1,033	1,033	1,033	1,033	1,033	1,033	1,033
Controls	✓	✓	✓	✓	✓	✓	✓	✓
σ^2	9.125	9.067	9.080	8.899	27.426	27.461	27.078	27.052
Wald Test (df = 1)	103.343^{***}	99.052^{***}	107.218^{***}	91.656^{***}	15.260^{***}	15.181^{***}	16.117^{***}	13.042^{***}
LR Test (df = 1)	95.571^{***}	92.483^{***}	99.101^{***}	86.638^{***}	14.461^{***}	14.384^{***}	15.094^{***}	12.420^{***}

Note: Results from spatial aurogressive (SAR) models. Each model controls for the following variables: elevation, water coverage, MONUSCO base (2017), and (log) population. Models 1-4 use the number of armed clashes events within the grid cell as the dependent variable. Models 5-8 use the number of looting events within the grid cell as the dependent variable. Models 1 and 5 use the total number of mines within each grid cell as the independent variable of interest. In Models 2 and 6, I replace this with a binary indicator of whether there is a competitive enviornment for control of mines locally; in Models 4 and 7 I use the eigenvector centrality of the road network within the grid cell; in Models 4 and 8 I use a binary indicator of whether there is competition within the grid cell for control of roadblocks. *p<0.1; **p<0.05; ***p<0.01

Table 2.2: SAR Model Results with Cross-Sectional Data

Contrary to existing theories, local competition between armed groups at the sites of extraction is negatively ($p < 0.001$) correlated with armed clashes between groups. Coefficients estimated from spatial lag models cannot be interpreted directly because of spillovers between the units and terms. Following the process described in Lesage & Pace (2010), I use Monte Carlo simulation (x1000) to obtain simulated distributions of the impacts that my independent variables have on

[31] Results not shown.

observed levels of violence. This process provides estimates of the direct (local, within grid-cell) effect, indirect (spillover, to neighboring grid-cells) effect, and total effect (the sum of the direct and indirect effects).[32] The total effect can be interpreted similarly to the interpretation of regression coefficients in standard OLS models.

In Model 2, I estimate that grid cells with multiple armed groups experience 123.4% fewer armed clashes than the modal grill-cell, neighboring grid-cells experience 63.8% fewer armed clashes, with the overall impact of 183.7% fewer armed clashes. Targeting civilians with violence is uncorrelated with grid-cells with mines or with multiple armed groups operating within grid-cells in Models 5 and 6, respectively.

The patterns presented in Table 2.2 are consistent with the theory presented in Section 2.2.1.2. In aggregate, cooperation between otherwise competitive armed groups disincentivizes armed clashes under *status-quo* conditions at points of extraction. Relatively stable protection rackets limit violence against civilians. These patterns do not mean that the minerals trade and violence are negatively or unrelated across space, however.

As noted in Section 3.2, armed groups leverage different parts of the supply chain across space to generate revenue. Differences in the the revenue generating process at different nodes of the supply chain create different incentives for violence. Consistent with my theory, the points of extraction incentivize cooperation and protection in aggregate. In the next section, I examine the relationship between downstream nodes in the transportation process.

2.5.2.3 Violence is Concentrated Around the Key Points on the Transportation Network

In Table 2.2, I empirically evaluate the relationship between key nodes in the transportation network and local levels of violence using the cross-sectional data. Again running SAR models, I run models with an independent variables that measure the importance of the grid cell to the transportation network and levels of violence as the dependent variable. In Models 3 and 7, I use the

[32]The direct impact refers to average total impact of a change of an independent variable on the dependent for each observation, i.e., $n^{-1}\sum_{i=1}^{n}\frac{\partial E(y_i)}{\partial X_i}$, the indirect impact which is the sum of the impact produced on one single observation by adjacent observations. The total effect is the sum of both the direct and indirect effect.

Eigenvector Centrality to measure how important a given node on the road network is to traffic minerals to international markets, and thus how lucrative it is for armed groups to control and tax. In Models 4 and 8, I more directly measure active taxation competition by using roadblock competition as my independent variable, which I define as two or more armed groups each controlling at least one roadblock within a grid-cell.

Consistent with my theory, violence is positively and significantly associated with key junctures on the road network and, in contrast to the relationship at point of extraction, competition between groups is positively correlated with levels of violence both between groups and against civilians. The magnitudes further point to the substantive importance of these key junctures to explaining spatial concentrations of violence. Based on Model 3, I estimate that increasing a grid-cell's eigenvector centrality score by 10% corresponds to an 62.9% increase in armed clashes within the grid-cell, a 12.59% increase in neighboring grid-cells, for a 75% increase in grid-cells overall using the same Monte Carlo simulation (x1000) process described in Section 2.5.2.2.

Having a competitive roadblock environment is even more strongly associated with violence within grid-cells and in neighboring grid-cells. A competitive roadblock environment is associated with a 309.10% increase in the cell itself of armed clashes, a 151.78% increase in neighboring cells, and a 460.89% increase in armed clashes in total based on simulations on Model 6. Based on Model 8, I estimate that a competitive roadblock environment is associated with a 401.14% increase in looting events in the cell itself, a 67.47% increase in the neighboring cells, and 468.61% increase overall.

It may be that these results are driven by reporting bias, as violence in proximity to central nodes on the transportation network may be more visible than other areas. I evaluate this possibility by using alternative measures of centrality in the Appendix, Section A.4 and by examining whether less central but still highly visible portions of the road network are similarly correlated with violence in Section A.5. I find no evidence that my results are driven by such reporting bias.

Combined, the cross-sectional analysis shows that in aggregate, the points of extraction and key junctures in the transportation process are deferentially associated with violence. The different roles that these junctures play the revenue generating process for armed groups who participate in the minerals trade create incentives to use or refrain from using violence on average that vary over space. As noted in Section 2.2.1.3, however, conditions may change over time in ways that upend these incentives.

2.5.3 Panel Analysis

2.5.3.1 Large Exogenous Fluctuations in Mineral Prices Increase Levels of Violence at Mines

Because the value of the mines themselves vary over time, I expand on the cross-sectional analysis by transforming my data into a panel. In particular, I examine how changes in the value of controlling mines changes over time and how those changes are correlated with observed levels of violence. Cooperation between armed groups at the mines may become less stable when market forces make controlling specific mines much more valuable, such as an exogenous price shock. According to my theory, these shocks can undermine the incentives for armed groups to cooperate in proximity to the mines.

First, I exploit an exogenous fluctuation in the value of tungsten on global markets. DRC is a price-taker for tungsten and the price shifts I analyze are driven by political dynamics in China, which fills about 80% of the global tungsten demand. In 2018, the value of tungsten increased rapidly in the wake of an environmental crackdown in China, which curtailed supply and pushed tungsten's price upwards. It subsequently collapsed in early 2019 after China eased environmental restrictions due to the price rise. Second, I exploit a collapse in the price for diamonds internationally beginning 2019 driven by the rise of lab-based diamonds and the Chinese-US trade war. Third, I exploit a steady rise in gold prices beginning in 2019 driven by the US-China trade war, which created strong demand for gold from emerging market central banks. Each of these shocks was exogenous to the conflict dynamics I am interested in.[33]

[33] To further verify that the price fluctuations are unrelated to conflict dynamics in eastern DRC, I use one and two month lags on the price shock as the independent variable and conflict events as the dependent variable. They are uncorrelated.

In the panel analysis, I restrict the sample to grid-cells with mines to explore temporal trends in violence within mining areas. As described in the cross-sectional results, status-quo levels of violence in non-mining areas may distort comparisons and undermine our ability to observe conditions under which points of extraction themselves become violent. Restricting the panel sample to mining areas ensures I make valid comparisons and can more clearly observe how the the exogenous changes influence the protection and cooperation agreements I describe above.

In Table 2.3, I analyze the temporal trends in violence in mining areas to better understand the conditions under which mines become the center of violence. I create indicator variables for exogenous price shocks. Using this measure, my explanatory variable is whether there is an exogenous shock in that month/year for the mineral mined locally. Models 11 and 12 use Armed Clashes as the dependent variable; Models 13 and 14 use Looting events as the dependent variable. All models include a battery of control variables. Models 11 and 13 include grid-cell fixed effects. Models 12 and 14 include controls, grid-cell fixed effects, and month-year fixed effects.

Armed Clashes events are positively and significantly associated with price shocks in both models, with substantively important magnitudes. In Model 12, month-years with price shocks, grid-cells with an additional mine are associated with a 5.8% marginal increase of armed clash events between armed groups. Price shocks are also positively associated with increased levels of looting events in Model 13, but Model 14 falls from statistical significance when including both month-year and grid-cell fixed effects.

Together, the panel results suggest that under certain conditions, mines can become the epicenter of violent competition. In particular, armed groups respond to rapid fluctuations in the value of monopolizing a mine. Relatively stable prices incentivize groups to maintain the status quo and cooperate. But rapid increases or collapses in the price for a mine can upend those incentives to maintain the status quo. Instead, price shocks break down cooperation agreements and incentives to maintain peace.

The panel analysis is constrained by a number of factors. First, as show in Figure 2.3, although the fluctuations I analyze are exogenous, they are relatively modest in scope. Second, I am forced to rely on violence at the mines as a proxy for the disintegration of the cooperation at the mines. While I do expect that violence is an observable manifestation of such ruptures, it is also possible that the dissolution of such pacts may take non (overtly) violent forms. Both of these constraints bias against finding significant relationships, giving the patterns I observe even more credence.

	Dependent variable:			
	Armed Clash		Looting	
	(11)	(12)	(13)	(14)
Price Shock	0.033^{***}	0.057^{**}	0.018^{**}	0.001
	(0.009)	(0.024)	(0.009)	(0.023)
Observations	7,956	7,956	7,956	7,956
Controls	✓	✓	✓	✓
Grid-cell Fixed Effects	✓	✓	✓	✓
Month-Year Fixed Effects		✓		✓
Adjusted R^2	0.115	0.115	0.319	0.321
F Statistic	3.978^{***} (df = 346; 7609)	3.789^{***} (df = 371; 7584)	11.782^{***} (df = 346; 7609)	11.135^{***} (df = 371; 7584)

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from fixed-effects panel regressions. Each model controls for the price of beans in the nearest market the previous grid-cell month, the price of palm oil in the nearest market the previous grid-cell month, the price of rice in the nearest market the previous grid-cell month, a binary indicator for whether it is the dry season, and a lag of the number of violent events in the previous period.

Table 2.3: Panel Models: Exogenous Global Mineral Price Shocks and Local Violence at the Mines

2.6 Conclusion

In this paper, I re-examine the relationship between mines and the spatial distribution of violence. I argued that armed group revenue generating schemes in resource-rich conflict zones explain why minerals incentivize fighting on transportation networks and disincentivize violence at the mines themselves. Only severe price shocks for the mineral mined locally upends the armed groups' incentives to cooperate at the mines, resulting in episodes of violence in the direct vicinity of mines.

Using fine grained geospatial information on the artisanal mining sector, the road network, and the violence throughout the Kivus, I build both a cross-sectional and a panel dataset that incorporates exogenous variation in global demand for the minerals. Using spatial autoregressive models to capture spatial dependencies in the political economy and the violence, I find support for my theory: Grid-cells with mines are not more likely experience violence, nor are neighboring grid cells. Indeed, the presence of multiple armed groups around mines is negatively correlated with the intensity of armed clashes, providing support for my collusion and protection expectations. Instead, violence is more likely on the roads that take minerals to international markets, in particular in areas where multiple armed groups are operating and competing for taxation opportunities.

My empirical analysis indicates that the different roles in the revenue generating process create different incentives that structure local patterns of cooperation and conflict. Based on these findings, future research should be careful not to conflate the presence of mines within a region and the presence of violence in that region as evidence that fighting occurs at mines or for the control of mines. While aggregating above the highly localized research design in this paper is of course not a problem in and of itself, it is crucial to account for differences in how armed groups generate revenue through the minerals trade across space. Failing to do so may result in faulty inferences or ecological fallacies.

Finally, I note that the distinction between violence at the mines and on trade routes is not trivial or pedantic. The theoretical and policy implications from this corrective are profound. By accepting the simplest narrative on the connection between resources and armed groups, research and advocacy on the minerals-violence nexus has promoted relatively straightforward policy solutions [5], exemplified by Section 1502 of the Dodd-Frank Act. Meant to punish companies who supported armed groups by buying "conflict minerals" sourced from armed-group controlled mines in eastern DRC, Section 1502 undercut demand for minerals sourced from Congolese mines [146]. While targeting source mines appears like a good strategy when looking at the regional level, doing so actually undermined the armed groups incentives to protect civilian communities around mines and cooperate with each other, causing an increase of violence in these areas [117]. Understanding the nuances of how armed groups actually generate revenue – including where they do and do not use violence to compete for control – can fundamentally change the conclusions we draw from aggregate relationships between the mining sector and violence as well as the implications of this line of research for protecting vulnerable populations.

The findings in this paper thus have important policy implications: if policymakers design sanctions or embargoes that target the mine itself, the sanction may undermine armed group incentives to protect civilians. Conversely, a mine can be a "clean" but its products can still fund armed groups indirectly through taxation in transit to international markets. Efforts meant to curtail violence must navigate the complicated and sometimes contradictory web that connects armed groups, civilians, natural resources, and illicit economies. Failing to appreciate the nuances of the localized political economies they rely on can stymie peace-building efforts and, potentially, have tragic unintended consequences.

CHAPTER 3

The Demand for Protection, Predictable Extortion, and Civilian Perceptions of Security

Abstract

Armed actors leverage their coercive power to establish protection rackets in which they provide civilians security from rival armed actors in exchange for tribute. Do such protection rackets actually improve civilian perceptions of their security? In this paper, I theorize and evaluate civilian perceptions of informal security provision arrangements. I argue that informal, exploitative security arrangements improve civilian perceptions of their security when the community in which they live has recent experience with banditry, which increases local demand for protection, and when the armed actors institute routinized tribute schemes, which while extortive and costly to civilians, provides highly valuable predictability to both the armed actors and civilians in contrast to roving banditry. I empirically evaluate my theory using responses to an original survey in eastern DRCongo, where state absence has given rise to privatized local protection rackets, which I pair with fine-grained data on violence and the location and operators of roadblocks. These results demonstrate how local security vacuums can produce exploitative informal institutions that undermine macro state-building projects while paradoxically providing crucial protection to vulnerable civilians.

3.1 Introduction

In the absence of state-imposed political order, informal institutions rooted in illicit political-economic systems structure and enforce order locally [149, 2]. Armed actors[1] frequently establish such institutions to raise revenue and enforce their control over local populations, including

[1] I define "armed actors" as both non-state armed groups and elements of the state military. Even in states or areas of a state where the government does not exert significant control, there remains a meaningful difference between state

predatory tribute schemes [136]. Civilians[2] have limited means to protect themselves from armed actors, making them vulnerable such exploitation and abuse.

As armed actors seek to establish and maintain control of territory,[3] however, they come to rely on civilian labor, taxes, and other forms of non-material support. While armed actors can achieve the monopoly on violence over a territory through force, voluntary compliance [99] is highly valuable, as it allows armed actors to lower transaction costs, maximize their revenue-generating schemes, and make their nascent rule more sustainable.

To incentivize civilian compliance, a variety of armed actors ranging from mafias [53], to gangs [98], to rebel groups [106] provide public goods in addition to their military campaigns. The first order priority for any political entity is to guarantee the basic right of security for members [74, 22]. Armed actors are particularly well suited to leverage their coercive power to provide security from rival armed actors to civilians [10]. When they do so, armed groups and local civilian populations become entangled in a *protection racket*.

Do such protection rackets actually improve civilian perceptions of their security? In this paper, I theorize and evaluate civilian perceptions of informal security provision arrangements. In particular, I analyze the conditions under which civilians perceive protection rackets as improving their security.

I argue that informal, exploitative security arrangements improve civilian perceptions of their security when the community in which they live has recent experience with banditry, which increases local demand for protection [53], and when the armed actors institute routinized tribute schemes, which while extortive and costly to civilians, provides highly valuable predictability to both the armed actors and civilians in contrast to roving banditry [112].

Dynamics in zones of prolonged "state failure"[4] create conditions which allow us to approx-

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and non-state actors. This difference may be in name only and not reflective of different incentives or behaviors. For clarity, I label actors nominally acting on behalf of the state as state agents and any actor wielding coercive power that is not an official state agent as rebels. When discussing both state and non-state armed actors together, I refer to them as armed groups.

[2]Civilians are defined as "those who are not full-time members of an armed group" [86].

[3]By take and maintain control of territory, I mean that the armed group begins to act as a "stationary bandit" [115].

[4]The labeling of such contexts is contested. Some reject the idea of a "failed" or "failing" state and prefer "hybrid orders," "limited statehood," or "fragile." While such debates are beyond the scope of this article, my focus is on

imate and test these propositions. Soldiers from both state and non-state armed groups are "expected to provide for themselves by preying on the civilian population" [156] in a number of contemporary "failed" states, such as Central African Republic, Chad, Democratic Republic of Congo, Libya, Somalia, and Syria. As a result, civilians must simultaneously navigate acute physical and economic insecurity, dangers posed by non-state armed groups, as well as the predatory carcass of state institutions, whose agents retain their titles and means of coercion but lose any sense of centralized accountability.

In particular, the eastern provinces of the Democratic Republic of Congo (DRCongo or DRC) are tragically well suited to analyze how civilians evaluate fluid security provision arrangements. The Congolese state collapsed under the rule of former President Mobutu See Seko, who established a highly kleptocratic system in which state agents could take advantage of the asymmetry of power to systematically extract payments from civilians [183]. State institutions are considered among the weakest and most predatory in the world. The Congolese military, *Forces armées de la république démocratique du Congo* (FARDC) is perhaps the most notoriously predatory government organization: not only does it fail to provide civilians with security from non-state armed groups, it is often a source of insecurity itself [157], routinely extorting and attacking the population it is meant to protect. FARDC units actively participate in illicit revenue generating schemes. Its monopoly on the legitimate use of violence is challenged by an estimated 120 non-state armed groups [153], who also use illicit revenue generating schemes to sustain their mobilization.

At the local level, FARDC units and non-state armed groups privatize their coercive capacity to provide protection in exchange for regular tribute,[5] effectively creating protection rackets. These local protection rackets provide a unique set of conditions[6] and variation to better how civilians

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national or sub-national political contexts in which the state chooses not to or lacks the ability to maintain the monopoly on the legitimate use of force and "lacks the ability to implement and enforce rules and decisions" across all or portions of its territory [128]. Although the phenomena are closely linked, such conditions should not be conflated with the presence of political violence and conflict, as even states without ongoing conflict have uneven administrative capacity across time and space [23].

[5]As described below, this is not the expansion of official taxation. They are ad-hoc revenue generating schemes for FARDC local units, with an implied *quid pro quo* that continued payment is contingent on security provision.

[6]While these conditions are provide unique analytical leverage into the question of where state legitimacy comes from, they also provide a number of scope conditions that may limit the possible external validity of the findings. For example, by studying the sources of trust in areas where the central government does not exert meaningful control but

perceive security provision in a context of acute insecurity. There is substantial variation in how communities view and respond to these protection rackets, enabling me to analyze the factors that produce and undermine civilian perceptions of their consequences. Moreover, the consistency of common observable manifestations of local protection rackets – namely specific taxation schemes and/or the presence of roadblocks – allows me to operationalize where security is being provided, by whom, and, in some instances, for how long.

Empirically, I analyze more than 6,000 responses to an original survey in which civilians report whether they have paid various illicit but common security tribute systems as well as their perceptions of their security. The survey responses are collected in two provinces in eastern DRCongo where ongoing violence, banditry, and predation by armed actors and the state military are routine. I combine the survey responses with fine-grained data on the vast network of roadblocks, a key mechanism by which security tribute taxes are collected, including who controls the roadblocks, as well as a unique geo-located dataset capturing the location, type, perpetrators, and scale of violent events throughout eastern DRCongo. Together, the data provides a granular depiction of the spatial dynamics of the political-economy of security provision and civilian perceptions of security in a zone of ongoing violence.

I find consistent support for my theory. Civilians who report paying or living near these security tribute schemes are not more likely to perceive themselves or their communities as secure. Rather, improved perceptions of security from these fluid security provision arrangements are driven by a conditional relationship between the demand for security, which is a function of recent experiences of banditry, and the predictability of the security tribute payments. This windfall does not extend to a similar security tribute system that is characterized by irregular collection and unpredictable payments, however, even if the protection racket is filling a security void. I report a set of robustness checks to ensure that findings are not sensitive to any particular regression specification and use qualitative work to ground and validate my quantitative analysis. These results underscore the complex relationship between security provision and civilian perceptions at the micro-level.

is nominally represented by actors that it has extremely limited vertical accountability over, I analyze a fundamentally different set of circumstances than classical state building. The judicial state is already in place, as are its agents [84].

The primary contribution of this article is to literature that seeks to better understand how civilians experience and navigate zones of conflict and violence. Although there is a robust existing research stream on why armed groups choose to target [161] (or refrain from targeting [151]) civilians with violence and how and why armed groups rely on civilian support [173], we understand comparatively little about the civilian perspective in their relationships with armed groups. As Lyall, Blair, & Imai (2013) argue, "civilian attitudes may represent a substantial omitted variable in most statistical accounts of civil war dynamics" (696). A growing body of work shows that, in contrast to common assumptions, civilians are not merely passive observers or wells of information [86] who have violence done to them [82]. Instead, civilians have agency to negotiate with and influence the behavior of armed groups [87, 41]. I contribute to our understanding of how civilians negotiate with and perceive armed actors. To do so, I provide unique survey evidence of how civilians evaluate their security and leveraging a number of unique characteristics of the political-economy of the conflict in eastern DRCongo to isolate the conditions under which civilians perceive security provision as improving their own perceptions of security.

The rest of this paper proceeds as follows: in Section 3.2, I outline a theory of the conditions under which civilians perceive protection as improving their security. In Section 4.3, I describe the core features of the political economy of the conflict in eastern Congo. In Section 3.4, I describe my data and research design, which I use to empirically evaluate my theory in Section 3.6. Finally, in Section 3.7, I discuss the implications and limitations of my results and conclude with directions for future research.

3.2 The Demand for Protection, Institutionalized Extortion, and Civilian Perceptions of Security Providers

In the absence of state-imposed political order, violent and illicit political-economic systems arise where armed groups fund themselves through predatory extraction of resources and extortion. Civilians who live in such contexts are vulnerable to local social, economic, and political systems in which they are routinely extorted and abused with little or no means to protect themselves. Armed actors compete for loot as "roving bandits," who pillage, or for territory and the means of production as "stationary bandits," setting up more stable but nonetheless extractive rule [115].

As armed actors establish territorial control and transition from roving to stationary banditry [115], they must subjugate the population that lives on the land they aim to monopolize. This first stage of "penetration" (the "process of establishing control and establishing the presence, authority and visibility" [162]) triggers a strategic interaction between the stationary bandit and civilians under their rule. Armed actors who seek to penetrate an area and establish themselves as stationary bandits rely on civilians for taxation and labor. The wartime violence that occurs in the background of such dynamics creates a "strong grassroots demand" for security provision among civilians [61, 21]. Civilians prioritize their survival and assess their context based on their own perceived security interests.[7]

In contexts where the state cannot provide security – or state actors actively undermine civilian security – protection against predation and banditry arises through privatization [53, 10, 137]. Armed actors are particularly well suited to leverage their coercive power to provide security to civilians from rival armed actors [10]. When they do so, armed groups and local civilian populations become entangled in a *protection racket*. Such protection rackets are premised on an (uneven, extortive) exchange of security provision on the side of the armed actor and compliance with the armed actor's rule on the side of civilians.

Even in areas of mass violence, though, a protection racket does not necessarily translate to improved outcomes for civilians. Civilians often lack the requisite capacity to refuse, deter, or repel would-be stationary bandits from penetrating their communities.[8] While they can choose to flee [71], passively resist payment [144], or rebel [143], doing so would undermine the security provider's revenue generating schemes and disincentivize security provision, leaving the local

[7]Only a small fraction of civilians have strong connections to the armed groups and thus strong preferences beyond survival, especially when the conflict is not fought primarily along a master cleavage such as ethnicity or religion.

[8]This assumes that the stationary bandit does not arise from within the community, such as a self defense group [87]. Although such groups do frequently form, they are unlikely to have sufficient capacity to hold back larger, more powerful groups.

community without any protection. Such acts of resistance may also increase the likelihood of abuse by the armed group as they attempt to subjugate the population.

Indeed, the central problem for civilians with privatized protection in contexts of ongoing violence is that protection rackets mean accepting as protectors the very armed groups that caused insecurity in the first place. Prior misbehavior, neglect, or abuse by the state or other armed actors may further erode trust in and demand for centralized security provision. Not all civilians necessarily want to live under a centralized political entity [142, 71] as it entails significant risks (such as state based violence) and costs (such as taxation). Further, civilians navigate these threats under high levels of uncertainty about the armed actor's ability and commitment to deter or defend against external threats. This concern is amplified as the armed actor's presence may make the community a target for violence from rival armed groups. The armed actor's willingness to use their coercive power to abuse the civilians they purport to protect is also unknown, compounding the risk for civilians.

Living under a protection racket, which has the power to harm and few meaningful constraints from doing so, thus poses significant risks for civilians and may exacerbate the underlying insecurity that prompted the protection racket in the first place. At the same time, the pervasive insecurity that occurs in the background of such arrangements may make these associated risks more or less palatable. What, then, dictates whether civilians perceive a protection racket as beneficial? Civilians perceive protection rackets positively when two conditions converge: 1) local demand for the security provision that the stationary bandit provides and 2) predictable tribute systems from state agents.

First, higher demand for security renders the costs of protection rackets — in freedom, potential threats from the armed group operating locally, and security tribute payments — more palatable, but that demand varies over space and time. Personal and contextual experiences, in particular recent exposure or proximity to unpredictable violence, make it more likely that civilians will agree to pay the costs associated with a new stationary bandit. Civilians worst outcome is roving banditry which is costly, dangerous, and unpredictable. Recent experiences with or proximity to banditry increase the demand for the (relative) security and predictability a stationary bandit provides, thereby making the costs associated with living under stationary bandits less onerous by comparison.

Even if there is demand for a stationary bandit to provide security, civilians further assess the impact of protection rackets based on the stationary bandit's behavior and reputation. An armed actor builds reputation with civilians by reciprocal fulfillment of expectations [7], which can give rise to contingent consent and legitimacy [99]. The expectations that nascent stationary bandits and civilians have of each other are relatively limited: civilians expect the stationary bandit to provide security and to demand reasonable tribute at predictable intervals; the stationary bandit expects civilians to comply with their tribute schemes [147].

If civilians know and expect the security tribute payments that stationary bandit will demand, then such extortion may not have diminishing effect if it is both predictable and consistent. Because civilians can plan and account for the payment, stable extortion lets civilians price in corruption, amounting to a normal and accepted tax.[9] When the payment of the tax is accompanied by the credible threat of violence or coercion, civilians may pay the tax but not believe in its purpose or the institution it is paying the tax to [44]. Predictable taxation may under such conditions have the opposite effect and make civilians resentful towards the stationary bandit. It is thus not sufficient to only have predictable taxation schemes – as noted above, such predictability must be coupled with a demand for security provision. Tribute schemes, while resented on their own, can paradoxically improve civilians perceptions of security and enhances their trust in the stationary bandits that are extorting them over time [112]. If the security tribute schemes are unpredictable, though, civilians cannot price the tax into their lives and render the benefit of having security provided moot. Unpredictable security tribute schemes are, to the civilians who are forced to participate in them, equivalent to roving banditry.

In addition to these behavioral elements, the identity of the stationary bandit influences civilian

[9]The act of paying taxation may be seen as an observable manifestation of trust and legitimacy [100, 1] in the stationary bandit. It is important to not conflate observed compliance with trust, however: payment of these taxes are a signal that the armed actor is present and institutionalizing the taxation, but not necessarily that civilians view the tax or the presence of the stationary bandit as legitimate.

perceptions of their security when living under a protection racket. In contexts with ongoing violence, civilians demand for a strong, centralized state protection increases [74], even when state is one of the core abusers of civilians [21]. While non-state armed groups can provide security in such contexts in ways that mirror the state's core functions [106, 137], security provided by non-state armed groups is considered temporary. This impulse is consistent with a series of findings that civilians exposed to violence are more likely to demand a strong, centralized state [77, 21]. Thus, civilian perceptions of their security, in general, improve only when protection – even if that protection is not part of a coherent, centralized strategy – is extended by agents of the state.

In summary, civilian perceptions of their security are improved when protection rackets fill security vacuums, experiences with which increases demand for protection, and when the stationary bandits institute predictable taxation schemes. These assessments are bench-marked against recent experience and relative in nature. Over time, civilians consistently re-evaluate and demand more from the stationary bandit in exchange for their taxation [171]. They demand such protection from state agents in particular.

The empirical implication of this theory is that in areas of ongoing violence where armed actors provide local security, civilians perceive that informal security provision arrangements such as protection rackets improve their security when two conditions are met: a high demand for protection due to previous experiences with banditry paired with routinized and predictable tribute taxes. Unpredictable tribute taxes should be trust diminishing, even in areas where the stationary bandit is filling a security void. Finally, such improvements should only be observed when it is the state extending security provision; no such windfall should occur in contexts where non-state actors provide security.

3.3 State-Military-Civilian Relations in Eastern DRCongo

In this section, I provide background information on strategic interactions between the state, the military, non-state armed groups, and civilians in eastern DRCongo. I focus especially on how and why state military units and civilians negotiate for protection and describe the observational manifestations of these protection rackets. These background conditions inform the empirical strategy that I use to evaluate my theory in Section 3.6.

3.3.1 Violence, Revenue, and the Roots of Systematized Predation

The eastern provinces of the DRCongo – in particular North Kivu, South Kivu, and Ituri – have been embroiled in episodic cycles of violence for decades. Although the violence reached its peak during the First (1997-1997) and Second (1998-2003) Congo wars, consistent instability and violence continues to plague the east despite the formal end of the wars [3]. One of the world's most acute and longest running humanitarian crises, more than half the population in eastern DRCongo has never experienced life without some degree of violent conflict [168]. The central government exerts only limited control over the eastern provinces. At least 120 different armed groups were actively operating in 2017 in North and South Kivu alone [168] compared to 70 in 2015 [153], highlighting the rapid escalation in armed group proliferation and the inability of the state to control challenges to its monopoly on the use of violence.

Despite the state's weakness, state agents are omnipresent in certain areas and are frequently cited as the classic example of a predatory governance [157]. State institutions collapsed under the rule of former President Mobutu, who established a highly kleptocratic system that encouraged state employees to use their power to extract their salaries from civilians since the state would not pay them [183]. As a result, employees of Congolese state institutions privatized their public positions by collecting illicit taxes from civilians, a practice that continues today [157, 9].[10] It is still common to cite the fictitious "Mobutu's Article 15" of the constitution: *"débrouillez-vous"* (translation: "fend for yourself"), when discussing the behavior of government employees. In areas where the state and its agents are absent, non-state armed groups often set up similarly predatory arrangements.

[10] This process is different than the privatization of state violence, where states delegate violence to non-state actors [130]. Here, it is state agents privatizing their roles in response to the state's inactions (especially related to oversight and payment).

The largest and most important parasitic state institution is the Congolese military, FARDC, which sits at the nexus of the conflict related violence and the systematic predation of civilians. Like other parts of the state apparatus, the Congolese military must generate the revenue that its soldiers live off of. Military salaries peak at around $100/month for the highest ranking officers [168], but soldiers are paid irregularly. Soldiers thus leverage their coercive capacity to extort payments from civilians [167]. These extortion schemes are organized by unit-level commanders and staffed by soldiers, who then must redistribute the revenue collected up the chain of command [63]. These illicit revenue streams dwarf official salaries [168].

When controlling territory, FARDC units are forced to deal not just in economic predation; they must also sell protection to ensure the medium and long-term viability of these revenue-generating schemes [76]. Most often, civilians work through local leaders to negotiate an agreement with the armed groups, including the state military, to comply with the revenue generating schemes in exchange for protection. Within the military, civilians seek protection from various "Big Men," who combine political power and the means of coercion [165, 167]. Civilians use their (albeit limited) bargaining power to exchange compliance for protection [124]. If civilians do not trust that the FARDC unit providing protection is willing or able to carry out its promises, civilians can evade, flee, or undermine the revenue-generating schemes that FARDC relies on [166]. Non-state armed groups follow a similar blue-print when they establish control over territory as well.

When local communities and armed actors – including FARDC units – negotiate for protection, units set up a number of consistent collection mechanisms. First, when armed actors begins administering an area, it sets up a system of roadblocks where soldiers tax anything and anyone who passes [138]. Requiring almost nothing other than a makeshift barrier and tactic civilian compliance to be effective at generating revenue, roadblocks make up a significant portion of armed actors' territorial reach and revenue. Local commanders strategically place these roadblocks not to maximize the security benefit,[11] but rather to maximize the income of the soldiers manning the roadblock and thus the profits of their superiors. The decision to erect a roadblock is made locally

[11] There are a few roadblocks significant strategic value militarily, but these are exceptions.

and rarely part of a centrally planned military strategy.

Second, the military generates revenue through regular extortion schemes such as regular tribute payments negotiated between local leaders and military officers, colloquially called *lala salama*,[12] or through an indentured servitude program called *Salongo*.[13] As described by Garrett et al (2009, pg. 10):

> Under the [*Salongo*] system the miners are forced to surrender parts of their production for up to three days per week. While a small number of soldiers have a permanent presence at the mine, during "*Salongo*," which can happen at any time, more appear in groups under orders to confiscate a portion of the mine's production.

In addition, non-state armed groups set up informal taxation mechanisms such as field access taxes in the areas they control and administer.

At the core of the political economy of the state and the conflict, therefore, is illicit but routinized extortion of civilians by state agents and non-state armed groups through consistent mechanisms of extraction. These mechanisms are based on a very limited definition of spatial control: soldiers set up road blocks, demand fees under the guise of taxation, and create indenture labor systems to live and profit off of, creating a predatory cycle where civilians need protection from those who are meant to protect them.

The observational manifestation of a FARDC protection racket is thus FARDC controlled roadblocks or the presence of *lala salama* or *Salongo* security tributes payments. Likewise, the observational manifestation of non-state armed groups implementing a protection racket are the presence of tribute schemes to non-state armed groups.

3.4 Research Design and Measurement Strategy

In this section, I describe how I empirically evaluate my theory. I combine a number of datasets to construct a granular picture of the local political economy in which respondents live as well as the

[12] "*Lala salama*" is Swahili for "sleep well." Civilians say "*lala salama*" when giving the payment.
[13] In Lingala (the lingua franca of central and western DRCongo), "*salongo*" means "work."

dynamics of local security provision.[14]

3.4.1 Surveys of Civilians

My analysis relies on responses to original surveys of adults in two provinces of eastern DRCongo: North Kivu and South Kivu. The Kivus are shaded red in Figure 3.1. The Kivu provinces have been the epicenter of violence and instability in DRCongo since the end of the Second Congo War and provide variation in local violence dynamics, economic characteristics, and patterns in security provision. They also represent a range of ethnic groups. While the surveys are not a representative sample of the Congolese population at large, they do provide a rare representative sample of civilians in an on-going zone of state absence and conflict.

The surveys were collected in two waves, first in June and July 2018 and the second in July and August 2019.[15] In total, 5,581 civilians were interviewed in the 2018 sample and 4,429 in the 2019 sample, for a combined N = 8,947 individual respondents. The breakdown of respondents by province and *territoire* is presented in Table 4.1. In the empirical analysis, I exclude urban centers from the sample as urban residents face fundamentally different dynamics of protection, leaving an sample of 6,056 responses. The samples are gender balanced.

Given the lack of reliable census data and high levels of internal displacement[16] throughout eastern DRCongo, the sampling and weighting procedures are necessarily conservative. 9 *groupements* (or *quartiers* in cities) were randomly selected in each *territoire* within the three provinces. Then, within the randomly selected *groupements*, 3 villages were selected (or *avenues* in cities), creating 27 clusters per *territoire*.[17] Enumerators carried out 8 interviews per cluster using a random walk procedure. The samples are gender balanced and the interviews were carried out by

[14] While my analysis is primarily quantitative, I use qualitative data collected by others and my own fieldwork to motivate my measurement strategies and inform the interpretation of the quantitative results. See a discussion of related qualitative findings in the Appendix, Section B.7.

[15] The survey waves I analyze are part of a series of polls designed to measure civilian perceptions of the various actors in the conflicts throughout eastern DRC as well as their experiences at regular intervals. These surveys are part of a longer term data collection project that surveys civilians throughout the Kivus (and Ituri province, which is excluded from the analysis in this paper due to its fundamentally different dynamics of protection) at regular intervals.

[16] 15% of respondents in the sample report being displaced at some point within the past year.

[17] I provide additional details on the sampling procedure and the structure of administrative units in the Appendix.

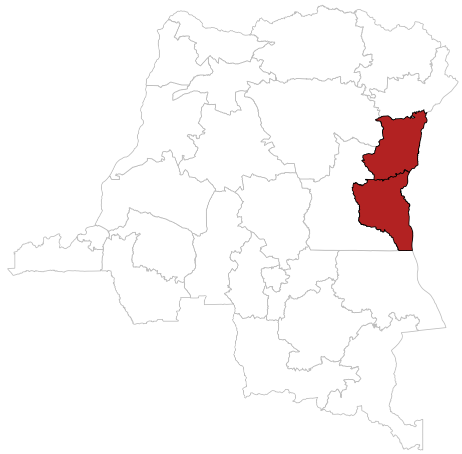

Figure 3.1: Map of the Democratic Republic of Congo, with North and South Kivu provinces shaded in red

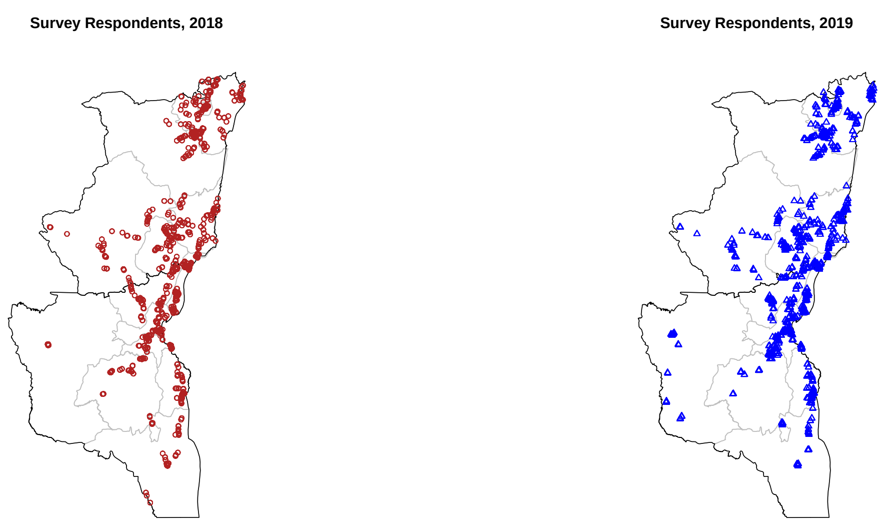

Figure 3.2: Maps showing randomly jittered geo-locations of survey respondents

	2018	2019	Total
North Kivu	**2138**	**2242**	**4380**
Beni	221	232	453
Lubero	216	216	432
Masisi	241	240	481
Nyiragongo	209	214	423
Rutshuru	221	227	448
Ville de Beni	299	308	607
Ville de Butembo	300	383	683
Ville de Goma	215	206	421
Walikale	216	216	432
South Kivu	**2380**	**2187**	**4567**
Fizi	218	214	432
Idjwi	216	216	432
Kabare	214	215	429
Kalehe	213	214	427
Mwenga	216	216	432
Shabunda	204	204	408
Uvira	287	216	503
Ville d'Uvira	297	298	595
Ville de Bukavu	299	286	585
Walungu	216	108	324
Total	**5518**	**4429**	**8947**

Table 3.1: Number of Respondents Per Province, Territoire and Wave

enumerators of the same ethnicity and gender as the respondent to minimize enumerator-induced response bias. Enumerators also capture the coordinates of each interview using their tablets. I plot the spatial distribution of survey responses in Figure 4.1.

3.4.2 Measuring Civilian Perceptions of their Security

To measure civilian perceptions their security, I use responses to a battery of questions designed to capture respondents perceptions of their personal security in their communities.

Each respondent reports how confident they are in their security across five questions: how safe they feel doing their daily activities, going to the nearest town or village, walking alone, walking alone at night, speaking openly about the conflict, and complaining to authorities. These questions capture the multifaceted nature of perceptions of security and the variety in threats that civilians face in eastern DRCongo.

The options for each question are a five point Likert scale, ranging from very unsafe to totally safe. As I am interested in measuring the extent to which protection rackets improve perceptions of security, I create a binary indicator if respondents report feeling either "safe" or "totally safe" to each question. I then create a measure that sums across the questions.[18]

Directly asking civilians in an ongoing zone of violence for their perceptions of their security prompts concerns of response bias. But response bias in this case is smaller than it might originally appear. As has been observed in other war zones, respondents are most often willing to openly share their opinions and wanted their stories heard [177]. Moreover, it is not taboo (to the contrary, it is exceedingly common) to discuss FARDC and its failings to provide security in eastern DRCongo openly. To minimize response bias, the survey was administered by Congolese college students from the surveyed areas. Respondents were also given the option to refuse to answer all questions and repeatedly reminded that their answers were anonymous.

3.5 Measuring Local Political, Economic and Violent Dynamics

3.5.1 Operationalizing Experiences with and Points of Extortion

I use four different operationalizations of the presence of armed group revenue generating schemes to proxy for whether a given respondent lives in an area where a FARDC unit or a non-state armed group established a protection racket. Because each measurement strategy is limited in specific ways, I triangulate among both survey responses and independent geospatial data.

First, I use self-reported payments into specific tax schemes to proxy for the presence of a

[18] In additional robustness tests, I unpack the measure and use each of its component questions as individual variables. Results not shown.

security provision locally. Each respondent is asked whether they paid *lala salama* or *Salongo* tribute to FARDC units within the past year.[19] These taxes are a widely accepted practice and, although extortive, the frustration they cause are often talked about in the open. Indeed, that a form of extortion is called *lala salama*, which translates to "sleep well," is indicative of the extent to which it has been routinized and accepted. While the presence of both tribute schemes reliably capture the presence of an FARDC protection racket, *lala salama* and *Salongo* have a number of significant and analytically important differences. The presence of *lala salama* is indicative of a routinized security tribute scheme. Although extortive and likely to breed resentment, the payment is predictable and collected at regular intervals. In contrast, *Salongo* is a more ad-hoc and unpredictable form of extortion. By analyzing these tribute schemes separately, I can proxy for the relative difference between predictable tribute schemes and unpredictable ones, while holding the organization constant.

In addition, respondents are asked whether they have paid taxes to non-state armed groups (i.e. not necessarily FARDC) to access their fields, a common arrangement for non-state armed groups to collect revenue when they establish protection rackets. This question is broader in nature so as to not make respondents uncomfortable. Such taxes reliably signal the presence of protection racket, but they do not necessarily signal that the protection racket has improved security locally. Non-state armed group taxation does not have corresponding levels of details on the form of payment in the survey, so I cannot test this aspect of the theory using this question.

Because the survey responses only capture whether an individual respondent paid the taxes, I pair survey responses with geo-spatial data on the location of roadblocks[20] throughout North

[19] The survey does not ask civilians precisely when or how often they pay due to concerns of recall bias. Moreover, since the presence of these extortion schemes is a reliable signal of the presence of FARDC as a stationary bandit, a binary measure sufficiently captures the underlying concept.

[20] Roadblocks, per Schouten, Murairi, & Batundi (2017), are defined as:

> "A roadblock (or checkpoint) is an obligatory passage point erected by an entity that exercises *de jure* or *de facto* authority over a given road crossing. In addition, the roadblock constitutes a principal inscription of politico-military might in the physical landscape. As a mechanism of taxation, it is light and effective, and deployed by all kinds of "entrepreneurs of imposition" – whether civilian or military, state or rebel. The roadblock itself can take the shape of a barrier, or more discreetly, an improvised roadside chair or grass hut. The roadblock can also be referred to as a "post" because it is a place where agents from within a certain hierarchy have been deployed" (12).

and South Kivu. As described above, these roadblocks are a major source of (illicit) funding for FARDC units and non-state armed groups throughout eastern Congo and a reliable proxy for local security provision. Each roadblock includes information on who controls the roadblock [141, 138], which I use to identify where FARDC is acting as a stationary bandit.

Figure 3.3 plots the spatial distribution of roadblocks in the Kivus. There are more than 940 roadblocks in North and South Kivu, a staggering number given the limited road network in these provinces. Schouten, Murairi, & Batundi (2017) calculate that there is a roadblock for every 18km of road on average in North and South Kivu. State actors are present at 69.2% of roadblocks. It is important to note, though, that the density of state actors at roadblocks should not be conflated with the strength the state. To the contrary, roadblocks are not orchestrated in a centralized, strategically planned fashion to expand state control, but rather popped up by local commanders who are often in competition with other local commanders of the same umbrella organization.

To measure proximity to roadblocks, I capture how many roadblocks are within 5km of each respondent. I then calculate what percent of the roadblocks within that buffer are FARDC controlled or rebel controlled.[21] I create an indicator variable if there is at least one roadblock within a given respondent and if FARDC controls all roadblocks within the 5km buffer ("FARDC Roadblock Monopoly").

The different revenue generating schemes are not mutually exclusive;[22] indeed, they are complimentary revenue schemes to FARDC. Importantly, the choice of which revenue-generating scheme – especially the decision to implement either *lala salama* or *Salongo* – to adopt is non-random for the FARDC unit: they choose which revenue generating scheme is likely to maximize profits. This decision is driven local economic characteristics such as the proximity to and type of mines.

Together, these measures represent the main revenue generating schemes for armed groups who

Further information on the data generating process and coding decisions for the roadblocks data are presented in the Appendix.

[21]The roadblocks data collection could not access Beni and Lubero *territoires* as well as a portion of Walikale in North Kivu or Lulenge sector in South Kivu. As a result, I drop survey responses from these areas to avoid making inferences based on non-random measurement error in the roadblocks data.

[22]This is especially true for the specific security tribute schemes and roadblocks, but less true for *lala salama* and *Salongo*. It is common to have both roadblocks and *lala salama* or *Salongo*, but uncommon to pay both *lala salama* and *Salongo*.

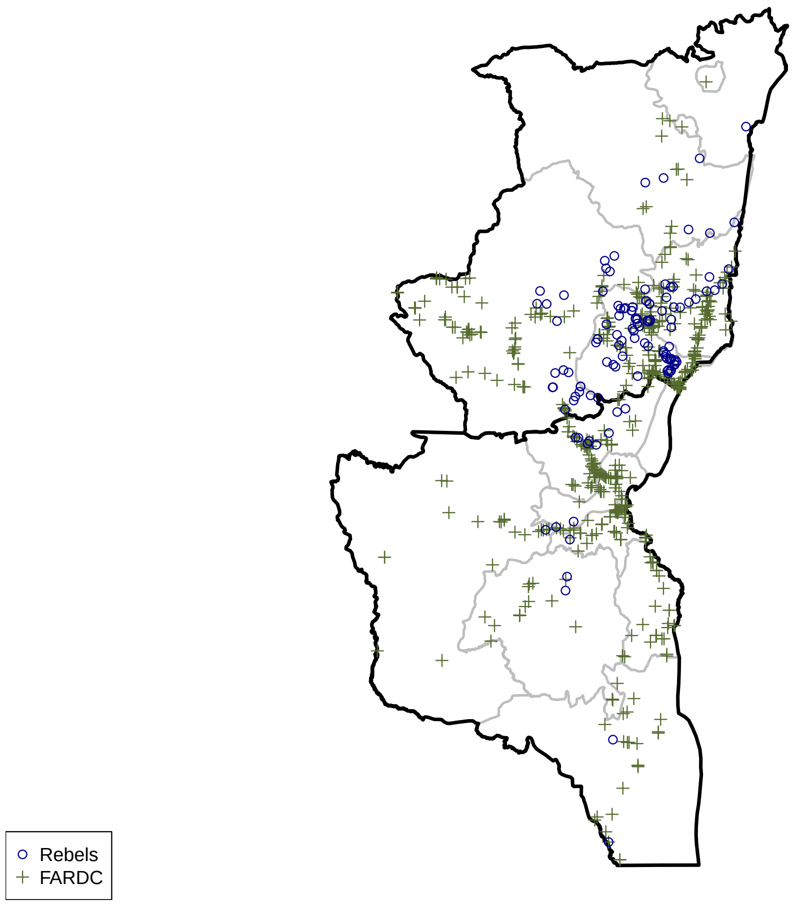

Figure 3.3: Map of North and South Kivu showing spatial distribution of roadblocks

	Protection Racket	Predictable	Direct Payment	Provider	Source
Lala salama	✓	✓	✓	FARDC	Survey Responses
Salongo	✓		✓	FARDC	Survey Responses
Field Access Taxes	✓		✓	Non-state Armed Groups	Survey Responses
Roadblocks	✓	✓		Both	IPIS Data

Table 3.2: Characteristics and Measurement of Security Tribute Systems

operate protection rackets locally. That said, each produces unique measurement challenges all have different sources of bias. For example, response bias likely exists in the survey data, which the independent nature of the roadblocks data helps overcome. But the roadblocks data are limited in that the dataset captures roadblocks at a specific point in time, and dynamics may evolve. I thus triangulate among these measurement strategies to build confidence in my results. There is little reason to expect these biases to have the same magnitude or direction, so consistency across the measures should lend credence my results.

3.5.2 Operationalizing the Demand for Security

In my theory, I explain that experiences with unpredictable forms of violence increases the demand for security, which conditions civilian perceptions of their security. Indeed, when asked for main cause of insecurity, more than 50% of survey respondents listed either banditry or being robbed as their main cause of insecurity.

Measuring exposure to such violence is challenging given systematic under-reporting of the violence in eastern DRCongo in media and thus standard violent event-based datasets [163]. I use data provided by the Kivu Security Tracker (KST), a Human Rights Watch program that employs a network of researchers throughout North and South Kivu to track and independently verify violent events. KST has significant advantages over commonly used events based datasets such as ACLED, UCDP, and SCAD. By relying on a network of local researchers who leverage their connections with the UN and the government, KST expands the pool of potential cases from just those that end up in the media, a particularly problematic assumption for the violence in eastern Congo.

To ensure consistency with other measures, I create a 5km radius buffer around each survey respondent and capture how many violent events, how many violent deaths, and characteristics (such as the perpetrator and type of violence) within that geographic buffer of each respondent. Using this information, I create a normalized measure of the severity of banditry in the 2-year period before each survey wave to proxy for the demand for security ("Banditry").

3.5.3 Controls

Because the presence of a FARDC unit or a non-state armed group acting providing a protection racket and experiences with banditry may be endogenous to a number of contextual or individual characteristics, I include a series of relevant controls. Respondents self-report whether they have or held a paying job within the last month, whether the respondent was displaced within the past year, and their age. I also control for distance to the nearest MONUSCO peacekeeping base, as contact with UN peacekeepers can influence civilian perceptions of security. To account for the fact that armed actors have incentives to provide security beyond revenue generation, I also control for whether a respondent lives within 5km of a strategically valuable roadblock, which may distort the armed group's incentives and behavior towards civilians. I also control for proximity to mines to account for selection effects that could drive experiences with *Salongo* especially. I also control for gender to account for the fact that men may be more likely to pay the taxes that I discuss.

3.5.4 Empirical Strategy

To evaluate my theory, I present results from a series of models that analyze the relationships between experiences with banditry, participation in armed group revenue generating schemes, and civilian perceptions of their security. My empirical strategy proceeds in a number of steps to iteratively build a set of results which, while each limited in their own way, together provide a consistent pattern which clarifies the conditions under which civilians perceive protection rackets as improving their security. My analysis thus is not a doubly-decisive test of a hypothesis [164], but rather a series of complementary results that each aim to address different sources of bias in the data. Consistency across the analysis should lend credence to the empirical patterns I describe.

First, I analyze individual survey responses to explore how direct participation in a protection racket and experiences with banditry correlate with perceptions of security. When I do so, I cluster standard errors at the *groupement* in all models.[23] Additionally, models include geographic fixed effects (at the *Territoire* level) to account for unobserved differences in context and survey wave fixed effects to account for differences in the political environment between the two years. Observations are weighted by the inverse probability of sampling at the *Territoire*.

To account for the fluidity of the protection rackets and evolving civilian assessments of their security, I then analyze change in local protection dynamics between survey waves. Because respondents are not re-sampled but jurisdictions are (specifically *groupements*), I aggregate the percentage of respondents who report paying *lala salama*, *Salongo*, and/or payment of taxes to non-state armed groups to the *groupement* in each survey wave. I create indicator variables for whether there is a 10% or greater expansion[24] in security tribute payments in each respondent's *groupement*, signaling a recent expansion in a protection racket.[25]

3.6 Results

3.6.1 Pooled Individual Analysis

First, I analyze whether self-reported payments into *lala salama*, *Salongo* or non-state armed group field access tribute systems are associated with improved perceptions of security, conditional on the demand for security due to previous instances of banditry. As noted above, paying *lala salama*, *Salongo*, or field access taxes are indicative of an armed group acting implementing a protection racket, but not necessarily that civilians paying the tax view FARDC or the armed actor as legitimate or as effectively providing security.

While all serve as observable manifestations of protection rackets, the different collection meth-

[23] Additional details about the structure of administrative units in DRCongo are provided in the Appendix.
[24] This is calculated by subtracting the 2018 wave percentage from the 2019 percentage.
[25] The date of roadblocks being newly instituted is too complete to confidently allow similar analysis, so I focus exclusively on self-reported measures in this section.

ods provide analytical leverage to understand conditions under which civilians do and do not respond positively to protection rackets. Although implemented by the same umbrella organization and used for the same purpose (to collect tribute from those who they claim to protect), *lala salama* tribute payments are predictable while *Salongo* are relatively unpredictable, allowing me to isolate the relative impact that predictability has on perceptions while comparing similar levels of recent banditry. Field access taxes enable another axis of variation, as they enable comparisons of non-state armed group protection rackets to FARDC protection rackets.

Table 3.3 provides the results from a series of OLS models that explore these relationships in greater detail. For each model, the dependent variable is the perceptions of security index, the unit of analysis is the individual survey respondent, observations are weighted according to the inverse probability of sampling, and the standard errors are clustered at the *groupement*. In Models 1, 3, and 5, I run regressions with self-reported payments as the independent variable of interest to establish a baseline relationship between living in a protection racket and perceptions of security. In Models 2, 4, 6, and 8, the coefficient of interest is the interaction term between the self-reported payments and prior banditry experiences in the area.

The results in Models 1, 3, and 5, provide evidence that paying into the tribute schemes that I analyze is itself not a function of existing positive security perceptions, alleviating the most pressing concern of reverse causality. *Lala salama*, *Salongo*, and field access payments are all negatively associated with perceptions of security. This negative and statistically significant relationship holds when run with and without controls, geographic fixed effects, and across genders.

However, the results in 3.3 also indicate circumstances under which the presence of a stationary bandit that uses predictable tribute schemes to generate revenue can improve civilian perceptions of security: when the protection racket also fills a security void. In Model 2, the interaction term Pay *lala salama* $*$ Previous Banditry is positively and significantly correlated with perceptions of security. When respondents live in areas that experienced banditry, predictable security tribute payments can become palatable and improve perceptions of security. However, without prior experiences of banditry, even predictable tribute collection associated with protection rackets is not perceived as improving security.

In contrast to the results in Model 2, paying *Salongo* shares no such conditional relationship with the likelihood that a respondent expresses trust in FARDC. Even when FARDC is filling a security void, unpredictable tribute schemes such as *Salongo* are not correlated with an increase in perceptions of security. Since the core difference between the security tribute systems is their level of predictability, the divergence in the results in Table 3.3 suggest that the predictability of the security tribute systems influences civilian perceptions of their security more broadly.

Interestingly, I do not find that relationship between security provision and filling a security vacuum does not extend to non-state armed groups. Instead, Model 6 estimates that the relationship is negative. I cannot tease apart the predictability of such payments, but in general field access payments are considered predictable once established by a group running a protection racket locally. As such, even though FARDC operates as a armed actor in ways that are similar to non-state armed groups, it does appear that the state retains some level of normative importance. Civilians, based on the results in Table 3.3, feel more secure in a protection racket run by state agents than by non-state armed groups.

Next, because directly paying taxes is a particularly restrictive test for the existence of a protection racket and direct payments are potentially endogenous with a number of other factors that may influence perceptions of security,[26] I analyze proximity to roadblocks as an alternative manifestation of the presence of a protection racket. Roadblocks do not provide (observable) variation in the predictability of the tribute payment, but civilians generally consider the roadblock payments predictable. By analyzing roadblocks, I do not restrict my measure of security provision to only those who self-report paying directly into the tribute systems.

In Models 7 and 9 of Table 3.3, I run the same OLS regression as in Models 1, 3, and 5, but substitute self-reported direct payment with proximity to a FARDC roadblock monopoly or a

[26]For example, it could be that those who are able and willing to pay armed actors such payments may pay because of an existing comfort with their presence. Likewise, it may be their ability to pay gives them security from the armed group, and that the relationships I show are driven by that mechanism. I discount these mechanisms because the positive correlations between payment and perceptions of security are conditional on prior experiences of banditry, but nonetheless examine the robustness of the relationship with less restrictive proxies of the presence of a protection racket, such as roadblocks.

non-state armed group monopoly.[27] Consistent with the results from the self-reported payments, simply being in proximity to a roadblock monopoly is negatively and significantly associated with perceptions of security, again indicating that protection rackets are not themselves security improving. Model 9 replaces a FARDC roadblock monopoly with a non-state armed group roadblock monopoly the same for non-state armed groups and is again negatively associated with perceptions of security.

I examine the conditional relationship between security provision in areas where there is demand for security and perceptions of security in Models 2, 4, 6, which examine *lala salama*, *Salongo*, and field access payments to rebel groups, respectively. The results are consistent with my expectations. Provided a respondent lives in an area that has experienced banditry in the recent past, paying *lala salama* taxes is associated with a 2.466 unit increase on the perceptions of security index (out of 5). In contrast, provided recent experiences of banditry, payment of field access taxes to non-state armed groups is associated with a 1.79 unit decrease in the perceptions of security index. *Salongo* payments are not significantly associated with perceptions of security in areas with recent episodes of banditry.

Proximity to roadblock monopolies show similar patterns. In Model 8, I estimate that living in an area with a FARDC roadblock monopoly is associated with a 1.67 unit increase on the perceptions of security index, contingent on there being recent experiences of banditry. The interaction term with non-state armed group roadblock monopolies in Model 10 is not significantly correlated with perceptions of security.

3.6.2 Analyzing Recent Expansions of Security Provision

The results in Table 3.3 provide consistent support for the hypothesis that protection rackets improve civilian perceptions of security if they fill a security vacuum and if they institute predictable tribute schemes. However, these individual results are limited in a number of ways. Most im-

[27] Defined as a single non-state armed group control all roadblocks within the 10km buffer. If multiple non-state armed groups control roadblocks within the buffer, I consider that area contested.

	Dependent variable:									
	Perceived Security (Index)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lala Salama Payment* Banditry		2.466***								
		(0.866)								
Salongo Payment * Banditry				−0.765						
				(0.809)						
Field Access Payment * Banditry						−1.791**				
						(0.822)				
FARDC Roadblock Monopoly * Banditry								1.671**		
								(0.819)		
Non-state Armed Group Roadblock Monopoly * Banditry										−1.158
										(4.055)
Lala Salama Payment	−0.404***	−0.572***								
	(0.085)	(0.101)								
Salongo Payment			−0.208***	−0.170**						
			(0.071)	(0.086)						
Field Access Payment					−0.600***	−0.499***				
					(0.073)	(0.087)				
FARDC Roadblock Monopoly							−0.164**	−0.194**		
							(0.064)	(0.084)		
Non-state Armed Group Roadblock Monopoly									−1.205***	−1.223***
									(0.203)	(0.249)
Banditry Experience		−1.276***		−0.997***		−0.954***		−1.963**		−0.742***
		(0.255)		(0.258)		(0.255)		(0.782)		(0.248)
Constant	2.489***	2.519***	2.488***	2.514***	2.482***	2.506***	1.617***	1.752***	1.667***	1.737***
	(0.086)	(0.086)	(0.087)	(0.087)	(0.086)	(0.086)	(0.118)	(0.117)	(0.113)	(0.116)
Observations	5,689	5,689	5,660	5,660	5,678	5,678	4,472	4,455	4,455	4,455
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Territoire FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Groupement CSE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Results from OLS regressions. Each model controls for employment, displacement status, age, gender, distance to the nearest MONUSCO base, proximity to strategic roadblocks, and distance to the nearest mine. *p<0.1; **p<0.05; ***p<0.01

Table 3.3: Individual relationship between protection racket tribute payments and perceptions of security

portantly, they cannot distinguish between relatively new protection rackets and more established ones, which may mask important variation at the initial stages of penetration from longer-term relationships. Moreover, these results may miss spillover effects where expansion into a respondent's area can improve perceptions of security even without directly paying into the protection racket, as the individual level analysis considers only those individuals who self-report paying into protection rackets or observable manifestations of protection rackets nearby (roadblocks).

To account for such temporal change and indirect impacts on perceptions of security, I leverage changes in local political dynamics and consistent sampling units across the survey waves. Although the survey data is not a panel (i.e. the same respondents are not re-interviewed), the surveys are repeated cross-sectional and do provide consistent coverage at the *groupement* level in both waves. Both the 2018 and 2019 waves sample all 180 *groupements* in North and South Kivu. *Groupements* are the second smallest administrative unit in eastern DRCongo and typically include 10-20 villages.[28]

This consistent sampling design enables a number of comparisons from the 2018 sample to the 2019 sample. 21% of 2019 respondents live in a *groupement* where *lala salama* taxation rose more than 10% since 2018 and 10% of respondents live in groupements with a 10% or greater expansion in *Salongo*, indicating that FARDC units only recently established or expanded protection rackets locally. 21% live in *groupements* where there was a similar expansion in non-state security provision (proxied by an increase in field access taxes to non-state armed groups) between survey waves.[29]

I create a binary indicator for whether each survey respondent lives in a *groupement* that experienced a 10% or greater growth in respondents reporting that they recently paid either *lala salama*, *Salongo*, or field access taxes between the 2018 and the 2019 waves as a proxy for the presence of relatively new stationary bandit. As such, the measure does not require that an individual directly pay into the protection racket; instead, it requires that the person live in a *groupement* where

[28] I do not aggregate to village level because the sampling strategy is not designed to be representative at the village level.

[29] Histograms of these changes are presented in the Appendix.

more respondents report paying than the previous survey wave. This entails analytical trade-offs: it assumes that respondents do not necessarily need to pay to benefit from security provision, that protection rackets that are newer are different than those that are older, and that a *groupement* is an appropriate level of aggregation to examine the implications of a protection racket for perceptions of security. While each of these are potentially problematic, these concerns are essentially the inverse of the biases in Table 3.3. My goal is thus to triangulate and sequentially discount different sources of bias.

In Table 3.4, I run 3 OLS regressions to estimate the relationship between these interactions and perceptions of security. As my independent variables, I rotate through different operationalizations of changes in local security provision. I use change in the percent of respondents who report paying either *lala salama* (Δ *lala salama*) *salongo* taxes (Δ *salongo*), and field access taxes (Δ field access taxes) in Models 11, 12, and 13, respectively. I interact the indicator of recent expansion of a protection racket with both a binary indicator of whether the response is from the 2019 survey wave and a binary indicator of whether they experienced banditry in the recent past. The interaction terms of interest is thus the triple interaction of whether the expansion occurred locally, response being in the 2019 wave, and prior experiences of banditry locally. As above, I include the battery of controls, *Territoire* fixed effects to account for unobserved heterogeneity in context, and cluster standard errors at the *groupement*.

The results are consistent with the findings in Table 3.3. The recent expansion of protection of *lala salama*, conditional on experiences of banditry, is positively correlated with perceptions of security, while the recent expansion of *Salongo* is not significantly correlated with perceptions of security. These correlations are based on comparisons to other survey respondents in the same area in the year before or to respondents in similar circumstances within that year. Also consistent with the results in Table 3.3, Model 13 shows that increases in non-state security provision is negatively correlated with perceptions of security, given recent experiences of banditry.

The results presented in Table 3.4 merit important caveats, however. While these results demonstrate that the expansion of predictable security tribute is correlated with perceptions of security

	Dependent variable:		
	Personal Security Index		
	(11)	(12)	(13)
Δ *lala salama* > 10% * 2019 Survey Wave * Banditry	0.545**		
	(0.249)		
Δ *salongo* > 10% * 2019 Survey Wave * Banditry		−0.0004	
		(0.583)	
Δ field access taxes > 10% * 2019 Survey Wave * Banditry			−0.762***
			(0.240)
Δ *lala salama* > 10%	−0.062		
	(0.096)		
Δ *salongo* > 10%		0.243	
		(0.152)	
Δ field access taxes > 10%			−0.040
			(0.087)
Δ *lala salama* > 10% * 2019 Survey Wave	−0.427***		
	(0.130)		
Δ *lala salama* > 10% * Banditry	−0.032		
	(0.186)		
Δ *salongo* > 10% * 2019 Survey Wave		−0.218	
		(0.231)	
Δ *salongo* > 10% * Banditry		0.773	
		(0.493)	
Δ field access taxes > 10% * 2019 Survey Wave			−0.788***
			(0.122)
Δ field access taxes > 10% * Banditry			0.862***
			(0.184)
2019 Wave * Banditry	−0.531***	−0.451***	−0.108
	(0.121)	(0.108)	(0.123)
2019 Survey Wave	0.248***	0.189***	0.321***
	(0.053)	(0.050)	(0.053)
Banditry	−0.322***	−0.345***	−0.553***
	(0.091)	(0.084)	(0.091)
Constant	2.466***	2.478***	2.456***
	(0.086)	(0.086)	(0.087)
Observations	5,707	5,707	5,707
Controls	✓	✓	✓
Territoire FE	✓	✓	✓
Groupement CSE	✓	✓	✓

Note: Results from OLS regressions. Each model controls for employment, displacement status, age, gender, distance to the nearest MONUSCO base, proximity to strategic roadblocks, and distance to the nearest mine. *p<0.1; **p<0.05; ***p<0.01

Table 3.4: Recent Expansion of Tribute Payments Locally and Perceptions of Security

when filling a security void, the aggregated data I analyze only captures relative change over one year, limiting my ability to draw inferences on the magnitude or sustainability of these changes. For example, because I can only capture change over a single period, I cannot capture whether changes in perceptions in security changed prior to the expansion of the extortion schemes. Moreover, as described above, the civilian-armed group dynamics I analyze play out at levels below – typically at the village level – the unit of aggregation employed here. Despite these important limitations, the results compliment the individually reported results analysis by incorporating as much temporal variation as possible in both the independent and dependent variables at a relatively local level.

3.6.3 Addressing Empirical Challenges and Alternative Explanations

My analysis faces a number of additional potential challenges and alternative explanations.

First, payment of security tribute and the presence of roadblocks are not randomly distributed. As such, the location of a roadblock or a tribute scheme may be endogenous to a number of characteristics – such as levels of income, prior level of compliance with the state, and the status of military battles for territorial control – that are also systematically correlated with civilian perceptions of security. As pointed out in the Section 4.3, FARDC units strategically choose where to establish protection rackets based on where they expect to make the most money, not where the population is especially pre-disposed towards them. And as shown in the analysis that focuses on newly formed protection rackets, the lucrative areas where FARDC units decide to expand to have similar levels of existing perceptions of security as areas where they do not expand.

Relatedly, my dependent variable (perceptions of security) may impact the decision to participate in or report participating in my independent variables (the presence of a protection racket and prior levels of banditry), prompting concerns of reverse causality. This concern is especially problematic for self-reported direct payment of tribute taxes such as *lala salama* or *Salongo* to FARDC, as civilians may avoid or refuse to report paying FARDC if they do perceive FARDC as improving their security. In this case, my findings could be the function of a selection effect. However, paying *lala salama* itself is not significantly related with positive perceptions of FARDC and all qualitative evidence points to such a selection effect not being present. Moreover, the fact that *Salongo* tribute payments – which are also indicative of FARDC operating as a protection racket and thus prone to the same selection concerns – do not follow a similar empirical pattern as roadblocks and *lala salama* suggest that this is not the case.

My results could also be a function of preference falsification due to fear of the local protection racket. I discount this possibility because, as described in the background section, the mechanisms of extortion that I use to indicate the presence of a protection racket are common and accepted, as is critiquing FARDC's behavior. The survey batteries were specifically designed after focus groups and piloting to ensure that civilians could convey their honest assessment of FARDC without fear. Moreover, the variation in response patterns – especially negligible non-response rates to the potentially sensitive questions and the high rates of respondents' willingness to respond in ways that are critical of FARDC or non-state armed groups even within areas where it was acting as a protection racket – also suggest that the results are not driven by preference falsification. Non-response patterns to potentially sensitive questions and characteristics that may distort a respondents willingness to articulate their true views, such as levels of violence, poverty, and FARDC presence are not systematically correlated with any such characteristics.

To further assuage concerns of preference falsification of reporting the presence of the FARDC security tribute schemes and selection effects of paying into them, I additionally use an alternative operationalization for the presence of a protection racket: FARDC controlled roadblocks. Because the roadblock data is collected independently of the survey, I can validate the self-reported measures I use to measure the presence of FARDC as a protection racket. Roadblocks are strategically placed to make it difficult for civilians to avoid them while conducting their necessary daily activities, such as going to fields to farm or walking to the mine where the civilians may work.

Nonetheless, although local military commanders and soldiers strategically place barriers to minimize civilians' ability to select out of participating in the extortion scheme, civilians may observe and strategically respond to the military's behavior or collaborate to avoid the roadblocks.

I note that the roadblocks are strategically placed to make it more difficult for civilians to avoid them while conducting their necessary daily activities, such as going to fields to farm or walking to the mine where the civilians may work. By combining these measures, which create different sources of bias, and finding similar patterns, I build confidence in my results and discount the possibility that reverse causality, selection effects, or preference falsification drive my results.

Spillover may occur if one village has protection from an armed group and neighboring communities receives a positive security windfall without contributing to or participating in the system. In this case, it may not be the demand for protection and the predictability of the payments that drive the result, but rather a simple improvement in aggregate security which drives the results. Such a scenario is not necessarily at odds with my theory or analysis. For example, I explicitly incorporate this possibility into my measurement strategy by measuring the distance to the nearest roadblock as well as aggregating the analysis of direct payments such as *lala salama* to the *groupement*.[30] The results indicate that the presence of a FARDC unit acting as a protection racket within the area does lead to improved perceptions of security if the demand for security provision is there, but that these improvements are concentrated among direct participants.

Finally, because of the contested nature of public authority in eastern DRCongo, it is possible that civilians view FARDC as just as another armed actor or come to view non-state armed groups that control territory and collect taxes as the state. In such a scenario, respondents may express positive perceptions of their security and in FARDC when they mean to express support for a non-state armed group or that respondents are unable to distinguish FARDC providing security from other actors providing security. But civilians are able to distinguish the organization from other armed actors. As Verweijen (2013) explains, FARDC "is popularly called "*jeshi ya serikali*" ("army of the government" in Swahili) or simply "*serikali*" ("government"), in part to distinguish them from non-state armed forces, generally called "*jeshi*." Moreover, the empirical patterns show that the windfall in perceptions of security does not extend to non-state armed groups who implement similar tribute schemes, indicating that civilians indeed distinguish between the armed actors

[30] Results not shown.

that operate locally.

3.7 Conclusion

In this paper, I outline the conditions under which civilians perceive protection rackets as improving their security amidst widespread ongoing violence. Civilian perceptions of their security improve when protection rackets fill a security void, which increases the demand for security provision, and if the protection racket sets up predictable tribute schemes, which create stable expectations and allow reciprocity to develop. But civilians perceive the extortion associated with protection rackets negatively if they do not have a need for them or if they do not provide predictability. I use a representative survey, fine-grained data on roadblocks and violence, and qualitative evidence to empirically evaluate my theory and find consistent support for my hypotheses in two provinces in eastern DRCongo.

My research has a number of limitations that future research should build on. First, much of the empirical basis of my work relies on self-reported data of potentially sensitive political dynamics which may be prone to a variety response biases. Second, although the data I analyze in this paper provides some temporal variation that I leverage, the empirical analysis is based on a limited snapshot of the political economy of conflict in eastern DRCongo. The survey data is fundamentally cross-sectional, inhibiting my ability to capture the variability of protective orders. Due to these limitations, an important caveat is in order: my analysis is not a doubly-decisive test of a hypothesis [164], but rather a series of complementary results that paint a consistent picture in line with theoretical expectations. As a result, I err on the side of sketching a broad portrait of a complex decision making process that civilians face rather than a narrow one based on tight inferences.

Despite these limitations, my findings having significant implications for how we understand the evolution of civilian-state relations in a number of post-conflict states. The dynamics I describe are not an example of effective state building in action, producing an endogenously strengthening state apparatus [156] based on rational-legal principles and conditional compliance [99]. But the protection rackets I describe do provide a modicum of predictability and security to civilians [112], though, and civilians in turn reward security providers with taxes and compliance for the privatization of state functions.

Instead, the dynamics I describe create a self-perpetuating cycle in which civilians perceive their improvements to their security institutions locally for privatizing public goods and state agents profit financially by doing so, thus undermining the state's long term capacity to create a monopoly on the use of violence [112]. Local security needs produce semi-organic responses, including the creation of exploitative but mutually beneficial informal institutions, that undermine macro state-building projects but provide crucial protection to vulnerable civilians locally. These localized protection rackets can, paradoxically, simultaneously enhance civilian perceptions of their own security while also making it less likely that the underlying conflict is resolved by undermining incentives for the elites who benefit most from the system to form a coalition to end the conflict [45]. Understanding the underlying process by which this happens clarifies why conflict induced incentives to provide protection and generate revenue does not always "make states," it can also undo them.

Finally, the findings of this project have a number of significant implications for international intervention seeking to create stability in conflict and post-conflict zones. First, I demonstrate that the privatization of security can, under certain conditions, actually improve outcomes for civilians. These political bargains are not based on Weberian bureaucratic norms, which the international community repeatedly attempts to impose as part of their state building project. As Autesserre (2010) notes, unless international actors understand the local sources of the conflict, they will not solve it. I compliment her warnings by arguing that local political bargains in such environments, although rooted in extortion, may help civilians in ways we have not considered. Disrupting those informal institutions may have perverse consequences.

CHAPTER 4

Seeing Blue Helmets is Believing: Exposure to Peacekeepers and Civilian Perceptions of UN PKOs

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Abstract

Civilian-peacekeeper relationships are essential for peacekeeping missions to fulfill their mandates. In this paper, we present and empirically evaluate a theory of civilian perceptions of international peacekeeping missions. We argue that civilians exposed to the mission are more likely to perceive the mission as successful. We find support for our theory leveraging over 16,000 responses to surveys across two waves and two sampling strategies in three provinces of the Democratic Republic of Congo, where one of the world's largest and longest standing peacekeeping missions, MONUSCO, operates. We show that exposure to MONUSCO is associated with improved perceptions of the mission, and that this relationship is not driven by selection effects. We additionally show that base closures, which abruptly decreased civilian exposure to Blue Helmets locally, are associated with decreased perceptions of the mission. Our findings suggest that missions can improve their relationships by increasing their visibility among host communities.

4.1 Introduction

United Nations (UN) peacekeeping operations (PKOs)[1] are a cornerstone of the international community's response to civil wars.[2] A large body of research shows that PKOs are effective at protecting civilians from violence [79, 78] by shaping the behavior of belligerents. Although the presence of Blue Helmets may curtail aggregate levels of violence, they often do so by sustaining a "negative peace" [58, 57], in which the absence of battle related deaths does not necessarily reflect a peaceful underlying political condition.

As such, the effectiveness of PKOs is not exclusively determined by levels of observed violence. Peacekeeping missions additionally seek to repair the broken social contract between citizens and war-wracked states [43][3] with broad mandates to rebuild government institutions, provide aid, and promote the rule of law [20, 19] in addition to their traditional focus on monitoring ceasefires and deterring belligerents from using violence.

The effectiveness of Blue Helmets is thus tied directly to local civilian perceptions of the mission, which are important both operationally and as a core outcome in and of itself for the mission. Indeed, Blue Helmets primary interaction is with civilians at the local level [24]: much of the work of PKOs do is the highly localized, every-day daily work of patrols and direct assistance to the civilian communities they are sent to protect. Operationally, Blue Helmets must cultivate positive relationships with civilians to gather intelligence and develop the situational awareness needed to effectively operate in violent, contested, and often unpredictable environments [64, 32].[4] In this way, positive civilian-peacekeeper relationships create a positive feedback loop, where civilian support makes the Blue Helmets more effective in their work.

[1]We define peacekeeping operations as interventions into potential, ongoing, or recently ended violence conflicts by an international body, such as the United Nations (in contrast to NGOs who operate in the same space, for example). In this paper, we refer to UN peacekeeping missions interchangeably as "PKOs", "missions", and "peacekeeping missions." We refer to "peacekeepers" and "Blue Helmets" as individual representatives of the peacekeeping missions. So as not to conflate UN peacekeeping missions with NGO peacebuilding activities, we refer to all activities associated with the UN peacekeeping mission as peacekeeping.

[2]While a variety of actors, such as regional organizations like the African Union, send peacekeeping missions to conflicts [14], the theoretical and empirical focus of this paper is on United Nations peacekeeping.

[3]Lake & Fariss (2014) detail the difficulties that international intervention faces in achieving such fundamental goals as outside interveners.

[4]Missions themselves are generally poorly equipped to directly gather such intelligence [47, 46].

More fundamentally, positive civilian perceptions are a goal of the mission in and of itself: a core outcome that PKOs evaluate themselves on is whether they improve civilian perceptions of their own security. Indeed, the Department of Peacekeeping Operations (DPKO) has repeatedly recognized the importance of civilian perceptions to their own effectiveness to the point that it is considered policy orthodoxy within the UN [175]. The UN DPKO Capstone Doctrine, for example, states that a peace operation must be "perceived as legitimate and credible, particularly in the eyes of the local population, in order to succeed" [158] and the Brahimi Report asserted that "effective peace-building requires active engagement with the local parties," including civilians [159].[5]

But PKOs face a number of barriers in their relationships with civilians. Blue Helmets are foreign forces who often operate in environments with fraught legacies of past international interventions, including colonial occupation.[6] In addition, PKOs are staffed by soldiers and civilians who often face language barriers and standard operating procedures that inhibit long-term relationship building with civilians. As a result, PKOs are often distrusted by civilians and perceived as divorced from the local population [30] and lacking local knowledge [6], rendering them ineffective in the eyes of many civilians [69].

Existing work suggests that exposure to PKOS may have contradictory implications for civilian perceptions of the mission: number of ethnographic studies find that the daily practices [155, 6] of peacekeepers make Blue Helmets seen as ineffective. At the same time, exposure to peacekeepers can increase cooperation between civilian groups [113] and receiving assistance can increase levels of cooperation with the mission itself [64].

In this paper, we study civilian trust in peacekeeping missions ability to carry out central mandate objectives and civilian perceptions of PKOs' contribution to mandate-related outcomes. We argue that exposure to Blue Helmets – such as receiving assistance or observing PKO activities from afar – improves civilian perceptions of PKOs. Without exposure to the Blue Helmets, civil-

[5]The UN DPKO has repeatedly reaffirmed the central importance of civilian perceptions to their effectiveness. The 2015 United Nations (UN) Secretary-General's High-level Independent Panel on Peace Operations (HIPPO) also argued that engagement with civilians is core to mission success [160].

[6]Although Gilligan & Stedman (2003) find that PKOs are not more likely in the former colonial states of P5 members, Paris (2002) explains how PKOs build on colonial legacies by promoting or projecting a certain form of acceptable governance models.

ians rely on negative prevailing narratives of the mission. Individual exposure to the mission, however, makes civilians more likely to view the missions' work positively, as civilians evaluate missions based on the impact on their own sense of physical and economic security, which exposure to Blue Helmets can improve. But these evaluations are relatively unstable: without sustained exposure, positive perceptions of the mission decay and can even produce a sense of abandonment.

We evaluate our theory by analyzing civilian relationships with and perceptions of an active UN peacekeeping mission. We surveyed a representative random sample of adults in three provinces in eastern Democratic Republic of Congo, where one of the world's largest, most expensive, and longest standing peacekeeping missions, MONUSCO, operates.[7] To account for spatial differences in civilian-peacekeeper relations, we complimented our representative sample of three provinces with a separate sampling strategy that focused on jurisdictions with MONUSCO bases. We find exposure to peacekeepers makes civilians more likely to express positive perceptions of the mission across both security and stabilization objectives. We triangulate among a variety of empirical strategies to discount the possibility that these results are driven by a selection effect. We additionally find that the abrupt departure of Blue Helmets from areas surveyed in 2018 were more likely to have negative perceptions of the mission when resampled in 2019. Our findings clarify the conditions under which civilians evaluate Blue Helmets positively and the (lack of) durability of these positive perception windfalls.

4.2 Exposure to and Perceptions of Peacekeeping Operations

In this section, we explain why exposure to Blue Helmets improves perceptions of international peacekeeping missions. The nature of relationships between peacekeeping operations and local populations is quite distinctive. Peacekeeping forces are multi-national foreign forces sent under an international banner to ongoing conflicts. As such, our theory is specific to international in-

[7] The acronym "MONUSCO" is derived from the mission's official French title, *Mission de l'Organisation des Nations unies pour la stabilisation en République Démocratique du Congo*. The mission was originally deployed as the United Nations Mission in the Democratic Republic of Congo or MONUC, an acronym of its then-official French name *Mission de l'Organisation des Nations Unies en République démocratique du Congo*, until 2010.

terventions, especially from multi-national bodies such as the United Nations, into ongoing zones of political violence. Our theory does not seek to explain civilian perceptions of national armies operating in foreign territory, for example, or national armies interacting with civilians of their own country. Additionally, we explain civilian perceptions of Blue Helmets in the context of an on-going operation; we do not attempt to explain initial interactions between peacekeepers and civilians, when civilian perceptions are likely more malleable.

A number of factors inform civilians perceptions Blue Helmets in aggregate. The UN is more likely to deploy peacekeepers to conflicts with high levels of violence against civilians [78], precisely the most difficult contexts to operate in and successfully carry out the multi-dimensional peacebuilding objectives that PKOs are mandated to fulfill. And while PKOs reduces the duration of conflict locally between the belligerents [134] and the geographic spread of violence, they do in ways that can produce more stable armed group presence ("stationary bandits") [12]. As such, limiting violence in aggregate may not be felt directly by the civilians who Blue Helmets protect, who continue to feel insecure and exploited despite the presence of peacekeepers.

The structure of PKOs additionally shape civilian perceptions of Blue Helmets within the local contexts in which they operate. Peacekeeping missions are constituted of foreign soldiers, who often have language barriers and no experience with the country they are sent to [6]. Rotation patterns amplify barriers to relationship building over time: military peacekeepers only stay in the country for roughly a year on average before rotating back to their country of origin. Burnout and turnover levels are high among civilian staff as well. Civilians are thus unlikely to feel an intrinsic personal attachment to the mission or its soldiers [59]. The perception of Blue Helmets is further influenced by grievances over past foreign intervention and colonial occupations that predispose civilians to view PKOs suspiciously.

These structural elements of peacekeeping missions create widespread negative perceptions of Blue Helmets among local civilians. These negative perceptions are observed repeatedly in a number of peacekeeping contexts. Peacekeepers are often seen as divorced from the local population [30] and lacking local knowledge [6], rendering them ineffective in the eyes of civilians [69]. A sense of imposition or broken promises can spark local backlash against peacekeepers [155]. Civilians are often confused about what the security mandate of peacekeeping missions actually is [91]. Even when civilians do observe PKOs actions, overly militarized behavior can also alienate or intimidate [123]. In general, civilians thus view Blue Helmets skeptically. This is especially the case as missions accrue negative reputations, which harden over time.

But civilian perceptions of Blue Helmets are not static or fixed. Instead, civilians consistently re-evaluate their perceptions of all actors and institutions that operate in their communities. In evaluating peacekeeping missions, civilians assess peacekeepers based on what they observe the Blue Helmets doing [120, 64] and the impact that Blue Helmets have on their lives [30]. These evaluations are driven by assessments such as whether civilians expect the mission will improve their sense of security or economic standing and perceptions of how well the mission's performance is perceived to have matched the expectations civilians have for the missions' performance in these domains. As with other forms of aid, perceptions of outsiders is not necessarily a deeply rooted or driven by macro policy, but instead based on rather much more localized interactions and outcomes [**?**].

Observing Blue Helmets carrying out mission-related activities is the primary mechanism through which civilians can update their opinions and judge the performance of PKOs. Missions must give civilians the opportunity to observe the consequences of the mission's presence for their own security and livelihood. If civilians know that peacekeepers are present but do not observe them, civilians wonder what the mission does and why they stay behind their walled-off base [123].

Further, civilians must be able to attribute the benefits to the mission. Direct contact with Blue Helmets allows peacekeepers to demonstrate in the most tangible way the positive impact that the mission can have on civilian well-being. Such direct exposure can break down barriers between peacekeepers and civilians and force civilians to reconsider the dominant narratives about the mission. Such efforts can improve population perceptions by overcoming uncertainties regarding the attribution of benefits that the presence of Blue Helmets can bring [**?** **?**]. Exposure to Blue

Helmets can make civilians more optimistic about the mission and credibly signal the impact that peacekeeping has on their lives.

Seeing Blue Helmets on patrols, for example, can improve civilian perceptions of peacekeepers by making their work more tangible. Observing such patrols make individuals more optimistic about the security situation in their local community and make civilians more likely to cooperate with outgroups [113]. By improving perceptions of security through these mechanisms, Blue Helmets enable civilians to return to economic and social habits that they forgo in times of more insecurity [25].

Even with a PKO operating locally, however, exposure to the mission is not a given. PKOs are restricted by their limited operational footprint, insufficient budgets, and risk-averse chains of command, all of which limit civilian exposure to Blue Helmets. It is possible to live in a region with a PKO, for example, and never interact with or see a Blue Helmet or even know that a base is nearby. It is not necessarily a given that exposure in and of itself is conducive to improving perceptions of Blue Helmets, either. Some have observed that civilians may see Blue Helmets but lack the understanding of what the missions are doing: Pouligny (2006), for example, notes that "There is plenty of testimony recalling in particular the white all-terrain vehicles that invade the streets, and the hotels taken over and occupied by people moving around hither and thither. But there is an important reservation: 'We don't see what they are doing' " (108). Even though such dynamics may – and indeed likely do – occur, increasing the observability of actual peacekeeping activities such as patrols or direct service provision can signal precisely what the mission actually is doing and how it serves local communities.

Exposure to Blue Helmets does not indefinitely improve perceptions, either. Civilians judge missions based on their present impact. While they update these beliefs based on their perceptions of the mission's behavior and effectiveness in the past, civilians can judge a mission as ineffective in the past and effective in the present. We propose that exposure to the mission is a key mechanism that enables such a positive shift in perceptions. The converse is also true, however: civilians can judge missions as effective at one point in time but, presented with new information, judge them as ineffective in subsequent periods. Consistent with our theory of the positive impacts of exposure on civilian perceptions of Blue Helmets, a reduction in exposure locally can have the opposite effect.

Withdrawing exposure after the establishing the contribution of Blue Helmets locally decreases evaluations of the mission by creating perceptions of abandonment. Peacekeeping missions must strategically choose where to place their personnel, and such decisions are restricted by (often acute) budget pressure. Missions simply do not have the resources or personnel to maintain observability for the long-term. By removing their spatial footprint, missions abruptly sever their connections to communities and severely decrease levels of exposure. Unless the mission has left the area in a completely secure state – i.e. fully reestablished peace and security to the area, an unreasonably high threshold that PKOs almost never achieve – civilians perceive the mission as abandoning them.

In summary, we expect that perceptions of Blue Helmets are, in general, negative. But exposure to Blue Helmets can improve civilian perceptions of the mission by enabling civilians to attribute improvements in their security and local context to the mission. However, the perception gains achieved through such exposure are temporary and must be sustained through continued observable presence. If the Blue Helmets do not remain visible, they can create a sense of abandonment in the local communities they serve.

4.3 United Nations Peacekeeping in DRCongo: MONUSCO

In this paper, we analyze civilian perceptions of the UN peacekeeping mission in DRCongo: MONUSCO. The UN's presence in DRCongo predates this mission,[8] and the conflicts in eastern DRC are rooted in complex, inter-related local, national, regional, international forces. To contextualize our analysis, in this section we briefly outline relevant history of the violence in east-

[8]The UN first sent peacekeepers to Congo – Katanga province in particular – in 1960. We do not discuss this history because it occurred in a different portion of the country. For additional information see, for example, Gibbs (2000).

ern DRCongo and MONUSCO's evolution. In addition, we discuss the benefits and limitations of focusing on MONUSCO compared to other PKOs.[9]

There are many explanations for the political violence in eastern Congo – and indeed, each explanation is contested. The most commonly cited triggers are some combination of the weakness and inefficiency of state, spillover effects from the Rwandan genocide, ethnic polarization, and both domestic and foreign competition for access to the abundant natural resource wealth.[10] Since the end of the Second Congo War in 2003, eastern Congo has remained unstable and violent, with a large number of armed groups – including elements of the state military, FARDC – using violence against civilians and each other to pursue their political and economic agendas.

The UN has been an actor to these conflicts since 1999, a 20-year period during which the mission has evolved from a limited observer mission at its inception into one of the most robust and militarized PKOs in UN history [135]. Originally deployed under the acronym MONUC to monitor the Lusaka Agreement, a failed ceasefire meant to end the Second Congo War, the Security Council added a limited Chapter VII mandate in 2000 to "use any means to protect civilians under imminent threat of physical violence." Despite the end of the Second Congo War in 2003 and MONUCs presence, local violence and the targeting of civilians continued in the eastern provinces [3]. Between 2003 and 2007, a number of high-profile failures to protect civilians from violence and changing conflict dynamics prompted the mission to re-orient itself towards the eastern provinces, where the majority of the mission's footprint remains today.[11]

After the 2006 elections, the mission adopted an increasingly multidimensional profile Di Salvatore, Lundgren, Oksamytna, & Smidt (2020) adding rebuilding state institutions and addressing

[9]This section is not intended as a holistic review of the UN's experience in DRCongo or the violence in eastern DRCongo. Instead, we seek to review the salient events and behavior of the mission that may shape our respondent's perceptions of the mission. We do not, as one example, discuss MONUSCO's recent operations in the Kasaï region, as it is outside the geographic scope of our survey.

[10]The violence in eastern Congo can be broken into a number of phases. The First Congo War internationalized civil war in which most of the countries in the region participated [122]. The Second Congo War began after a falling out within the international coalition that won the First Congo War, eventually involving 9 countries and resulting in an estimated 3.8 million deaths and displacing millions more [31].

[11]In addition to the presence of MONUC, in May 2003, the European Union also deployed the International Emergency Multinational Force (IEMF) Artemis to Bunia, the capital of Ituri, in response to escalating violence and the targeting of civilians [127]. This was a short-lived and one-off deployment.

the underlying conditions that perpetuate violence to the missions' core protection of civilians responsibility. The mission renamed MONUSCO in 2010 to represent the addition of these broader "stabilization" objectives to the mandate. As part of this expanded mandate, MONUSCO increasingly worked with the Congolese government in a number of domains, including security. This increased collaboration with the state put the mission in the sometimes-awkward position of supporting the expansion of state authority while protecting civilians from abuses often perpetrated by agents of the very same state [176].

In March 2013, the UN Security Council established the Force Intervention Brigade (FIB) directed to 'take all necessary measures' to 'neutralize' and 'disarm' groups that pose a threat to 'state authority and civilian security' [89][12], the most aggressive peace enforcement component in the missions' history. The FIB was crucial to proactively fighting against non-state armed groups, in particular the M-23 movement and the ADLF.

Simultaneously, recognizing the need for improved relations with and information gathering from local communities with this broader mandate, MONUSCO expanded its Civil Affairs division as a complement to its more traditional military operations. For example, the created the position of Community Liaison Assistants ("CLAs"), Congolese nationals who serve as intermediaries between MONUSCO, local authorities, and the population [93, 148].[13] More recently, the mission has transitioned to a posture of "protection through projection" in the face of budget cuts [148], decreasing the number of bases and personnel increasing the number and reach of project activities (for example patrols) to compensate.

Despite a more than two-decade presence of the mission and increasingly aggressive mandate, peace remains an elusive goal. In 2015, The Kivu Security Tracker identified 70 armed groups operating in North and South Kivu [153].[14] That number rose to 120 in 2017 [153] and 130 in 2019 [152]. In North and South Kivu alone, 1,897 civilians were killed and 848 kidnapping incidents occurred between June 2017 and June 2019 [152].

[12]The FIB is comprised of African Union troops from South Africa, Tanzania, and Malawi.

[13]CLAs are formally employed by MONUSCO.

[14]The Kivu Security Tracker is a joint project of Human Rights Watch and the Congo Research Group. It only collects data in North and South Kivu and thus does not cover the third province in our analysis, Ituri.

MONUSCO is one of the largest and longest-standing peacekeeping operations, making it a crucial case for understanding the dynamics of peacekeeping operations more broadly [145]. MONUSCO is, however, in many ways a highly unique case that warrants caution when comparing to other cases. As discussed above, the UN in general and MONUSCO in particular has an extensive and complicated history in DRC, and that history has produced entrenched perceptions of the mission. It is thus fundamentally different from new missions, when civilian perceptions of the UN and peacekeepers are likely more malleable. Likewise, MONUSCO has an unusually aggressive protection and stabilization mandate. While PKOs have long been authorized to use force under Chapter VII of the UN charter [19], the extent to which MONUSCO is charged with peace enforcement and actively targets armed groups, in particular through the FIB, is unique among contemporary PKOs [89, 135].

One balance, however, the mandate and footprint of the mission is in many ways indicative of broader, more representative patterns of contemporary multidimensional PKOs. Peacekeepers are increasingly deployed to active conflicts where there is no peace to keep [89, 19]. UN PKOs with comparable peace-enforcement mandates include UNAMID in Darfur, MINUSCA in the Central African Republic (CAR), MINUSMA in Mali, and UNMISS in South Sudan [15]. MONUSCO's evolution is also indicative of a broader trend towards what Blair, Di Salvatore, & Smidt (2021) label "fragmented mandates" of "many dissimilar tasks," such as protecting civilians, peacebuilding (such as organizing elections or supporting state institutions), and cross-cutting tasks (such as gender equity and human rights). Even MONUSCO's FIB is not as unique as it might appear: In April 2013, the Security Council authorized the MINUSMA mission in Mali "to stabilise the key population centres ... [and] to deter threats and take active steps to prevent the return of armed elements to those areas" [89], a level of pro-active peace enforcement similar to MONUSCO's experience. As such, we do not believe it is likely our results are driven by unique or idiosyncratic characteristics of MONUSCO or DRCongo as a case. Instead, it is likely that MONUSCO is a particularly hard case to test our theory, as a particularly entrenched mission amid high levels of ongoing violence and relatively stable civilian perceptions of the mission.

4.4 Survey and Research Design

To capture civilian experiences with and exposure to the MONUSCO peacekeeping mission, we conducted surveys of civilian adults in three provinces of eastern DRCongo: Ituri, North Kivu, and South Kivu. These provinces are the epicenter of violence in eastern DRCongo and main operational focus of the MONUSCO mission.[15] These surveys are part of a longer-term effort (since 2014) to regularly survey representative samples of civilians in these provinces. In this paper, we analyze two waves (enumerated in June-July 2018 and July-August 2019, respectively) from this broader project, because they include specific questions that allow respondents to report their interactions with and perceptions of MONUSCO. We label these province representative samples as the "General Sample."

Each survey wave uses a multi-stage cluster sampling strategy capturing all *territoires*[16] in each of the three provinces. Given the lack of reliable census data and high levels of internal displacement in eastern DRCongo, our sampling and weighting procedures are by necessity conservative. We use administrative units to guide our sampling strategy. We randomly select 9 *groupements* (or *quartiers* in cities) within each *territoire*. Within selected *groupements*, we selected 3 villages (or *avenues* in cities), for 27 clusters per *territoire* and carried out 8 interviews per cluster using a random walk procedure.[17]

All samples are balanced on gender. Interviews were conducted by Congolese college students or professionals of the same gender and ethnicity as respondents to minimize enumerator-induced response bias. After the data is collected, responses are weighted to adjust for differences in probability of selection at the *territoire* level. We interviewed 5,951 civilians in the 2018 and 5,961 in the 2019 General sample, for a combined N = 11,912 across the General sample waves.

We are interested in analyzing whether exposure to MONUSCO impacts perceptions of the mission. Of course, exposure to MONUSCO is not randomly distributed across space. The geographic

[15] A map displaying MONUSCO's operational footprint is provided in the Appendix, Section A.4.

[16] *Territoires* are sub-provincial administrative units. Additional details on the structure of administrative units are available in the Appendix, Section A.2.

[17] Multiple attempts are made over the course of one day to contact selected respondents and if necessary, appointments are made for interview.

distribution of the mission's operational footprint – i.e. where the mission places its soldiers and staff, mainly through its placement of bases – dictates the likelihood that civilians are exposed to the mission. Those who live in proximity to the mission are more likely to see and benefit from the peacekeepers' activities. Given the budgetary and operational constraints that peacekeeping missions face, however, MONUSCO must strategically place their bases in areas where they can most efficiently and effectively protect civilians. Peacekeeping missions select into the locations with the highest levels of violence within conflict zones [121].

As a result, civilians living near MONUSCO bases may have systematically different exposure to the mission and/or conflict related violence. These differences may correlate systematically with underlying perceptions of the mission. We must therefore account for potential selection into exposure to the mission and potentially endogenous levels of baseline distrust in institutions in the areas in which MONUSCO operates.

To address this selection issue, we complement our general population samples by separately drawing a random sample of adults in jurisdictions (specifically *groupements*)[18] with a MONUSCO peacekeeping base. We call these samples the "MONUSCO Base sample." In drawing from only the communities directly around MONUSCO bases, we restrict our sample to adults with similar baseline potential for exposure to MONUSCO based on geographic proximity to the mission. The content of the survey instrument is the same as and was collected simultaneously to the General population sample.

We first randomly selected MONUSCO bases to sample around based on a list of all bases provided to us by MONUSCO. 24 of these were Company Operating Bases (COBs)[19] bases were COBs and 20 were Temporary Operating Bases (TOBs) or regional HQ. We restricted the potential pool of bases to COBs to ensure comparable forms of engagement with the local population surrounding the base.[20] We further restricted the potential pool of bases to relatively isolated COBs

[18]*Groupements* are the second smallest administrative unit in DR Congo. It encompasses a set of villages (the smallest administrative unit). The next highest administrative unit is the *Chefferie*, which is also known as the Sector. We provide additional information on the structure of Congolese administrative units in the Appendix, Section A.2.

[19]These bases are the forward deployments of the peacekeeping presence.

[20]Regional HQs were disqualified because they are typically situated in the largest city in the area. Diplomatic activity and logistical support is centered in these cities, but this presents a fundamentally different form of engagement

to ensure we could attribute civilian perceptions to MONUSCO's actions and not, for example, spillover effects. [21] We randomly selected one-third of the potential COBs proportionate to the size of the contingent, resulting in 8 selected COBs in 2018 and 9 selected COBs in 2019.

After drawing the COBs, we surveyed the adult population in the *groupements* around those bases. As with the General sample, our sampling procedure was based on administrative units. The target sample size for each selected *groupement* in the MONUSCO Base sample was 216 interviews. A list of all villages was established for each *groupement* and a total of 27 villages were randomly selected in the *groupement*. In each village, we conducted 8 interviews. The sample size for the Base survey was 1,777 respondents in the 2018 wave and 2,424 respondents in 2019, for a combined total of 4,199 respondents. As in the General sample, an equal number of men and women were interviewed.

Combined, we analyze survey responses from two waves and two sampling strategies. First, we analyze two waves of representative samples of the entire provinces and second, we analyze two waves of over-samples in *groupements* with MONUSCO bases. Table 4.1 provides the number of survey respondents across samples and waves.

	Wave 1: 2018		**Wave 2: 2019**		
Province	*Base Sample*	*General Sample*	*Base Sample*	*General Sample*	**Total**
Ituri	439	1390	656	1349	3834
North Kivu	862	2158	1127	2267	6414
South Kivu	343	2403	641	2345	5732
Total	1735	5951	2424	5961	16071

Table 4.1: Number of Respondents Per Province, Wave, and Sample

for the peacekeeping mission that forward-deployed, protection oriented elements of the mission such as COBs and TOBs. TOBs are short lived forward deployments without sustained engagement with the local communities.

[21] If exposure to MONUSCO in one area distorts opinions in neighboring areas through channels other than individual exposure (for example, conversations between civilians in two different villages, with one experiencing exposure to MONUSCO and the other not), our estimates will be biased. While we cannot completely discount such mechanisms given the structure of our data, spillover is not as significant a problem as it may appear. The lack of connectivity between villages in eastern DRCongo, especially in rural areas, mitigates the risk that exposure with peacekeepers in one location might affect citizens' attitudes in another. Moreover, we selected relatively remote *groupements* to minimize the likelihood of spillover.

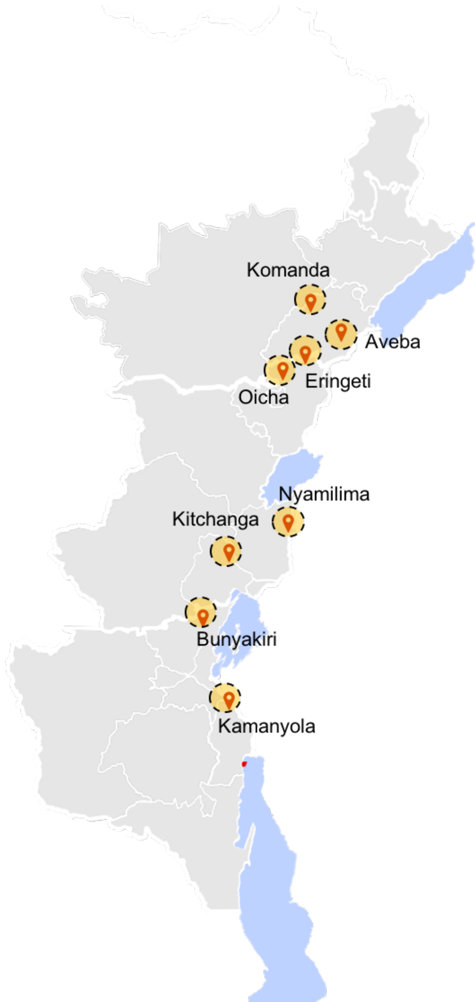


Figure 4.1: Bases Included in the MONUSCO Base Sample

4.4.1 Ethical Considerations and Participant Protections

Eastern DRCongo is a site of ongoing conflict and violence,[22] raising a number of ethical, methodological, and practical concerns about collecting such data. Consistent with calls for increased transparency and attention to ethics in such research Cronin, Furman, & Lake (2018), in this section we provide additional information on how we incorporated ethical considerations and protections into our fieldwork procedures and research design. Given the research context and the vulnerability of populations that we study, we took a number of steps beyond obtaining IRB approval to ensure

[22] While many, including the United Nations, view DRCongo as "post-conflict" [4], the eastern provinces that we analyze remain well above all standard thresholds of violence to constitute an ongoing conflict.

our research was ethical, safe, and rigorous.

An interdisciplinary research team, including public health scholars with expertise in trauma, crafted the survey instrument to keep questions general in nature to avoid specific triggers. We designed the survey instruments to minimize the risk of mental distress induced by potentially sensitive questions and by keeping questions on potentially triggering topics intentionally vague. Doing so allows us to collect general patterns while not forcing respondents to re-traumatize themselves, in line with best practices in public health and psychological research. During the enumeration process, respondents were reminded multiple times of their option to refuse to answer any questions or stop interviews. Enumerators also repeatedly reminded respondents of their anonymity. We also incorporated local research partners in the full research cycle to ensure our survey questionnaire was contextually appropriate.

To ensure the safety of respondents and enumerators, we created safety plans and determined the conditions under which enumeration would stop ahead of time. Security conditions on the ground were constantly monitored based on multiple sources, including contacts within MONUSCO. We made decisions about whether to pause enumeration in certain areas conservatively, always prioritizing the safety and security of our team and the respondents.

We additionally took a number of steps to protect respondents and the data they provided after the surveys were collected. We did not ask for any identifying information. Detailed location information was automatically degraded to prevent re-identification. Collected data were sent to a cloud-server using encrypted communication via KoboToolbox as soon as enumerators had access to internet and then wiped from Tablets. Once completed, data were downloaded and stored on encrypted laptops and data sharing applications.

4.4.2 Measuring Perceptions of MONUSCO

Our surveys ask respondents to share their perceptions of MONUSCO across a series of mandate-related criteria. We use their answers to these questions as our outcome variables. In particular, we ask batteries of questions that prompt respondents to report whether they trust MONUSCO to fulfill a series of mission related tasks, their perception of MONUSCO's contribution to a series of mandate related outcomes, their knowledge of MONUSCO's work in general, the implications of a hypothetical MONUSCO departure from the province in which they live, and the likelihood they would seek out MONUSCO's help in a variety of hypothetical scenarios. We summarize the questions we asked and the concepts we use them to measure in Table 4.2.

Perception Concept	**Dimension**	**Question**	**Respondent Options**
Trust	Security	ensure security in your neighborhood?	Yes/No
		protect you from armed groups?	
		protect you from thieves and/or bandits?	
	General	help you when needed?	
		fulfill the needs of the most vulnerable?	
Contribution	Security	protecting the population?	5p Likert
		demobilizing combatants?	
		assist victims of crimes?	
		fighting against armed groups?	
		your security?	
	General	maintaining peace?	
		creating conditions for peace?	

Table 4.2: Measuring Perceptions of MONUSCO

We use two dimensions of perceptions in our main analysis. First, trust in the mission to achieve mandate tasks and second, MONUSCO's contribution to mandate related goals. We measure these across two additional dimensions of MONUSCO's multidimensional mandate: security provision and stabilization activities. We then sum across the battery. We rotate across these measures as our dependent variable in our analysis to explore consistency across different dimensions of perceptions of the mission. We normalize all measures. In the Appendix (Section A.9), we use alternative measures of perceptions of the missions, including perceived implications of MONUSCO's departure and whether respondents would seek out the mission in a series of hypothetical scenarios.

Directly asking civilians for their opinions on actors involved in the conflict prompts concerns of response bias. We attempt to alleviate these concerns in multiple ways. First, we expect that the response bias in this case is smaller than it might originally appear: MONUSCO does not instill fear in the same way other institutions in such an insecure context might. It is not taboo to critique – to the contrary, it is even socially desirable in some circumstances – MONUSCO and its failings in eastern DRCongo openly. In addition, to minimize response bias, the survey was administered by Congolese college students from the surveyed areas and respondents were given the option to refuse to answer all questions. Respondents were also repeatedly reminded that their answers were anonymous.

4.4.3 Measuring Exposure to MONUSCO

We expect exposure to MONUSCO is associated with improved civilian perceptions of the mission. We use a series of questions that prompt respondents to self-report[23] whether they had exposure to MONUSCO and, if so, under what circumstances to measure exposure. Based on respondent answers to these questions, we create three variables – *General Exposure*, *Positive Exposure*, and *Negative Exposure* – which we use as our independent variables. We summarize the questions we use to construct these measures in Table 4.3.

Variable	**Self-Reported Exposure**	**Contact Quality**	**Respondent Options**
General	Direct contact in last 6 months	Neutral	Yes = 1
	MONUSCO base nearby	Neutral	Yes = 1
	See MONUSCO soldiers regularly	Neutral	Daily, weekly, or monthly = 1
Positive	Personally assisted by MONUSCO in last year	Positive	Yes = 1
Negative	Victim of misbehavior by MONUSCO personnel	Negative	Yes = 1

Table 4.3: Measuring Exposure to MONUSCO

We use answers to three neutral questions[24] about exposure to the mission to create the *General Exposure* measure. These questions are "have you had direct contact with MONUSCO in the last 6 months," "is there a MONUSCO base nearby?" and "how frequently do you see MONUSCO soldiers?" We do not prescribe what "nearby, " "direct contact," or "see MONUSCO soldiers." Instead, we are interested in respondents' *perceptions* of these concepts and whether they perceive themselves as experiencing these loose forms of exposure to the mission. We code any respondent who reports either seeing MONUSCO soldiers daily, weekly, or monthly, who answers yes to direct

[23]We rely on self-reported exposure to MONUSCO because the mission does not make systematic data on their civilian or military activities publicly available.

[24]By neutral, we mean that the respondent does not have to report whether their exposure to the mission is positive or negative.

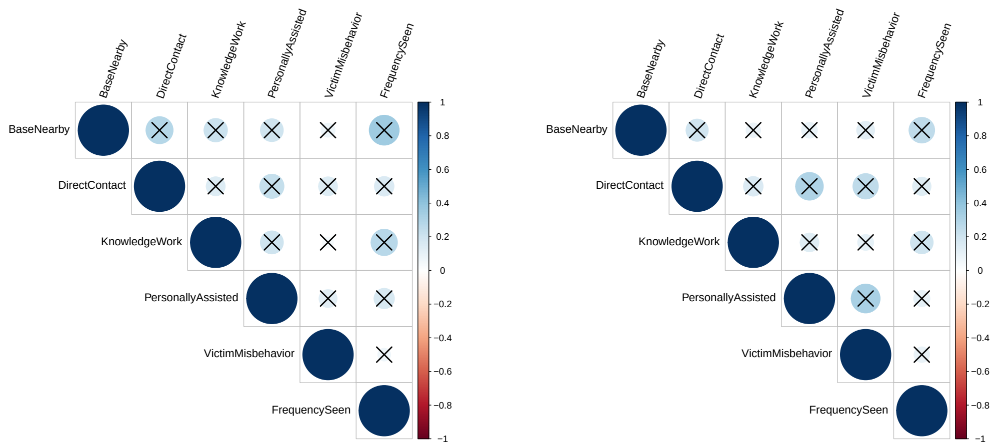
contact, and/or who answers yes to living near a MONUSCO base as having exposure.[25] Even with this relatively broad definition of exposure, only 32.81% in the 2018 wave and 20.13% in the 2019 wave self-reported exposure to the mission in general sample. As expected, the MONUSCO Base samples have higher levels of exposure than the general population: 44.43% in the 2018 wave and 44.89% in 2019 wave.

Of course, the quality of exposure may differentially impact perceptions of the mission as well. Two questions allow us to measure the quality of exposure to MONUSCO. First, we ask whether respondents have been personally assisted by MONUSCO in the last year. This captures positive interactions with the mission, although we do not stipulate what assistance means and, again, instead capture broad perceptions. Second, to capture negative interactions with the mission, we ask respondents a yes/no question in which they report whether they have ever been a victim of misbehavior by MONUSCO personnel. Both positive and negative interactions with the mission are rare: less than 4% of respondents in both the regular sample (3.443% in 2018; 2.073% in 2019) and the MONUSCO Base sample (3.778% in 2018; 2.979% in 2019) reported they were personally assisted by MONUSCO in the last year. Even fewer reported they were victims of misbehavior: in the General Sample, 1.085% of respondents in 2018 and 0.918% of respondents in 2019 reported they were victims of MONUSCO behavior. The proportion of respondents in the MONUSCO Base sample was marginally higher: 3.362% in 2018 and 1.061% in 2019.

It is important to note that, in particular for those who report being a victim of misbehavior, there are serious response bias problems. Respondents may be reluctant to report such misbehavior for a variety of reasons. Likewise, there are multiple channels through which such misbehavior can influence perceptions of the mission, and direct victimhood is an extremely restricted channel. It is likely that such misbehavior would get passed through social networks and/or media. Our data limit such measurement, so we caution against reading too much into those results and use the general exposure measure as our main independent variable.

We plot the correlation between the various manifestations of exposure to the mission in Figure

[25] In the Appendix, we deconstruct this aggregate measure by using the three variables separately.



(a) 2018

(b) 2019

Figure 4.2: Correlation Between Exposure to Mission Questions

4.2 (in 2018 in Figure 4.2a and 2019 in Figure 4.2b). Both correlation plots show that the measures are weakly related, suggesting that while there is limited overlap in the exposure types, they are not mutually exclusive. It also means that those who have neutral exposure are not necessarily perceiving the forms of exposure we classify as neutral as direct assistance. Put differently, respondents can separately perceive exposure while not perceiving that exposure as direct assistance.

4.4.4 Measurement of Control Variables

Our empirical analysis controls for a range of potentially confounding variables.[26] We control for standard demographic characteristics that may influence a given respondents' perceptions of the mission, including *Gender*, *Age*, and *Education*.[27] We control for a composite index of *Household Assets* to measure household economic wellbeing, which may influence perceptions in general and perceptions of security and institutions in particular. We also control for a binary indicator of whether the respondent is a member of a minority ethnic group in their *groupement* (*Ethnic*

[26]Summary statistics for all variables used in the models are presented in the Appendix.

[27]*Education* is a binary indicator that takes a value of 1 if the respondent self-reports attending (but not necessarily completing) secondary school or higher.

Minority), as local ethnic minorities may disproportionately require protection from the mission. Additionally, because MONUSCO collaborates with the Congolese government in a number of domains, we control for a composite government trust score (*Trust Gov't*).

PKOs are primarily concerned with and evaluated by their ability to protect civilians. As such, it is important to control for exposure to conflict-related violence, which likely impacts perceptions of the mission. Controlling for exposure to violence is challenging given systematic underreporting of violence in eastern DRCongo in media (and thus standard event-based datasets on the conflicts [163]) as well as the frequency of forced displacement in our sample, making it impossible to know whether respondents location at the time of nearby violent events is the same as when violent events happened [119]. As a result, we do not rely of standard events based datasets and instead, create a measure based on self-reported answers to questions about exposure to violence (*ExposureViolence*).

4.4.5 Strategies to Mitigate Selection Problems and Data Limitations

Our analysis faces a number of challenges in isolating whether exposure to MONUSCO improves civilian perceptions of the mission. In this section, we address the most pressing of these concerns and detail how we incorporate them into our empirical strategy. Although we are careful to rule out as many alternative explanations as we possibly can with the data available to us, we recognize that the structure of our data limits our ability to make causal empirical claims. Instead, we triangulate among a number of alternative specifications and empirical strategies to iteratively build confidence in our results.

Exposure to peacekeeping activities is not randomly assigned. MONUSCO may pro-actively target areas where the civilian population already trusts the mission to minimize its own security risks. In such a scenario, exposure to MONUSCO may be determined by existing civilian perceptions of the mission. Base location is dictated by logistical constraints (i.e. historical decisions, high ground, budget, nearby road choke points) and where missions can most effectively protect civilians from violence [121]. As such, we believe this selection concern is not as daunting as may appear. Nonetheless, we incorporated such a possibility into our sampling strategy through the MONUSCO Base sample. This sample is restricted to civilians in *groupements* with MONUSCO bases. In doing so, we restrict our comparisons when analyzing the MONUSCO Base sample to civilians in precisely the jurisdictions that MONUSCO selected into. Our comparisons within this sample thus mitigates such a selection effect.

Conversely, selection effects may drive our independent variable, exposure to MONUSCO, in ways that prompt concerns of reverse causality. If this were the case, civilians may self-select into exposure due to pre-existing perceptions of the mission or the economic incentives of living near a MONUSCO base [13]. Similarly, those who are not exposed to the mission may actively avoid exposure due to existing distrust or fear of the mission. We seek to address these problems in multiple ways. First, we note that exposure to MONUSCO is in most instances involuntary and driven by geography. Second, our MONUSCO base sampling strategy explicitly incorporates this concern by sampling who, by virtue of geographic proximity, is most likely exposed to the mission. Third, we leverage changes in MONUSCO's spatial footprint that exogenously influenced exposure to the mission by analyzing base closures that occurred after the 2018 wave but before the 2019 wave to further mitigate selection effects.

Exposure to the mission is not randomly distributed even within *groupements* with MONUSCO bases. As such, our analysis is still prone to omitted variable bias. As a first step, all empirical models control for a series of potentially confounding variables. Additionally, because the controls available to us are unlikely to completely overcome omitted variable issues, we triangulate among a series of empirical strategies to iteratively build confidence in our results. In the Appendix, we present results from propensity score matching (PSM) based on exposure. The goal of PSM is to reduce imbalance in covariates between the treated and control groups, thereby reducing the degree of bias in observational studies like ours [73].

4.5 Analysis and Results

Our analysis proceeds in a series of steps to iteratively build confidence in our results and grapple with the selection problems that we describe above. First, we examine the relationship between exposure and perceptions of the mission in the General sample. Second, we examine the relationship in the MONUSCO base sample. Third, we examine perceptions of the mission in the wake of the closure of bases in between our survey waves. Additionally, we present a series of robustness checks and additional empirical strategies in the Appendix to further probe the data and build confidence in our results.

4.5.1 Exposure to MONUSCO and Trust in the Mission in the General Population

We first analyze whether, in the general population, exposure to MONUSCO is correlated with perceptions of the mission to provide general benchmark of whether exposure to the mission is correlated with improved perceptions of the mission. As noted above, these results have important limitations, including the potential for selection effects at play, which we tackle in greater detail below.

We begin by running a series of four OLS regressions, with the unit of analysis as the individual respondent, and our independent variable as the binary indicator of whether the respondent self-reported exposure to the mission. The outcome variable rotates through each model: in Model 1 and Model 2, we use measures of perceptions of trust in and perceived contribution of MONUSCO's security provision as the dependent variable, while Models 3 and 4 use measures of MONUSCO's stabilization responsibilities. We include survey wave and *Territoire* fixed effects in each model to capture unobserved temporal and geographic differences. We also include the battery of control variables described above.

We present the results from these models in Models 1-4 in Table 4.4. Across each specification and measure of perceptions of the mission, exposure is positively and significantly associated with positive perceptions of MONUSCO. Exposure to MONUSCO is associated with an estimated 11% (CI: 0.09 – 0.13) increase in the likelihood that a trusts MONUSCO to provide security provision (Model 1) and a 9% (CI: .08 – 0.10) increase in how likely a respondent perceives MONUSCO as contributing to their security (Model 2) compared to those who are not exposed in the general population. Exposure to the mission and perceptions of MONUSCO's stabilization responsibilities are associated with increases of similar magnitudes: Models 3 and 4 estimate a 10% (CI: 0.077 – 0.1265) increase in trust in stabilization activities and a 9% (.0761 – 0.101) increase in contribution to stabilization goals, respectively. All of the estimates in Models 1-4 of Table 4.4 suggest a positive, relatively stable relationship in magnitude between exposure to the mission and perceptions of the mandate.

While these estimates are useful for understanding the relationship between exposure and perceptions of the mission broadly, they have a number of important limitations. For example, the structure of the data and Models 1-4 in Table 4.4 do not allow us to distinguish between whether selection or reverse causality drive the relationship between exposure and perceptions of the mission. It is possible that those exposed to the mission are precisely those civilians who perceive the mission positively. Alternatively, those who have negative perceptions of the mission may avoid exposure to the mission.

	General Sample				MONUSCO Base Sample			
	Dependent variable:							
	Trust		Contribution		Trust		Contribution	
	Security	Stabilization	Security	Stabilization	Security	Stabilization	Security	Stabilization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to MONUSCO	0.094^{***}	0.082^{***}	0.087^{***}	0.077^{***}	0.104^{***}	0.089^{***}	0.055^{***}	0.055^{***}
	(0.012)	(0.006)	(0.013)	(0.007)	(0.013)	(0.012)	(0.006)	(0.007)
Observations	8,489	8,489	8,489	8,489	2,841	2,841	2,841	2,841
R^2	0.16	0.31	0.15	0.27	0.25	0.44	0.27	0.31
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Territoire FE	✓	✓	✓	✓				
MONUSCO Base FE					✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the General Sample; Models 5-8 use the MONUSCO base sample. Models 1-4 include *Territoire* fixed effects. Models 5-8 include MONUSCO base fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table 4.4: Relationship between exposure and perceptions of mission

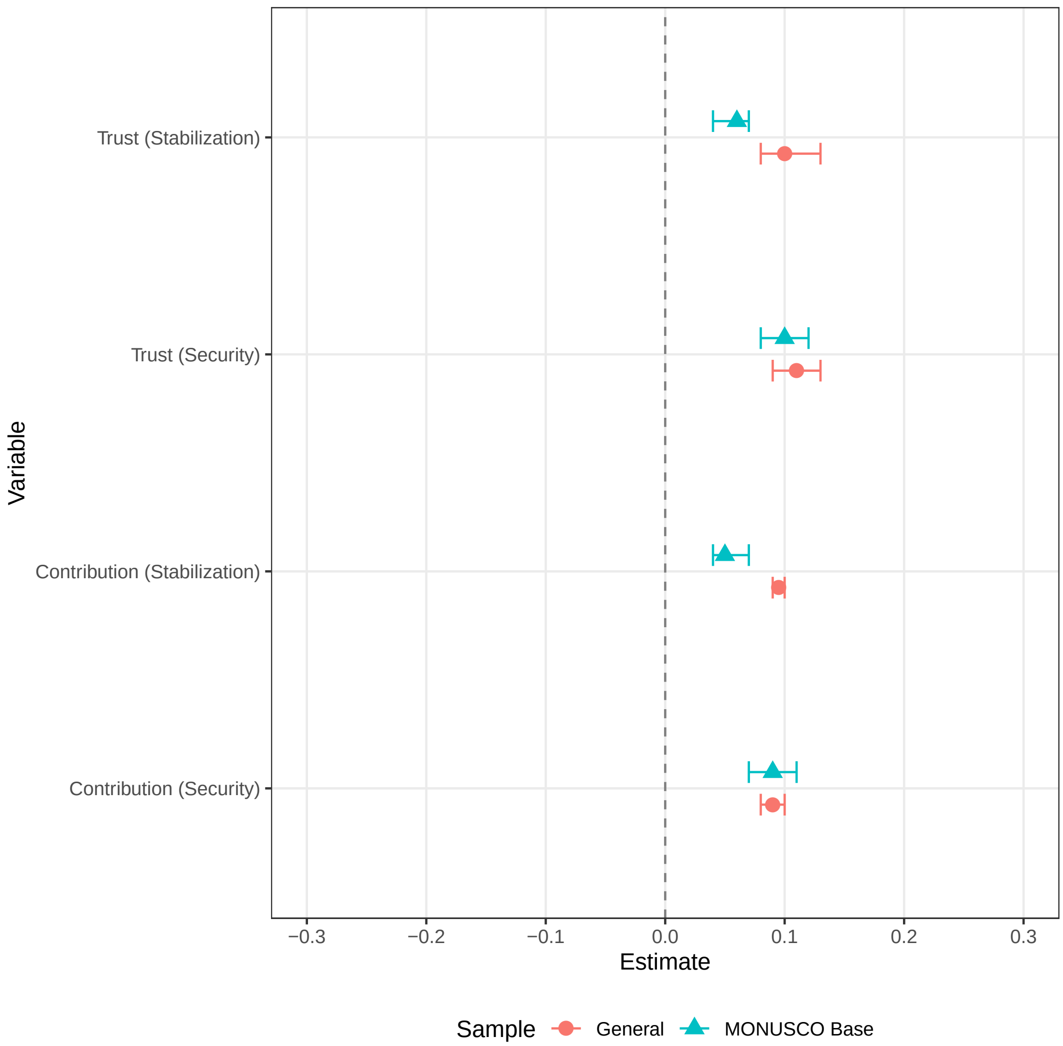


Figure 4.3: Estimates with 95% CIs from Models in Tables 1 and 2

4.5.2 Variation in Exposure Within the MONUSCO Base Sample

We begin to unpack the possibility that the results in Models 1-4 of Table 4.4 are driven by such selection effects by examining variation within communities with a MONUSCO base. Doing so enables us to analyze whether exposure is still positively associated with perceptions of the mission when analyzing only those civilians who, by virtue of proximity to the mission, are similarly likely to come into contact with the mission.

To do so, we re-run Models 1-4 of Table 4.4 using the MONUSCO Base sample instead of the

General Sample in Models 5-8 of Table 4.4. Because of the different sampling strategies between the samples, we replace *Terriotire* fixed effects from Models 1-4 with MONUSCO Base fixed effects in Models 5-8. We include the same battery of controls and again rotate through the four measures of perceptions of MONUSCO as the dependent variables.

Consistent with the results from the general sample, exposure to MONUSCO in the MONUSCO Base sample is positively and significantly associated with improved perceptions of the mission. The magnitude of the relationship is consistent across the different sampling strategies for the trust variables: we estimate a 9% (CI: 0.07 – 0.12) increase in trust in security provision and an 8% (CI: 0.06 – 0.10) increase in trust in stabilization activities compared to respondents in the MONUSCO Base sample that did not have exposure to MONUSCO. The perceived contribution magnitudes are marginally smaller. We estimate exposure as associated with a 5% (CI: 0.04 – 0.07) increase in perceived contribution to security and a 5% (CI: 0.04 – 0.07) increase in perceived contribution to stabilization goals within the MONUSCO Base sample. We visualize the results from Tables 4.4 and Table 4.4 in Figure 4.3.

Because we specifically selected relatively isolated bases, we can mitigate concerns of cross-contamination or spill over. Through sampling, we increased our level of confidence that exposure to the mission is directly attributable to the base we sampled around in the COB sample. As such, we are able to further probe whether heterogeneity based on the characteristics of the base, for example whether the base is a FIB (whose different mandate may fundamentally distort civilian perceptions) and the TCC that staffs the base, as the national origins of the peacekeepers likely have different levels of cultural distance [24] that shapes their interactions with civilians [60]. To address this potential heterogeneity, in the Appendix we explore whether exposure to the FIB bases (Section A.6.3) or whether the TCC (Section A.6.2) of the peacekeeping base influences the relationship.

4.5.3 Changing Perceptions after Local Base Closures

The results in Table 4.4 allow us to observe that those who come into contact with the mission are, in general, associated with more positive perceptions of the mission across both security and stabilization portions of MONUSCO's mandate. We find suggestive evidence that this relationship is not exclusively driven by selection effects by analyzing exposure within communities with a MONUSCO base. Despite this, our first two empirical strategies are unable to observe the duration of the positive windfall in civilian perceptions or the underlying mechanisms that drives these positive perceptions.

To begin to unpack these dynamics, we exploit changes in MONUSCO's operational footprint between our survey waves through base closures. The mission opens and closes bases in response to changing security environments and budget constraints. Our 2019 MONUSCO Base sample captures civilian perceptions of MONUSCO in the wake of five local base closures between survey waves, helping us analyze the extent to which the departure of peacekeepers from the community influences civilian perceptions of the mission. Three additional COBs (Kalonogo, Gety, and Nyabiondo) closed between survey waves but were covered exclusively in the 2019 COB wave. For these bases, we only have a post-closure snapshot, but we can compare perceptions in areas with a recent base closure to perceptions in areas where bases remained opened.

While not directly comparable to the results above, capturing civilian perceptions in the wake of base closures does enable us to observe whether removing exposure to the mission corresponds to reduced trust and confidence in the mission. In effect, we explore whether the converse of Tables 4.4 is true: whether base closures negatively impact perceptions of the mission.

We create an indicator variable for *groupements* where bases closed before the 2019 survey wave, which we use our independent variable. Using the 2019 MONUSCO Base sample, we run another four OLS regressions alternating between each of the perceptions MONUSCO measures as our outcome variables and the indicator for base closures as our independent variable. Because we collect only the 2019 post-closure snapshot in Kalonogo, Gety, and Nyabiondo, we compare civilian perceptions in those areas to civilian perceptions where bases remained open.

	Dependent variable:			
	Trust		Contribution	
	Security	Stabilization	Security	Stabilization
	(9)	(10)	(11)	(12)
Base Closure	-0.159^{***}	-0.080^{***}	-0.076^{***}	-0.092^{***}
	(0.029)	(0.027)	(0.014)	(0.016)
Observations	1,482	1,482	1,482	1,482
R^2	0.24	0.36	0.17	0.21
Controls	✓	✓	✓	✓
Territoire FE				
MONUSCO Base FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Survey analyzed in the 2019 MONUSCO Base sample. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 9-12 include MONUSCO base fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table 4.5: Relationship between recent base closure and perceptions of mission

The closure of bases is negatively associated with perceptions of MONUSCO across each dimension when compared to other respondents in areas with MONUSCO bases that do not close. We present the results from these models in Table 4.5. We estimate a -16% (95% CI: -0.22 – -0.10) decrease in trust in security provision (Model 9), a -8% (95% CI: -.13 – -0.03) decrease in trust in stabilization activities (Model 10), a -8% (95% CI: -0.10 – -0.05) decrease in perceived contribution to security (Model 11), and a -9% (95% CI: -0.12 – -0.06) decrease in perceived contribution to stabilization activities (Model 12) in the wake of a base closure.

4.5.4 Heterogeneity and Further Addressing Additional Empirical Challenges

The three empirical and sampling strategies above provide consistent support for our theory that exposure to MONUSCO is associated with improved perceptions of the mission. While each of these strategies enable us to address different challenges to our analysis, we further triangulate among a series of strategies in the Appendix to iteratively build confidence in our results. We first use propensity score matching (in Appendix Section A.7) to further alleviate the potential selection effect in exposure to the mission by comparing most-similar respondents who were exposed to MONUSCO versus those who were not. The results in our matched analysis are substantively consistent with the findings in the main text.

In addition, we explore whether there are heterogeneous results by Gender (Appendix Section A.6.1). We subset our samples by gender[28] and re-run the core models from the main text. The results are consistent within the General Sample in both the male and female samples, although the magnitude of the relationship is larger for men than it it is women. We further find that the results are consistent among men in the MONUSCO Base sample, but we find no significant relationship between exposure and perceptions of MONUSCO's contribution to either security or stabilization among women in the MONUSCO base sample. Combined, these results suggest that the impact of exposure is less prevalent among women than it is among men.

Our sampling strategy in the MONUSCO Base sample enables us to further explore potential heterogeneity by whether the MONUSCO base is a FIB base (Appendix Section A.6.3) and by MONUSCO TCC (Appendix Section A.6.2). We interact exposure with indicator variables for each TCC and for whether the base respondents are sampled from is a FIB. We find no significant relationship on the interaction terms for FIB bases except for the contribution to stabilization in the FIB, which is negatively signed. We also observe limited variation among TCCs, although we do find some negative relationship between the interaction terms for Bangladesh, but this should be treated cautiously since Bangladesh operates exclusively in Ituri.

4.6 Conclusion

In this paper, we present and empirically evaluate a theory of civilian perceptions of international peacekeeping missions. We argue that peacekeeping missions build trust through direct exposure with civilians. We find support for our theory leveraging over 16,000 responses to surveys across two waves and two sampling strategies in three provinces of the Democratic Republic of Congo.

[28] All of our samples are gender-balanced.

Civilians exposed to the mission are more likely to report positive perceptions of the mission. But we find some evidence that exposure to Blue Helmets is not a particularly durable mechanism to build positive perceptions: perceptions of the mission deteriorated rapidly in the wake of local base closures between survey waves. Combined, our results suggest that Blue Helmets can improve their relationships with civilians by increasing their visibility, but that such efforts must be sustained over time. This is a particularly difficult charge in an era of dwindling budgets and already overstretched missions.

Our primary contribution is to literature on international interventions into conflict, especially peacekeeping. While some find peacekeepers have a deterrent effect on violence targeting civilians [79, 80, 133, 50], others find that peacekeepers have minimal impact on deterring violence at the local level [33] or can change incentives of the warring actors in perverse ways [42]. A large body of research has also demonstrated that civilian-peacekeeper relations are characterized by tension and filled with civilian disappointment in the missions [120, 155, 6]. By theorizing civilian-peacekeeper relations from the perspective of civilians and gathering survey data on exposure to and perceptions of Blue Helmets, we help explain why curtailing aggregate levels of violence may not translate to healthy civilian-peacekeeper relationships locally. Further, we show how the visibility of peacekeepers locally can help improve civilian perceptions of the mission, which likely result in both operational and public perceptions benefits for UNPKOs.

Additionally, we contribute to a small but growing research agenda that leverages public opinion data to study civilian perceptions of PKOs. In line with our theory and findings, Gordon & Young (2017) find that exposure to abuse has the largest effect on beliefs about peacekeepers, while receiving benefits from the mission has the strongest relationship with the propensity to cooperate with MINUSTAH, the UN peacekeeping mission in Haiti. Kelmendi & Radin (2018) find that the population's level of support for UN forces fluctuates depending on whether the UN policy reflects public opinion in the Bosnia context. Our research suggests numerous avenues for future research in this strain. We analyze civilian perceptions of a peacekeeping mission in its 19th and 20th years in the country. Future research should analyze perceptions of peacekeeping missions that are in their infancy, allowing cleaner identification of the impacts of contact.

Finally, our findings have important implications for ongoing discussions on how to reform how UN peacekeeping operations to more effectively respond to the world's most acute crises. Especially in a context of dwindling budgets and intensified scrutiny of the behavior of peacekeepers, our findings demonstrate that PKOs can improve their relationships with the civilians they are sent to protect by being more visible in the communities in which they operate. A large body of research finds that peacekeeping is effective at protecting civilian lives especially as the size of the mission increases [78, 50]. We highlight a potential force multiplier for PKOs: exposure to civilians.

CHAPTER 5

Conclusion

In this dissertation, I presented three papers to answer a series of motivating research questions: When the state does not or cannot maintain and enforce political order, how do civilians, armed groups, agents of the state, and the international community interact to stabilize political, economic, and social conditions locally? How do these arrangements come about? What are their implications for patterns of political violence, civilian security, and peace-building efforts?

In answering these questions, I explained why natural resources shape armed group revenue generating schemes differently over space, thereby creating different incentives over space for cooperation between rival armed groups and for armed groups to protect civilians (Chapter 2), why different armed group taxation schemes differentially influence civilian perceptions of security (Chapter 3), and the unique challenges UN peacekeepers face in providing security to the civilians who they are sent to protect (Chapter 4).

Together, the findings in this dissertation illustrate that local political orders are often rooted in exploitative informal security provision arrangements between civilians and armed actors – both state and non-state – that operate in the area. These arrangements provide incentives to armed actors that vary over space and these incentives structure their behavior towards rival armed groups and civilians. Likewise, civilian perceptions of international interveners who are sent to protect them also fluctuate over space and time in ways that can influence the efficacy of peacekeeping efforts.

In many ways, the implications of my research and the results I present are troubling. The dynamics I describe are not an example of effective state building in action, in which an endogenously strengthening state apparatus [156] based on rational-legal principles [169] and conditional compliance [99] evolves over time in response to the demand for security from civilians [74]. Instead, the dynamics I describe create a self-perpetuating cycle in which armed actors selectively compete and cooperate with each other, civilians perceive their improvements to their security institutions locally for privatizing public goods, and state agents profit financially by doing so. Local security needs and the economic interests of armed actors produce semi-organic responses, including the creation of exploitative but mutually beneficial informal institutions, that undermine macro state-building projects. These dynamics give inertia to a conflict system in which many of the actors have little or no incentive to engage in sustainable peacebuilding processes.

The protection rackets I describe do provide a modicum of predictability and security to civilians [112], however, and civilians in turn reward security providers with tribute and compliance for the privatization of state functions. In doing so, armed actors are, under certain conditions, dis-incentivized from using violence in certain locations and can even cooperate with one another. Combined, these dynamics undermine the state's long term capacity to create a monopoly on the use of violence [112] by paradoxically enhance civilian perceptions of their own security while also making it less likely that the underlying conflict is resolved by undermining incentives for the elites who benefit most from the system to form a coalition to end the conflict [45]. Understanding the underlying process by which this happens clarifies why conflict induced incentives to provide protection and generate revenue does not always "make states"; it can produce self-fulling political-economies rooted in exploitation and abuse.

Finally, the findings of this project have a number of significant implications for international intervention seeking to foster stability in conflict and post-conflict zones. I demonstrate that the privatization of security can, under certain conditions, actually improve outcomes for civilians. These political bargains are not based on Weberian bureaucratic norms, which the international community repeatedly attempts to impose as part of their state building projects. Local political bargains in such environments, although rooted in extortion, may help civilians in ways we have not considered. Disrupting those informal institutions may have perverse consequences. At the same time, these bargains help sustain inefficient and highly predatory political and economic systems over time.

5.0.1 Directions for Future Research

My research opens a number of avenues for future research. Most generally, the research is conducted in two provinces of the eastern Democratic Republic of Congo. As noted in the Chapter 1, I analyze these provinces precisely because they are an outlier case: the ongoing conflicts in eastern DRC have gone on far longer than most conflicts, the level of violence in eastern DRC was and remains unusually high compared to similar cases, and the proliferation of armed groups is especially rapid. While these dynamics provide tragic but analytically important leverage to evaluate core processes in political science and the scale of the violence makes understanding the conflict important in its own right, such an outlier case does raise the question of the external validity of the research findings. I address the external validity in the body of each paper, but future research should seek to replicate the findings in other contexts. For example, how similar are the protection rackets that I describe? Replicating the granular analysis in this dissertation in similar contexts could inform the extent to which my theories and findings are Congo or regionally specific or more general. Chapter 4 in particular is well suited for analysis in contexts with other peacekeeping missions, including those that operate in their countries for shorter periods of time than MONUSCO has been in Congo.

Second, the analysis in this dissertation is in large part based on correlations. While I go to great lengths to discuss the potential biases and probe the limitations of my research designs, I nonetheless cannot entirely reject that my analysis – as all honest analysis is – subject to unobserved confounders and measurement errors. Future research should further probe the core relationships I demonstrate in this dissertation with more sophisticated identification strategies where possible, while recognizing the difficultly and ethics of designing such research for the dynamics under consideration.

Finally, my dissertation only scratches the surface on civilian roles and the implications of civilian perceptions in ongoing conflicts. Future research should continue to refine our understanding of how civilians navigate and perceive the local contexts in which they live. When doing so, we should not assume simply that they are passive actors in these systems, while also recognizing their vulnerability. Further clarifying how civilians navigate and create agency in ongoing conflicts can advance our understanding of conflict, of state-building processes, and, most importantly, of highlight potential pathways to craft more effective policy to respond to and mitigate the consequences of violent conflict for civilians.

APPENDIX A

Appendix: Mines and the Road to Violence

A.1 Comparing Units of Analysis by Shape and Size of Grid Cells

As robustness checks, I use differently sized and shaped grid cells, which produce as-if random differences in border cutoffs between cells.

Table A.1 lists the total number of grid-cells, the number of grid cells per province, the number of grid cells that straddle the North Kivu-South Kivu border, and grid cells that straddle an international border. I exclude those that straddle the North Kivu-South Kivu border from the counts in the provincial counts; those that straddle an international border are included in the provincial counts.[1] The percentage of total grid cells for each category is listed below the raw count in parentheses.

Figure A.1 plots the 100 km hexagons over the 100 km square grid cells. It shows how the different shaped and sized grid cells produce quasi-random differences in borders. The randomly distributed nature of these border differences alleviate concerns that any result is driven by artificial patterns. Consistency of results across different types of grid cells should increase confidence that the observed patterns accurately capture the local political dynamics.

[1]As a result, the sum of North Kivu cells, South Kivu cells, and Kivu border cells constitute the total cell counts. The sum of North Kivu cells, South Kivu cells, Kivu border cells, and international border cells will be larger than the total cells count, as international border cells are also counted in provincial or Kivu border cells.

	10x10km		15x15km	
	Square	Hexagons	Square	Hexagons
Total Cells	**1110**	**1113**	**774**	**762**
	(100%)	(100%)	(100%)	(100%)
North Kivu	522	523	359	362
	(47.03%)	(46.99%)	(46.38%)	(47.51%)
South Kivu	564	568	398	385
	(50.81%)	(51.03%)	(51.42%)	(50.53%)
Kivu Border	24	22	17	16
	(2.16%)	(1.98%)	(2.20%)	(2.10%)
International Border	73	76	61	64
	(6.58%)	(6.83%)	(7.88%)	(8.40%)

Table A.1: Comparison of Units by Shape and Size of Grid Cells

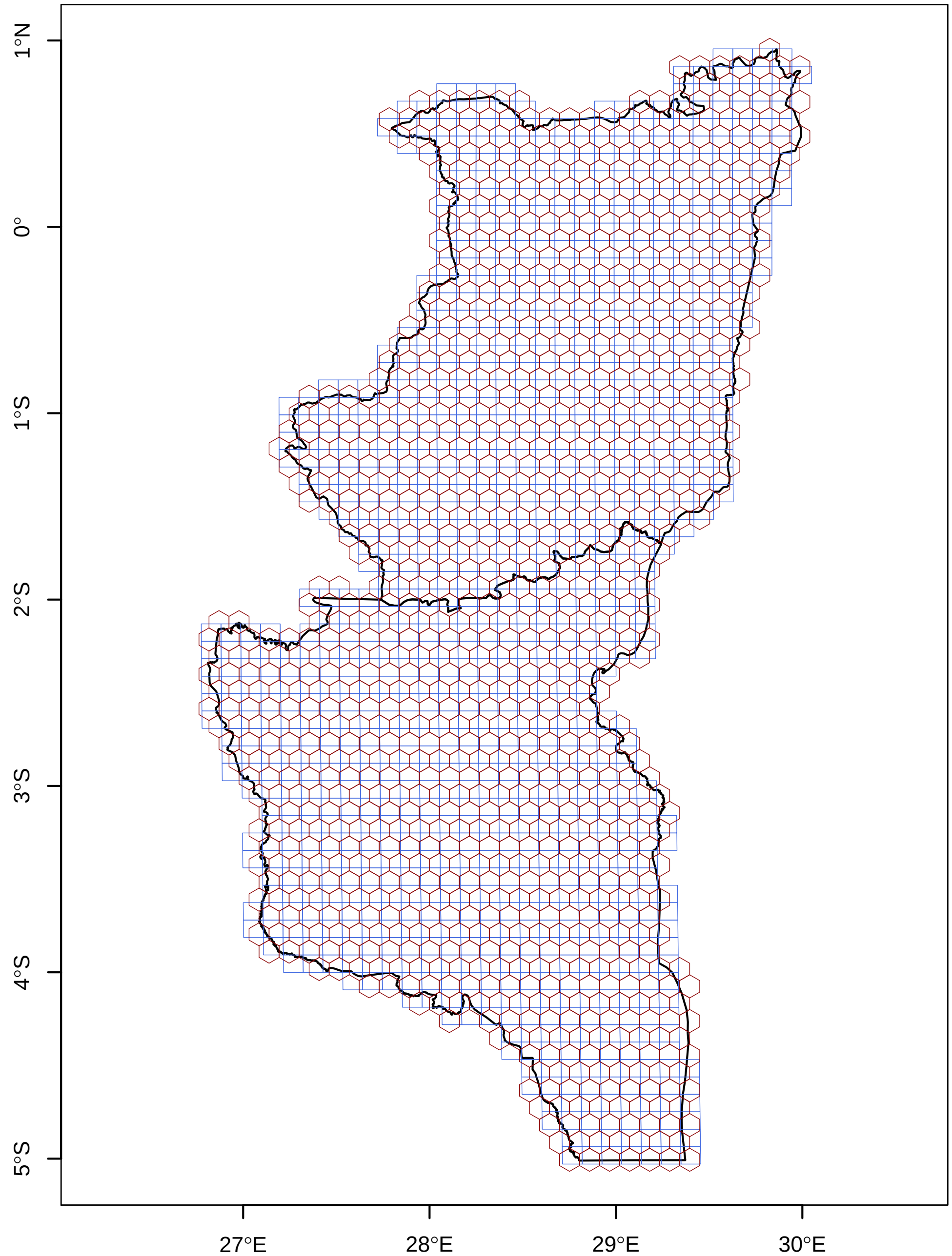


Figure A.1: Overlap of 100 km Area Hexagonal and Square Grids

A.2 Measuring Control Variables

A.2.1 Capturing Variation in Elevation

I use Shuttle Radar Topography Mission (SRTM) elevation dataset to measure the mean altitude in each grid cell as a control variable. SRTM captures 1 arc-second altitude measurements for global coverage ($\approx$ 30 meters),[2] which are then aggregated to 1 km resolution. To control for elevation, I calculate the mean elevation within each grid-cell. Figure A.2 displays the mean elevation of grid cells for the 10km diameter hexagonal grid cells.

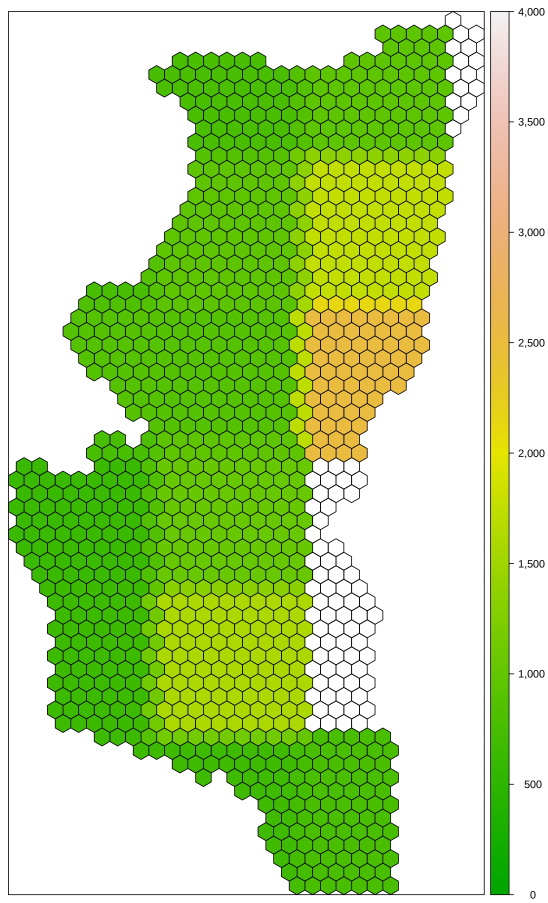


Figure A.2: Mean Elevation of Grid-Cells by Size and Shape of Grid-Cell

[2]SRTM data was collected February 11-22, 2000.

A.2.2 Using Globcover to Measure Land Use within Grid Cells

To measure land use within and between grid-cells, I use Globcover 2009. Globcover provides 300-m global land cover map produced from an automated classification of 22 land cover types. Figure A.3 displays the raw Globcover data over the Kivus. I further aggregate the landtypes into 10 categories: "Forest," "Cropland," "Shrubland," "Vegtation," "Urban," "Bare ground," "Water bodies," and "No data." I then calculate the percentage of each grid cell that is covered by each landtype.

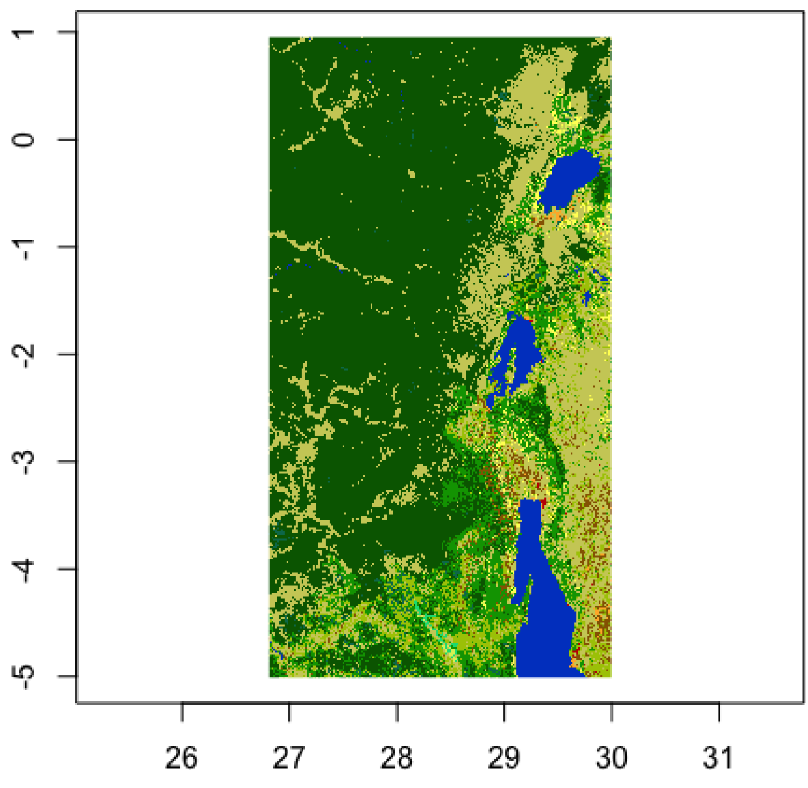


Figure A.3: Raw Data Globcover Coverage of the Kivus

A.2.3 Using LandScan to Estimate Population Density

Because a recent census and reliable administrative population counts are not available in DR-Congo (and in particular for eastern DRCongo), I rely on Oak Ridge National Laboratory's Land-Scan data to capture the distribution of the population in North and South Kivu. LandScan provides approximately 1 km resolution (30" X 30 ") estimates of the ambient population. Population counts are based on a combination of satellite imagery analysis of land cover, roads, slope, urban areas, village locations and existing sub-national population estimates. I use the 2015 LandScan estimates, as my observations begin in 2017. Figure A.4 visualizes the estimated population distribution aggregated to the grid-cell level in absolute (on the left) and relative terms (log + 1 of the absolute terms, on the right).

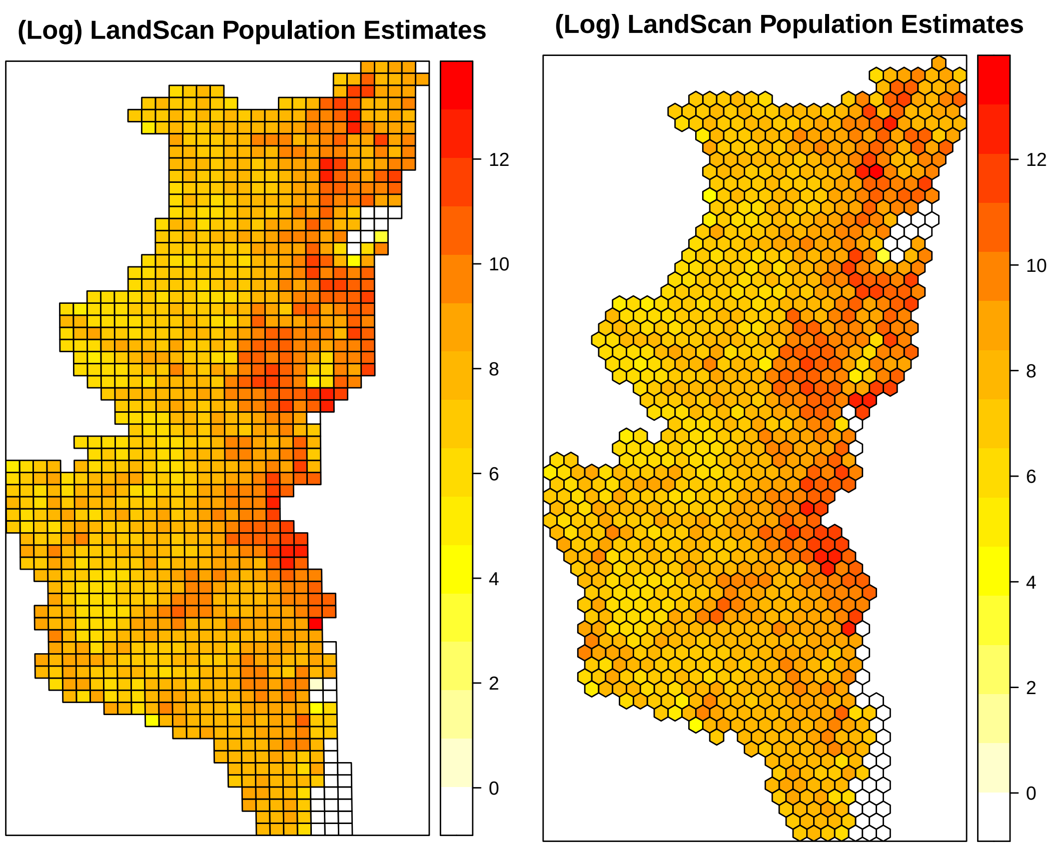


Figure A.4: Estimated Population Distribution, 10km Diameter Grid Cells

A.2.4 MONUSCO's Operational Footprint

Eastern DRC is the epicenter of one of the largest and longest-standing peacekeeping missions in the world, MONUSCO. The presence of peacekeepers may distort the incentives or opportunities for armed groups or state forces to use violence to achieve their goals [79, 68]. To control for this potential relationship, I use Cil et al (2019), which provides monthly locations and size of deployment for each UN peacekeeping base across the world. Using the geo-locations that they provide with each base, I create an indicator variable for whether the grid cells have a peacekeeping base within them in 2019. I also create a separate indicator variable for whether the grid cells are adjacent to a cell with a peacekeeping base in them. Finally, to account for differences in the size of the mission's presence locally, I aggregate the number of troops present within each grid-cell. I visualize the peacekeeping data in Figure A.5, which shows both the binary measure (on the left) and the count of MONUSCO troops (on the right) for the 10 x 10 hexagonal grid.

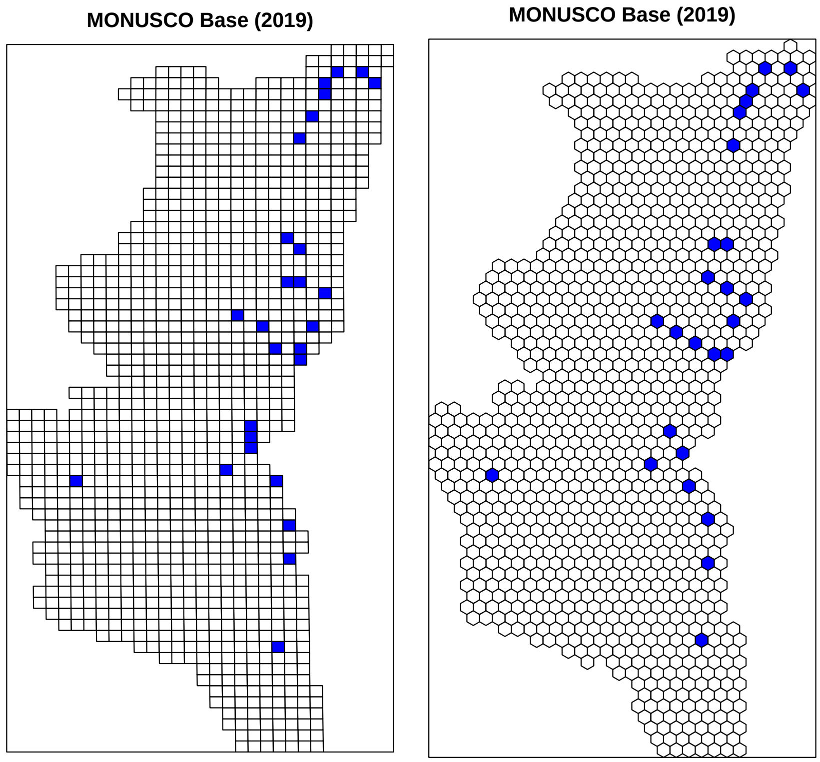


Figure A.5: MONUSCO Peacekeeping Presence, 10 x 10 km Hexagonal Grid

A.2.5 Rainfall, Seasonality, and Road Passability

Most roads in eastern DRCongo are not paved and become difficult to pass after rain in ways that may impact the minerals trade. Rainfall patterns in eastern DRCongo are relatively predictable by season, as shown in Figure A.6. In general, precipitation patterns are divided into four periods in each year: the short dry season (January - February), the short wet season (March - April), the long dry season (May to September) and the long wet season (October to December).

Based on these patterns, I create two indicator variables in the panel dataset to capture the expected state of the roads by season. First, I create indicator variable that takes a value of 1 for the long dry season and a 0 for any other months in the panel data. This is when the roads are driest and easiest to pass. Second, I create an alternative, more inclusive indicator variable that takes a value of 1 for months in either the long and short dry seasons together and 0 for either the short or long wet seasons in the panel data.

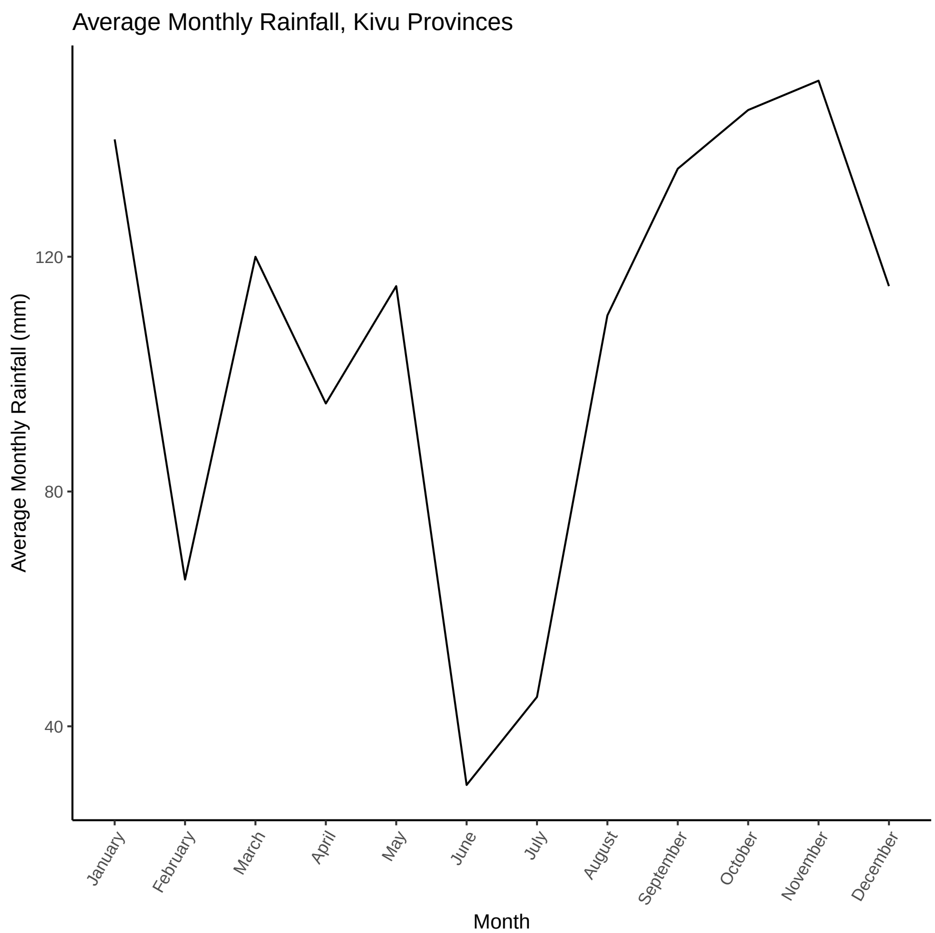


Figure A.6: Average Monthly Rainfall in Eastern Congo

A.2.6 Measuring Temporal Variation in Food Prices

Armed groups participate in and benefit from sectors of the economy beyond mining, especially trading agricultural goods. I use data provided by the Famine Early Warning Systems Network (FEWS NET) to measure temporal change in prices of key agricultural goods in North and South Kivu. It relies on a network of enumerators who monitor prices at regular intervals for key staple foods. In the Kivus, FEWS NET monitors four key markets, each of which are reliable indicators of the prices in the greater area. In North Kivu, they track prices in markets in Beni and Goma; in South Kivu, they track prices in markets in Bukavu and Uvira. In Figure A.7, I plot prices in four key staples: mixed beans, cassava flours, rice, and palm oil. I use these prices in the panel regression by aggregating prices to the market-month and identifying which market is closest to each grid-cell.

To determine which market is most relevant for each grid cell, I use the centroid of each cell's polygon. I then conduct a nearest neighbor analysis, giving the linear distance to the nearest market town. Each grid cell is assigned one market only and assumed that their prices will vary with that market. While this strategy may introduce noise (i.e. it may be that a given grid cell may respond to multiple markets depending on its position or that price shocks at the market towns may have less of an influence on local prices in some areas than others), in general it is as reliable a strategy to measure local, non-mining economic conditions as is feasible with the data that is available in eastern Congo.

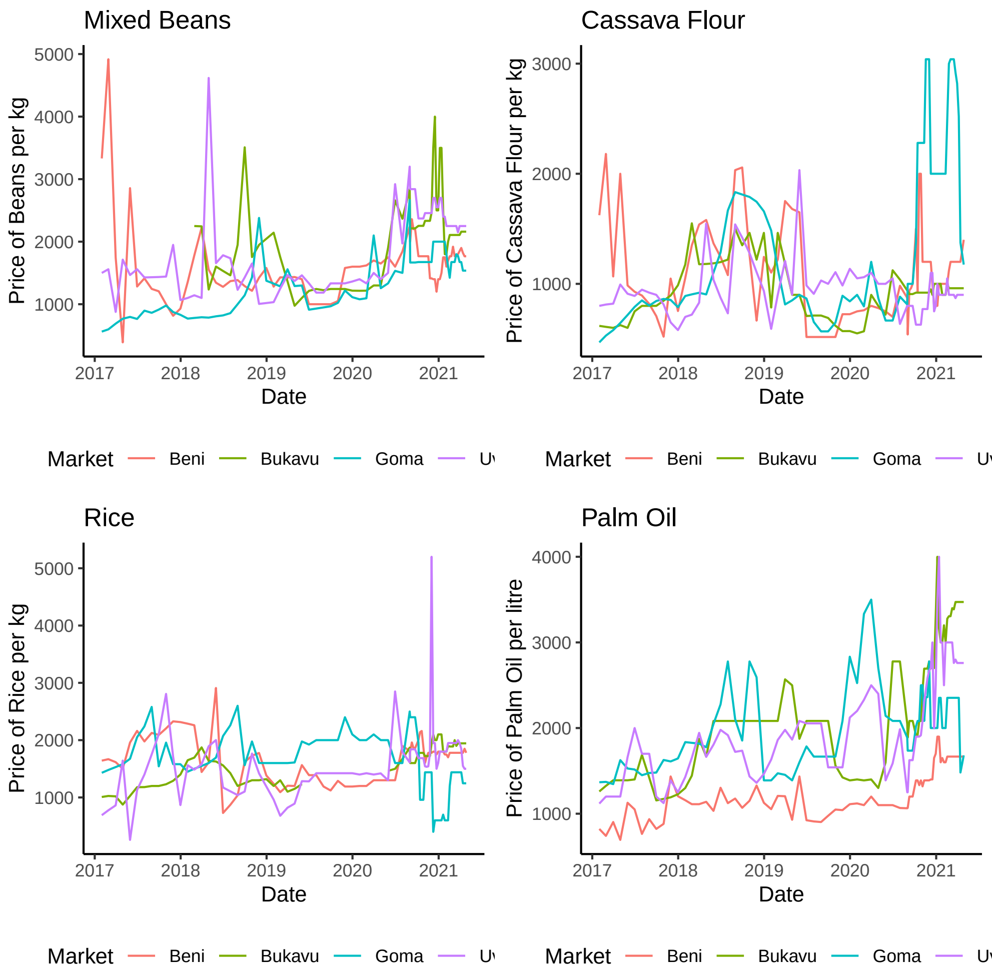


Figure A.7: Prices (in Congolese Francs) of Key Food Staples Over Time by Market

A.3 Comparing Kivu Security Tracker to Other Violent Event Based Datasets

Measuring violence using standard violent events-based datasets is challenging given the underreporting of the violence in standard violent event-based datasets on the conflicts in eastern DRCongo [163]. In the main text, I use the Kivu Security Tracker (KST) to measure violent events in North and South Kivu. KST has significant advantages over datasets such as ACLED, UCDP, and SCAD. By relying on a network of local researchers who leverage their connections with the UN, civil society, and the government, KST expands the pool of potential cases from just those that end up in the international media, a particularly problematic assumption for the violence in eastern Congo. Moreover, the local knowledge that KST's team has increases the confidence in the geolocations of the reported events, an important considering at the level of aggregation employed in this paper.

KST does have important limitations to consider, however. In this section, I analyze whether and how these limitations may influence my results by comparing KST to ACLED, the most similar dataset to KST in terms of substantive coverage.[3]

The biggest limitation to KST is that it is a relatively new effort and thus has limited temporal coverage. In particular, I analyze KST for the period between January 2017 (when KST first began collecting data) and July 2020, the last full month of coverage I have access to.[4] This amounts to 31 months of coverage, a substantial period that captures important fluctuations in conflict dynamics and changes in the political-economy of the conflicts, allowing me to evaluate portions of my theory that change with time.

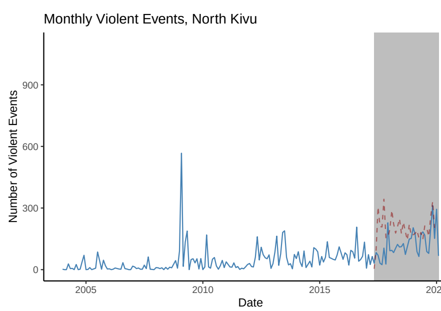
It is, however, only a snapshot of the full temporal scope of the violence in eastern DRC. The period of coverage that KST provides may present fundamentally different dynamics than other periods in the conflict in ways that are relevant to my theory. To explore whether and how this may

[3] UCDP's inclusion criteria only focuses on battles/armed clashes and violence against civilians, whereas KST and ACLED cover events such as civilian deaths, sexual violence, abductions, terrorist attacks, political repression, and destruction of property.

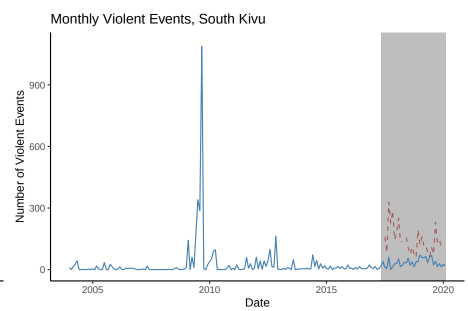
[4] KST is not a publicly available dataset. It publishes an online web-map with descriptions of individual events at https://kivusecurity.org/, but co-authors and I were generously granted access to the raw data as of July 2020 by the KST team.

be the case, I compare trends in violence in the period of coverage provided by KST to ACLED's [126] longer-term coverage. In particular, I look at the period after the end of the Second Congo War which ended in 2003.

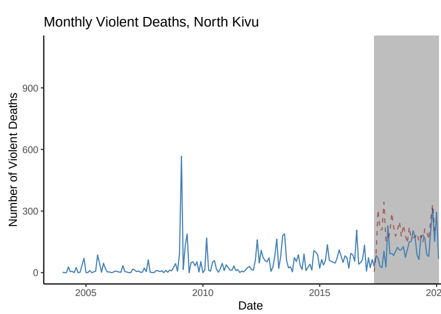
In Figure A.8, I plot the number of deaths per month in the three datasets. The period of KST coverage is shaded in gray and KST is plotted as a red dashed line. ACLED is plotted in blue. The trends show that the sample of violence captured by KST fits relatively well with overall trends in the conflicts in eastern Congo. Levels of violence in North Kivu in particular was rising in the period captured by KST, but otherwise the trend lines are well within the status quo of the conflict. The most important limitation of KST's temporal coverage is that it misses the biggest spike in violence in 2009-2010, a period of intense fighting in both provinces but in South Kivu in particular. The spike in violence observed in 2009-2010 was related to a DRC and Rwandan operation against the FDLR rebel group.



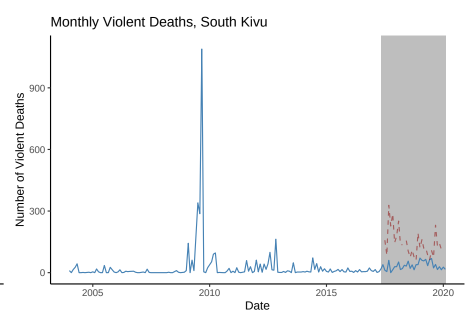
(a) North Kivu, Monthly Events



(b) South Kivu, Monthly Events



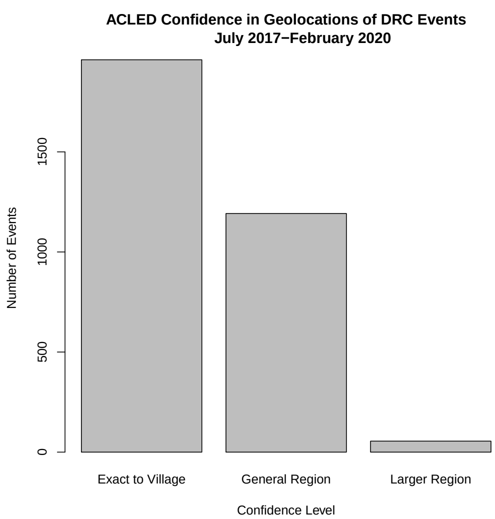
(c) North Kivu, Monthly Deaths



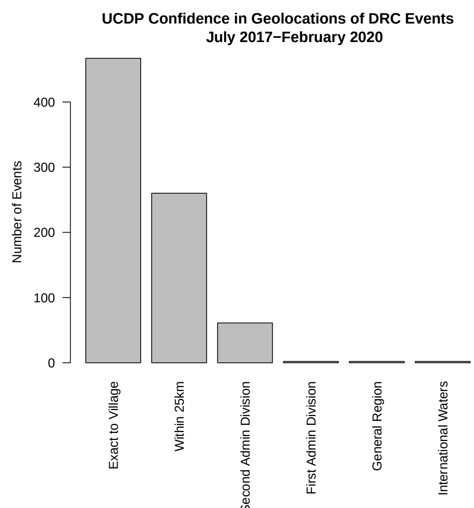
(d) South Kivu, Monthly Deaths

Figure A.8: Trends in Violent Event Measurements, ACLED versus KST

If the trends in violence are similar between ACLED and KST, why not simply use ACLED's longer coverage, in particular for the panel analysis? Self-reported reporting confidence in geolocations warrant further caution with using ACLED and UCDP at the level of aggregation analyzed in this paper. In Figures A.11a and A.11c, I plot barcharts with the self-reported accuracy ratings for each event in North or South Kivu in ACLED and UCDP, respectively, within the temporal scope of my analysis. KST does not include a similar geo-precision rating, but the local knowledge of their team and their data generating processes increases confidence in each of their placements relative to international efforts. While Figures A.11a and A.11c show that they are confident that a majority of events are correctly placed to the village level, close to 40% of events are only confident to the "general region" in ACLED and similar numbers within 25km or within the second administrative division for UCPD.



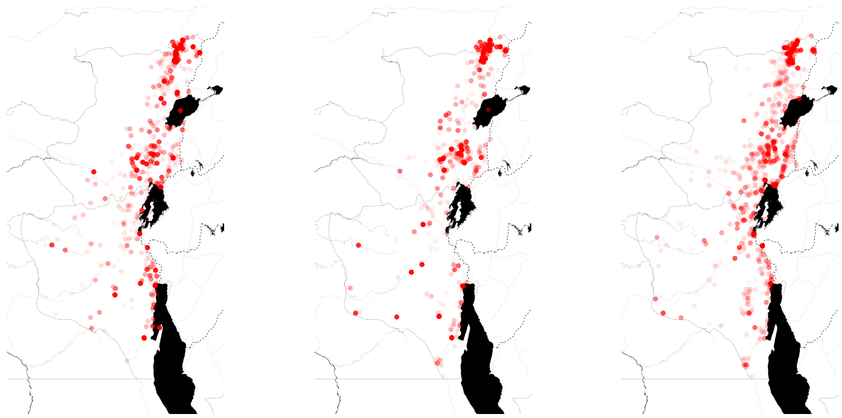
(a) ACLED



(b) UCDP

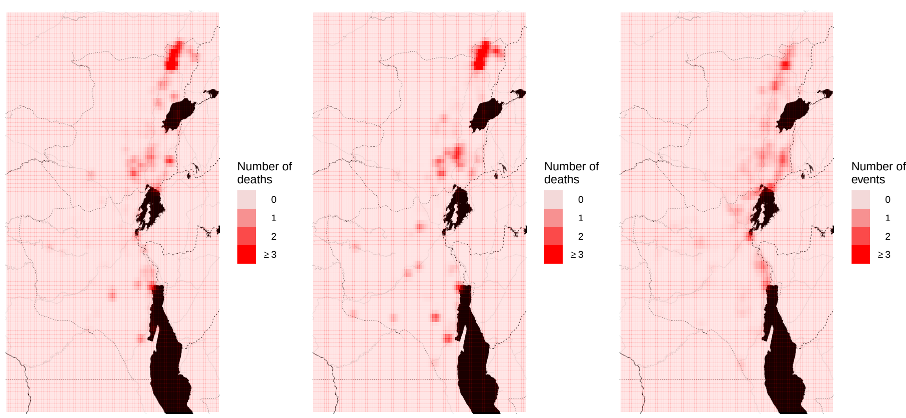
Figure A.9: Confidence of Placements of Violent Events Locations in DRC, ACLED and UCDP

Nonetheless, for the purpose of comparison, I plot points in space in Figure A.10 and the density of events in Figure A.11 for KST, ACLED, and UCDP. I restrict the events for each of the datasets to the period of temporal overlap with KST. Both sets of plots show mostly similar concentrations of violence as KST (in that the violence in concentrated to the east and away from the main concentrations of the mining sector), but KST's local knowledge and embedded research time increase the confidence of the spatial distribution of violent events.



(a) ACLED (b) UCDP (c) KST

Figure A.10: Placements of Violent Events Locations in DRC, ACLED, UCDP and KST



(a) ACLED (b) UCDP (c) KST

Figure A.11: Spatial Density of Locations of Violent Deaths in DRC, ACLED, UCDP and KST

A final major limitation is that KST is geographically limited to two provinces: North and South Kivu.[5] This spatial limitation is important to note, as there are other provinces that do experience regular violence in eastern DRC, in particular Ituri, and that have large mining sectors, such as Tanganyka and Haut-Katanga. Global violent events datasets are not similarly limited in their spatial coverage, potentially enabling more diverse comparisons. While I recognize this

[5]KST expanded to cover Ituri in April 2021, but it has not yet accumulated enough temporal coverage to warrant expanding the analysis to this province.

limitation, I choose to conduct a more micro level study, which allows from greater precision and more appropriate comparisons within these two provinces.

A.4 Alternative Measures of Road Network Centrality

In the main text, I present results using two measures to capture the concept of road network centrality. First, I use the eigenvector centrality of nodes on the network and second, I use the presence of observable competition for taxation opportunities measured through control of roadblocks.

Of course, there are many potential ways to measure the importance of a specific portion of the road network. While I argue that the two I use in the main text are the most appropriate to evaluate my theory, in Table A.2, I use two alternative measures of the importance of different stretches of the road network to the minerals trade to ensure my results are robust. In Models 1 and 3, I use the number of road intersections within each grid cell as my independent variable. In Models 2 and 4, I use the kilometers of national roads as my independent variable. As with the results in Table **??** of the main text, these alternative measures are positively and significantly correlated with levels of armed clashes and looting in each of the models.

	Dependent variable:			
	ArmedClashes		Looting	
	(1)	(2)	(3)	(4)
# Road Intersections	0.33^{***}		0.50^{***}	
	(0.27, 0.40)		(0.38, 0.62)	
National Roads (km)		0.08^{***}		0.29^{***}
		(0.05, 0.11)		(0.24, 0.34)
Controls	✓	✓	✓	✓
Observations	1,033	1,033	1,033	1,033
Log Likelihood	−2,579.37	−2,610.14	−3,147.49	−3,120.54
σ^2	8.44	8.90	25.87	24.54
Akaike Inf. Crit.	5,174.75	5,236.28	6,310.99	6,257.08
Wald Test (df = 1)	82.94^{***}	107.74^{***}	8.43^{***}	9.85^{***}
LR Test (df = 1)	79.89^{***}	99.32^{***}	8.10^{***}	9.22^{***}

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from spatial autoregressive models. Each model controls for the following variables: Elevation, water coverage, MONUSCO base (2017), (log) population, and a binary indicator of whether there are any urban area withins the grid cell.

Table A.2: Alternative Measures of Road Network Centrality

A.5 Are Roads in General Correlated with Violence?

My theory posits and my analysis finds that key junctures on the road network incentivize armed groups to compete for access to illicit taxation opportunities. Events-based data can be biased towards violent events in populated or highly accessible places, which are more visible to news outlets [170]. If violent events near roads are more likely to be reported or if violent events in relatively remote areas – where mines are concentrated – are less likely to be reported, I may observe a potentially spurious baseline correlation with the road network.

To check whether such a spurious correlation is present in my data, I run 6 SAR models in Table A.3 that alternate between independent variables that measure less important portions of the road network. In Models 1 and 4, I use the total km within the grid-cell as the independent variable. In Models 2 and 5, I use the km of local roads within the grid-cell as the independent variable. In Models 3 and 6, I use the total km of regional roads int he grid-cell as the independent variable. As with the models in the main text, I alternate between Armed Clashes (1-3) and Looting (4-6) events as the dependent variable.

The results in Table A.3 show that no such spurious relationship is present. In fact, local roads are negatively correlated with Armed Clashes and Looting events in the area. Even regional roads which are the relatively populated and accessible areas that are potentially the sources of bias, are not correlated with Armed Clashes in Model 3 and negatively correlated with Looting events in Model 6. Combined, these results suggest that my results are not driven by a spurious baseline correlation with the road network in general or by measurement bias towards more visible areas.

	Dependent variable:					
	ArmedClashes			Looting		
	(1)	(2)	(3)	(4)	(5)	(6)
Roads Total (km)	-0.01			0.01		
	$(-0.02, 0.01)$			$(-0.02, 0.03)$		
Local Roads (km)		-0.04^{***}			-0.06^{***}	
		$(-0.05, -0.02)$			$(-0.10, -0.03)$	
Regional Roads (km)			-0.02			-0.08^{***}
			$(-0.05, 0.02)$			$(-0.14, -0.02)$
Observations	1,033	1,033	1,033	1,033	1,033	1,033
Controls	✓	✓	✓	✓	✓	✓
Log Likelihood	$-2{,}622.56$	$-2{,}615.72$	$-2{,}622.73$	$-3{,}179.55$	$-3{,}171.76$	$-3{,}176.32$
σ^2	9.13	9.02	9.12	27.45	27.07	27.29
Akaike Inf. Crit.	5,261.12	5,247.45	5,261.47	6,375.10	6,359.52	6,368.63
Wald Test (df = 1)	102.29^{***}	94.38^{***}	104.89^{***}	15.71^{***}	12.10^{***}	14.30^{***}
LR Test (df = 1)	94.35^{***}	88.03^{***}	97.40^{***}	14.79^{***}	11.44^{***}	13.52^{***}

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from spatial autoregressive models. Each model controls for the following variables: Elevation, water coverage, MONUSCO base (2017), (log) population, and a binary indicator of whether there are any urban area withins the grid cell. 95% CI in parentheses

Table A.3: Less Central Portions of the Transportation Network and Violence

A.6 Replicating Static Analysis Using OLS Instead of SAR Models

In the main text, I use spatial autoregressive models (SAR) to account for spatial dependencies in the supply chain that takes minerals to international markets and spatial clustering in violent events. In Table A.4, I re-running my models using ordinary least squares (OLS).

Models 1 and 5 present regressions that analyze the relationship between the number of mines and Armed Clashes and Looting, respectively. Models 2 and 6 use the binary indicator for Competitive Mines, Models 3 and 7 use the eigenvector centrality measure, and Models 4 and 8 use the binary indicator for Competitive Roadblocks as the independent variable. Models 1-4 use Armed Clashes as the dependent variable. Models 5-9 use Looting as the dependent variable.

The results are consistent with findings from the SAR models in the main text. Mines and local competition at mines are negatively correlated with Armed Clashes and not significantly correlated with Looting events. Meanwhile, eigenvector centrality and competitive roadblocks are positively correlated with violence across each model.

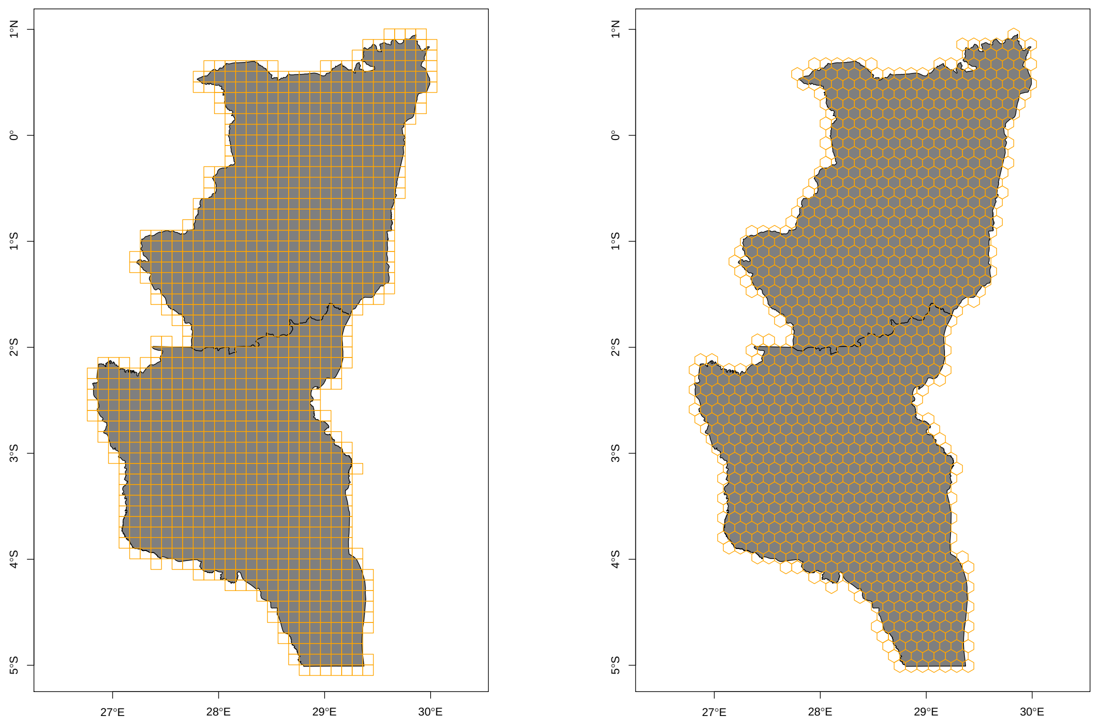
	Dependent variable:							
	ArmedClashes				Looting			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Mines	-0.02^{*}				0.02			
	$(-0.04, 0.0004)$				$(-0.01, 0.05)$			
Competitive Mines (Binary)		-1.59^{***}				-0.32		
		$(-2.40, -0.77)$				$(-1.66, 1.03)$		
Eigenvector Centrality			0.38^{***}				0.52^{***}	
			(0.31, 0.46)				(0.40, 0.64)	
Competitive Roadblocks (Binary)				3.70^{***}				4.07^{***}
				(2.59, 4.81)				(2.22, 5.92)
Observations	1,033	1,033	1,033	1,033	1,033	1,033	1,033	1,033
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.28	0.28	0.29	0.31	0.22	0.21	0.21	0.22

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Each model controls for the following variables: Elevation, water coverage, MONUSCO base (2017), (log) population, and a binary indicator of whether there are any urban area withins the grid cell. 95% CI in parentheses

Table A.4: Replication Using OLS Instead of SAR Models

A.7 Replicating Static Analysis with 10km Diameter Square Grid Cells

In the main text, I use hexagonal grid cells as my unit of analysis. As robustness checks, I use differently shaped grid cells, which produce as-if random differences in border cutoffs between cells, as described in Section A.1. These checks guard against inferences drawn from edge effects. I plot the different shape grid cells side-by-side in Figure A.12. In Table A.6, I replicate Table **??** in the main text.



!

(a) Square Grid

(b) Hexagonal Grid

Figure A.12: Structure of Square and Hexagonal Grids Imposed on North and South Kivu Provinces, DRCongo

The results and substantive effects are consistent when using the hexagonal grid cells. In the square grid cells, every additional road intersection is associated with a 12.5% increase in armed clashes within the direct cell, a 15% increase in neighboring cells, and 27.78% increase in armed clashes overall. Similarly, an additional intersection is associated with a 23.95% increase in looting events in the grid cell, an 11% increase in neighboring grid cells, and a 35% increase in looting events overall. An extra km of national roads is associated with a 7.2% increase in the cell itself for armed clashes, 8.8% indirect, and 16% total for armed clashes. 20% increase in looting directly and 7% increase in looting indirectly, for a 27% increase in looting events overall.

The results from having a competitive roadblock environment are even more stark. A competitive roadblock environment is associated with a 242.9% increase in the cell itself of armed clashes, a 279.85% increase in neighboring cells, and a 522.7% increase in armed clashes in total. The relationship with looting events is similarly extreme: a competitive roadblock environment is associated with a 232.58% increase in looting events in the cell itself, a 109% increase in the neighboring cells, and 341.6% increase overall.

	Dependent variable:			
	ArmedClashes		Looting	
	(1)	(2)	(3)	(4)
Total Mines	−0.008		0.014	
	(0.009)		(0.012)	
Competitive Mines (Binary)		0.048		0.437
		(0.247)		(0.353)
Observations	1,026	1,026	1,026	1,026
Log Likelihood	−2,564.001	−2,564.446	−2,916.239	−2,916.111
σ^2	8.188	8.188	16.757	16.749
Akaike Inf. Crit.	5,146.003	5,146.891	5,850.478	5,850.222
Wald Test (df = 1)	262.228***	267.509***	96.217***	97.011***
LR Test (df = 1)	211.782***	215.935***	82.957***	83.579***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.5: Cross Sectional SAR Models: Presence of Mines and Violence, 10km Diameter Square Grids

	Dependent variable:					
	ArmedClashes			Looting		
	(1)	(2)	(3)	(4)	(5)	(6)
# of Road Intersections	0.118***			0.235***		
	(0.023)			(0.039)		
Competitive Roadblocks		2.287***			2.286***	
		(0.421)			(0.698)	
National Roads (km)			0.068***			0.198***
			(0.011)			(0.018)
Observations	1,105	1,105	1,105	1,105	1,105	1,105
Controls	✓	✓	✓	✓	✓	✓
Log Likelihood	−2,754.898	−2,752.853	−2,747.748	−3,282.762	−3,295.738	−3,295.738
σ^2	8.096	8.093	7.990	21.912	22.437	22.437
Akaike Inf. Crit.	5,527.795	5,523.706	5,513.497	6,583.523	6,609.477	6,609.477
Wald Test (df = 1)	289.862***	265.103***	292.516***	59.920***	57.380***	57.380***
LR Test (df = 1)	239.899***	223.931***	243.621***	56.726***	55.017***	55.017***

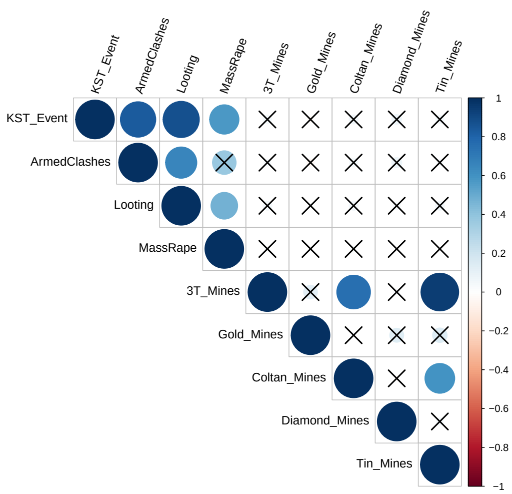
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from spatial autoregressive models. Each model controls for the following variables: Elevation, water coverage, MONUSCO base (2017), (log) population, and a binary indicator of whether there is any urban area within the grid cell.

Table A.6: Cross Sectional SAR Models: Transport Network and Violence, 10km Diameter Square Grid Cells

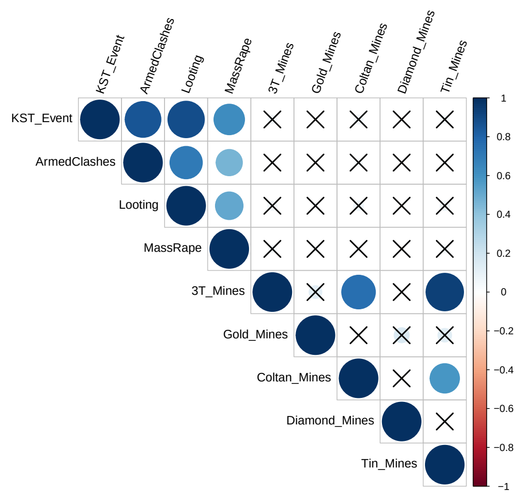
A.8 Replicating Static Analysis Using 15km Diameter Square and Hexagonal Grid Cells

A.8.1 Correlation Matrices for 225 km Area Grid Cells

In the main text, I show the correlation matrices for the 100 km area grid cells. In Figure A.13, I replicate the correlation matrices using the expanded grid cells (225km in area). They show that even with a broader inclusion criteria around the mines, the patterns observed and described in the main text hold.



(a) 225km Area Square Grid Cells



(b) 225km Area Hexagonal Grid Cells

Figure A.13: Correlation Matrices for the 225 km Area Grids. Color intensity and the size of the circle are proportional to the correlation coefficients. Crossed-out cells denote a P value $>$ .05 with α of 95%

A.8.2 Results Using 225 km Area Grid Cells

	Dependent variable:							
	ArmedClashes				Looting			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# Mines	−0.003				0.009			
	(0.010)				(0.016)			
# Mines: Concealable Minerals		−0.034				−0.008		
		(0.030)				(0.047)		
# Mines: Bulky Metals			0.001				0.012	
			(0.011)				(0.017)	
Local Competition (Mines)				−0.166				0.592
				(0.415)				(0.642)
Observations	772	772	772	772	772	772	772	772
Log Likelihood	−2,239.790	−2,239.200	−2,239.815	−2,239.743	−2,562.430	−2,562.597	−2,562.349	−2,562.186
σ^2	18.559	18.537	18.557	18.556	44.441	44.456	44.433	44.408
Akaike Inf. Crit.	4,497.579	4,496.400	4,497.631	4,497.486	5,142.861	5,143.195	5,142.698	5,142.372
Wald Test (df = 1)	134.730***	133.261***	135.375***	134.707***	14.036***	14.245***	13.948***	14.256***
LR Test (df = 1)	119.627***	118.765***	120.137***	119.784***	14.227***	14.459***	14.139***	14.467***
Note:						*p<0.1; **p<0.05; ***p<0.01		

Table A.7: Cross Sectional SAR Models: Presence of Mines and Violence, 225km Area Square Grids

	Dependent variable:							
	ArmedClashes				Looting			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# Mines	−0.005				0.018			
	(0.012)				(0.018)			
# Mines: Concealable Minerals		−0.014				0.031		
		(0.032)				(0.052)		
# Mines: Bulky Metals			−0.004				0.018	
			(0.013)				(0.020)	
Local Competition (Mines)				−0.160				0.454
				(0.429)				(0.685)
Observations	756	756	756	756	756	756	756	756
Log Likelihood	−2,231.552	−2,231.553	−2,231.597	−2,231.574	−2,569.366	−2,569.679	−2,569.487	−2,569.641
σ^2	20.529	20.527	20.529	20.527	52.310	52.351	52.327	52.346
Akaike Inf. Crit.	4,481.103	4,481.107	4,481.193	4,481.148	5,156.732	5,157.358	5,156.975	5,157.282
Wald Test (df = 1)	113.330***	113.606***	113.674***	113.822***	4.232**	4.322**	4.224**	4.338**
LR Test (df = 1)	104.293***	104.734***	104.659***	105.113***	4.189**	4.279**	4.181**	4.296**
Note:						*p<0.1; **p<0.05; ***p<0.01		

Table A.8: Cross Sectional SAR Models: Presence of Mines and Violence, 225km Area Hexagonal Grids

	Dependent variable:					
	ArmedClashes			Looting		
	(1)	(2)	(3)	(4)	(5)	(6)
# Road Intersections	0.211***			0.282***		
	(0.036)			(0.056)		
Competitive Roadblocks		3.859***			3.541***	
		(0.649)			(1.009)	
National Roads (km)			0.067***			0.173***
			(0.014)			(0.022)
Observations	772	772	772	772	772	772
Log Likelihood	−2,223.384	−2,222.477	−2,228.437	−2,550.297	−2,556.502	−2,531.251
σ^2	17.877	17.858	18.071	43.114	43.807	41.147
Akaike Inf. Crit.	4,464.767	4,462.953	4,474.874	5,118.595	5,131.005	5,080.502
Wald Test (df = 1)	121.442***	115.560***	127.950***	11.898***	11.931***	5.984**
LR Test (df = 1)	108.329***	104.507***	114.235***	11.932***	12.085***	6.013**
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A.9: Cross Sectional SAR Models: Transport Network and Violence, 225km Area Square Grid Cells

	Dependent variable:					
	ArmedClashes			Looting		
	(1)	(2)	(3)	(4)	(5)	(6)
# Road Intersections	0.222***			0.329***		
	(0.036)			(0.057)		
Competitive Roadblocks		3.270***			3.510***	
		(0.680)			(1.086)	
National (km)			0.061***			0.227***
			(0.019)			(0.029)
Observations	756	756	756	756	756	756
Log Likelihood	−2,212.676	−2,220.212	−2,226.239	−2,553.396	−2,564.654	−2,540.291
σ^2	19.619	20.024	20.283	50.172	51.687	48.519
Akaike Inf. Crit.	4,443.352	4,458.424	4,470.479	5,124.792	5,147.308	5,098.581
Wald Test (df = 1)	104.417***	99.491***	107.789***	3.342*	3.331*	1.034
LR Test (df = 1)	96.477***	93.240***	100.451***	3.286*	3.305*	1.030
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A.10: Cross Sectional SAR Models: Transport Network and Violence, 225km Area Hexagonal Grid Cells

A.9 Cross-Sectional SAR Models Broken out by Type of Mine

	Dependent variable:							
	ArmedClashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gold Mine	−0.01							
	(−0.05, 0.04)							
3T Mine		−0.02						
		(−0.06, 0.02)						
Coltan Mine			−0.02					
			(−0.11, 0.06)					
Copper				−0.31				
				(−2.01, 1.40)				
Diamond Mine					0.80**			
					(0.13, 1.48)			
Tin Mine						−0.01		
						(−0.06, 0.04)		
# Mineworkers (log)							−0.03	
							(−0.09, 0.03)	
Local Competition for Mines								0.07
								(−0.41, 0.55)
Observations	1,105	1,105	1,105	1,105	1,105	1,105	1,105	1,105
σ^2	8.25	8.25	8.25	8.25	8.21	8.25	8.25	8.25
Wald Test (df = 1)	301.47***	299.12***	301.51***	301.36***	302.38***	300.79***	297.42***	302.97***
LR Test (df = 1)	248.61***	247.58***	249.46***	249.57***	250.26***	248.39***	245.21***	249.93***
	Looting							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gold Mine	0.01							
	(−0.06, 0.08)							
3T Mine		0.02						
		(−0.05, 0.08)						
Coltan Mine			0.03					
			(−0.11, 0.16)					
Copper Mine				−0.54				
				(−3.36, 2.28)				
Diamond Mine					0.49			
					(−0.63, 1.61)			
Tin Mine						0.05		
						(−0.03, 0.13)		
# of Mineworks (log)							−0.02	
							(−0.12, 0.08)	
Local Competition for Mines								0.39
								(−0.40, 1.18)
Observations	1,105	1,105	1,105	1,105	1,105	1,105	1,105	1,105
σ^2	22.62	22.62	22.62	22.62	22.61	22.59	22.62	22.60
Wald Test (df = 1)	62.13***	61.95***	61.86***	61.76***	62.04***	61.78***	61.59***	62.50***
LR Test (df = 1)	59.54***	59.39***	59.31***	59.25***	59.49***	59.25***	58.98***	59.87***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS regressions.

Table A.11: Relationship between mines and armed clashes, 100km area hexagonal grid cells

A.10 Panel Results by Type of Mine

In Table A.12, I examine whether exogenous variation in global demand for the mineral extracted from a given mine is correlated with observed violence. I interact the number of mines for different types of minerals with the global price for that mineral in that month. The dependent variable is the number of Armed Clashes (Models 1-5) events and the number of Looting events (Moles 6-10). These results are constrained by a number of factors. First, as show in Figure 2.3, there is limited variability of market prices in the time frame for which I have data on violent events. Second, I am forced to rely on violence at the mines as a proxy for the disintegration of the cooperation at the mines. While I do expect that violence is an observable manifestation of such ruptures, it is also possible that the dissolution of such pacts may take non (overtly) violent forms.

	Dependent variable:									
	ArmedClash					Looting				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Diamond Mine * DiamondIndex	0.003					0.01^{*}				
	(0.003)					(0.003)				
Gold Mine * Gold		−0.0000					−0.0000			
		(0.0000)					(0.0000)			
Tin Mine * Tin			0.0001					−0.0001		
			(0.0000)					(0.0000)		
3T Mine * Tungsten				0.0000^{**}					-0.0000^{*}	
				(0.0000)					(0.0000)	
3T Mine * Tantalum					0.0000^{**}					-0.0000^{*}
					(0.0000)					(0.0000)
Observations	23,994	23,994	23,994	23,994	23,994	23,994	23,994	23,994	23,994	23,994
F Statistic (df = 2; 23218)	19.76^{***}	2.18	5.87^{***}	7.00^{***}	7.38^{***}	1.69	2.68^{*}	10.57^{***}	15.76^{***}	17.39^{***}

Note: Results from panel regressions *p<0.1; **p<0.05; ***p<0.01

Table A.12: Exogenous Variation in Global Prices for Minerals and Observed Violence Near Mines

Despite these limitations, the results provide suggestive, although limited, evidence of change in the stability of the cooperation that occurs at mines in response to market prices. Market fluctuation in tungsten and tantalum are correlated with higher levels of armed clashes, but the effect sizes are minuscule. Again, this is likely because of the lack of a sufficiently severe shock to global demand in the temporal scope of my data. Increased global demand for diamonds is weakly correlated (at the $p < .1$ level) with localized increases in looting events, suggesting that armed groups may be less likely to respect their protection racket responsibilities if more lucrative predatory options exist. Each of the results in Table A.12, it should be noted, have such small effect sizes that strong substantive conclusions are impossible to draw. The patterns, however, are consistent with the broader findings on price shocks increasing violent competition at the source of the mineral, in contrast to the patterns described in the cross-sectional data.

APPENDIX B

Appendix: The Demand for Protection, Predictable Extortion, and Civilian Perceptions of Security

B.1 Data Collection and Field Research Ethics

Eastern DRCongo is a site of ongoing conflict and violence,[1] raising a number of ethical, methodological, and practical concerns about collecting such data. Consistent with calls for increased transparency and attention to ethics in such research Cronin, Furman, & Lake (2018), in this section I provide additional information on how we incorporated ethical considerations and protections into our fieldwork procedures and research design. Given the research context and the vulnerability of populations that I study, I took a number of steps beyond obtaining IRB approval to ensure our research was ethical, safe, and rigorous.

An interdisciplinary research team, including public health scholars with expertise in trauma, crafted the survey instrument to keep questions general in nature to avoid specific triggers. We designed the survey instruments to minimize the risk of mental distress induced by potentially sensitive questions and by keeping questions on potentially triggering topics intentionally vague. Doing so allows us to collect general patterns while not forcing respondents to re-traumatize themselves, in line with best practices in public health and psychological research. During the enumeration process, respondents were reminded multiple times of their option to refuse to answer any questions

[1]While many, including the United Nations, view DRCongo as "post-conflict" [4], the eastern provinces that we analyze remain well above all standard thresholds of violence to constitute an ongoing conflict.

or stop interviews. Enumerators also repeatedly reminded respondents of their anonymity. We also incorporated local research partners in the full research cycle to ensure our survey questionnaire was contextually appropriate.

To ensure the safety of respondents and enumerators, there were safety plans in place and determined the conditions under which enumeration would stop ahead of time. Security conditions on the ground were constantly monitored based on multiple sources, including contacts within MONUSCO. Decisions about whether to pause enumeration were made in certain areas conservatively, always prioritizing the safety and security of our team and the respondents.

Detailed location information was automatically degraded to prevent re-identification. Collected data were sent to a cloud-server using encrypted communication via KoboToolbox as soon as enumerators had access to internet and then wiped from Tablets. Once completed, data were downloaded and stored on encrypted laptops and data sharing applications.

B.2 Survey Details

B.2.1 Administrative Units in DRCongo

The sampling strategy for the survey used in the empirical analysis relies on administrative units within DRCongo. As such, I provide more information about the structure of these units here.

I graphically represent the administrative unit structure in Figure C.2. DR Congo is subdivided into 26 provinces, 3 of which are in the sample used in this paper (Ituri, North Kivu, and South Kivu). Below the province, jurisdictions are divided into either cities or *territories*, with differing subsequent paths depending on whether it is an urban or rural jurisdiction. Cities (*villes*) are further subdivided into *communes*, which are then subdivided into *quartiers* or *groupements*. In contrast, areas outside major cities are first split into *territoires* and further subdivided into *communes*, *sectors*, and *chefferies* (chiefdoms), before being further subdivided into *groupements* and then villages. Our sampling strategy relies on provinces, territoires (or *villes*), and then *groupements* (or *quartier*), and finally villages.

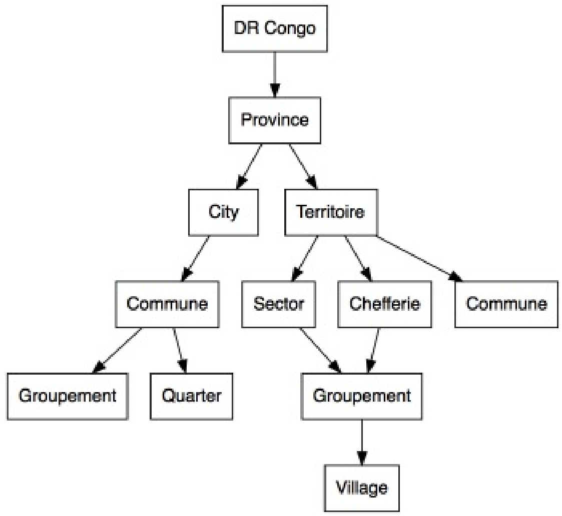


Figure B.1: Structure of administrative units in DRC

B.3 Additional Information on Roadblocks Data in Eastern Congo

B.3.1 Data Generating Process and Limitations

The roadblocks data I leverage in this paper are based on a data collection by International Peace Information Service between March 2016 and August 2017. The data collection is detailed in Schouten, Murairi, & Batundi (2017).[2] As they describe their data generating process:

> "Teams were deployed in the field with digital questionnaires to identify roadblocks

[2]For further information and a more contextualized discussion of the historical antecedents of roadblocks, see Schouten (2022).

> along key axes and to interrogate the stakeholders involved (different types of road users and, where the security situation allowed it, roadblock operators). A limited number of the roadblocks mapped are sourced from another IPIS project, which maps mining sites and mineral supply chains in eastern DR Congo...These both data sources are supplemented by confidential sources within MONUSCO, reporting in the media, and exchanges with human rights defenders." (Schouten, Murairi & Batundi 2016, pg. 7)

Schouten, Murairi, & Batundi (2017) note a few specific limitations in the data, which I incorporate into my empirical strategy. The data collection could not cover North Kivu's Beni and Lubero *territoires* or Lulenge sector in South Kivu due to security concerns. It also does not cover a portion of Walikale occupied by the Raia Mutomboki group. As a result, I drop survey responses from these areas to avoid making inferences based on non-random measurement error in the roadblocks data.

Schouten, Murairi, & Batundi (2017) also caution that they are interested in roadblocks, not "highwaymen." In eastern DRCongo, banditry on roads from highwaymen is a common occurrence but distinct from the logic and logistics of roadblocks: "The difference between the two is that the roadblocks studied are static points where the posted elements impose taxes, whereas highwaymen are bandits who punctually hold up road users to engage in looting, robbing, kidnapping, and sometimes kill them" (Schouten, Murairi & Batundi 2016, pg. 8).

B.4 Measuring Violence Using Kivu Security Tracker

Controlling for exposure to violence in the eastern DRCongo is challenging given the underreporting of the violence in standard event-based datasets on the conflicts [163]. I use data provided by the Kivu Security Tracker (KST), a Human Rights Watch program that employs a network of researchers throughout North and South Kivu to track and independently verify violent events.[3] It has significant advantages over commonly used events based datasets such as ACLED, UCDP, and SCAD. For example, by relying on a network of local researchers who leverage their connections with the UN and the government, they expand the pool of potential cases from just those that end up in the media, a particularly problematic assumption for the violence in eastern Congo.

To measure each respondent's exposure to violence, I create a 5km radius buffer around each survey respondent (the large green circles in Figure B.3). Then, I plot the geo-located violent events from KST (orange dots in Figure B.3). I then capture how many violent events, how many violent deaths, and the characterization of each violent event within the 5km geographic buffer of each respondent.

B.5 Combined Map of Roadblocks, Mines, and Violence

To demonstrate the combined spatial dynamics that civilian face in the data, I plot roadblocks (triangles) and mines (squares), which I project onto a heatmap of the intensity of violence as measured by violent deaths according to KST. Colors are broken by type of mineral for mines and operator of the roadblock.

[3] Unforunately KST does not collect data on violence in Ituri, so when we use KST we exclude Ituri from the sample.

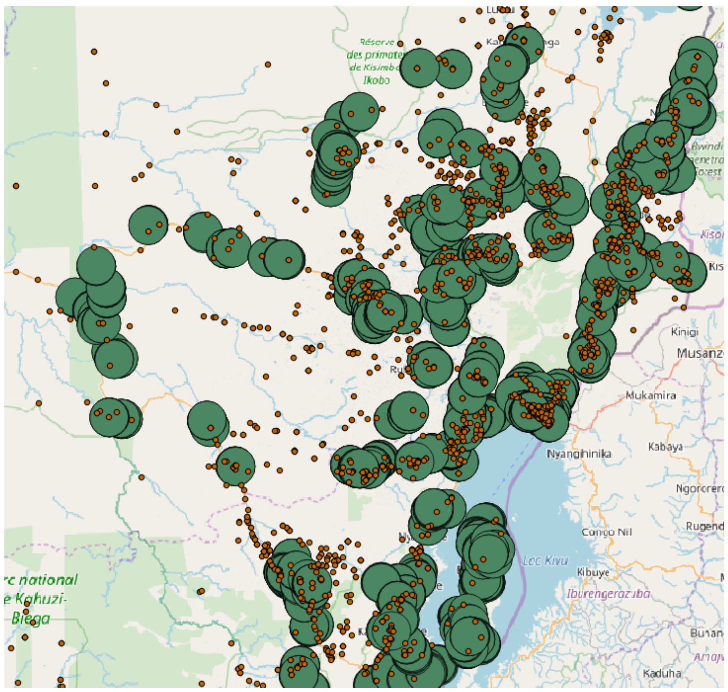


Figure B.2: 5km buffer polygons (green) and KST conflict events (orange) in sample near border of North and South Kivu

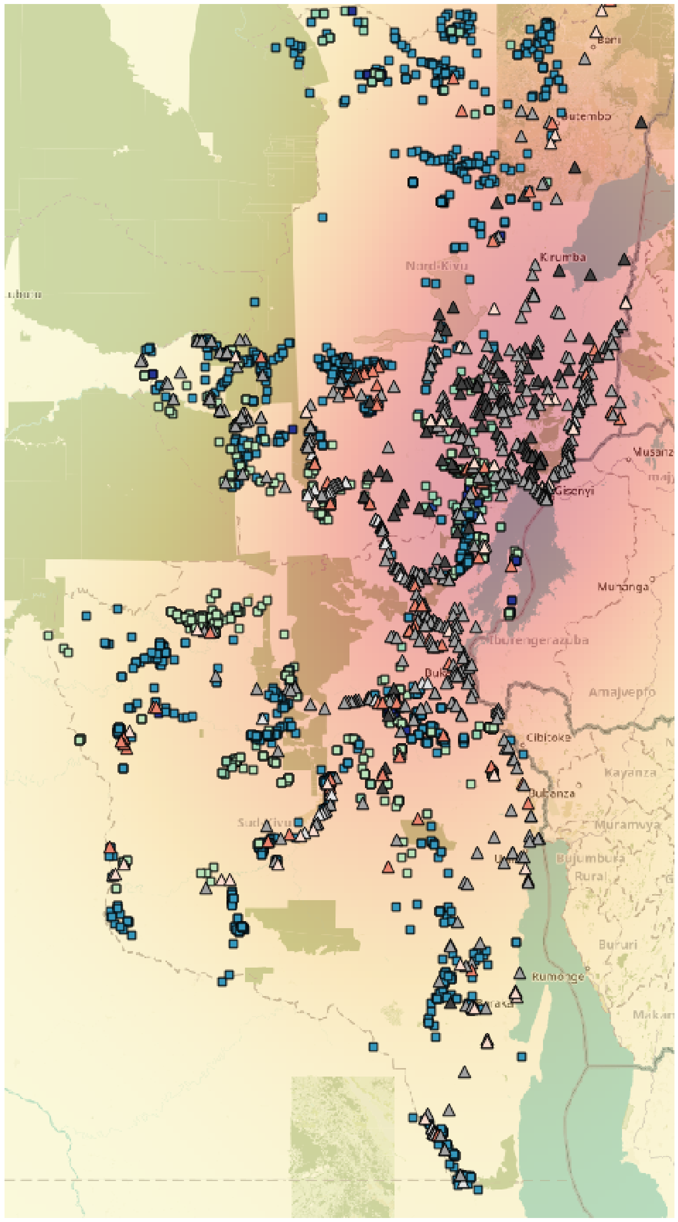
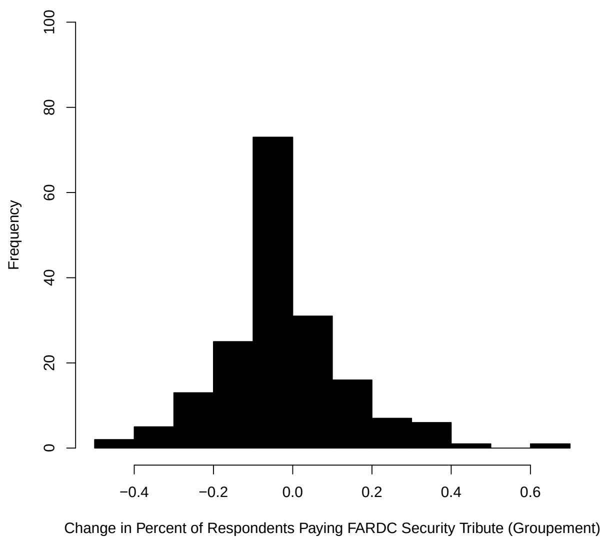
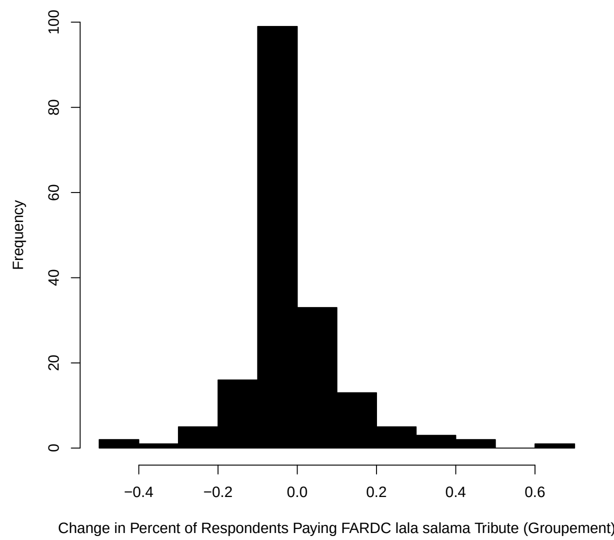


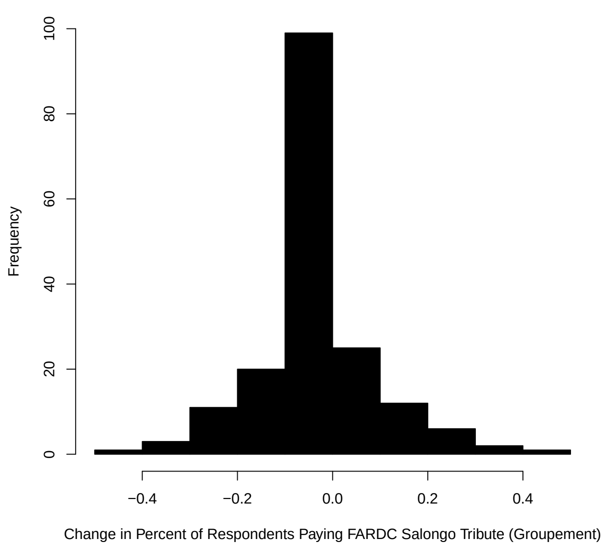
Figure B.3: Combined map plotting roadblocks (triangles) and mines (squares) projected onto a heatmap of the intensity of violence as measured by violent deaths according to KST. Colors are broken by type of mineral for mines and operator of the roadblock.

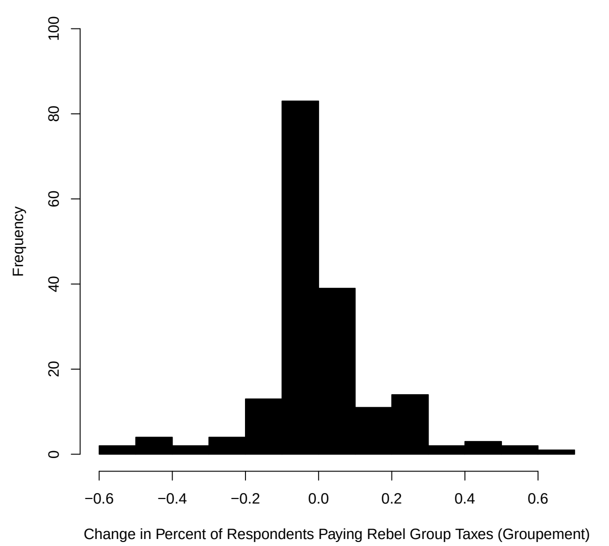
B.6 Histograms of Change in Percent of Respondents within *Groupements* Reporting Paying Various Taxes

Below, I present histograms of the percentage change between 2019 and 2018 of respondents who self-report paying various taxes to armed groups. These measures are used as independent variables in Table 3.4. The plots also demonstrate the fluidity of the security providers over time.









B.7 Supporting Qualitative Evidence

The regressions presented in the main text provide consistent evidence in support of my theory. Given the complicated nature of generating trust generally and the political-military dynamics in eastern DRCongo especially, I compliment the quantitative analysis with qualitative insights from ethnographers who specifically analyze how civilians interact with and navigate armed actors, including FARDC.

A number of ethnographic studies find that, under certain conditions, civilians in eastern DR-Congo can come to accept or even support stationary bandits despite extortive behavior. Hoffmann, Vlassenroot, & Marchais (2016), for example, report:

> "these [taxes] were considered as harassment by the local population, but in some cases they were seen as taxes which provided a modicum of security in return. This was the case with some of the roadblocks set up in mid-2010, to deter attacks by bandits and rebels who were targeting buses and trucks transporting goods. In Kahuzi-Biega National Park, which was regularly frequented by bandits targeting vehicles, the roadblock erected by the army was welcomed by the population and was experienced as a public security service providing protection. Similarly, the customary authorities of Buloho chiefdom successfully approached the army to deploy troops to secure the road connecting the main town of the chiefdom, Maibano, to the main market in Bulambika. The road was the economic lifeline of Buloho and even though road users had to pay the troops, this was generally accepted because petty traders were protected against attacks from the mainly Rwandan Hutu rebel group FDLR." (1449-1450)

Similarly, in an ethnography of FARDC-civilian relations, Verweijen (2013), found:

> "for the majority of non-elite civilians, in particular the FARDC's perceived performance in the domain of security has a very strong impact on the experienced legitimacy of its power position. The legitimacy also strongly influences perceptions of military revenue-generating practices. Especially where these are justified as contributing to the performance of the FARDC's security duties, or where they enhance people's own livelihoods opportunities, they can come to be seen as relatively licit. For example, roadblocks are less resented in areas where banditry abounds and where the FARDC is believed to reinforce security: 'Better pay 500 Francs Congolais to the military than have all your belongings looted by the FDLR,' as a small-scale trader stated at a roadblock in a forest in Fizi that is infamous for frequent ambushes." (78)

In both of the above passages, civilian assessments of FARDC's presence and its revenue generating schemes are contingent on both the context of banditry and the predictability that the tribute systems provided. Importantly, both passages also suggest that the taxes are perceived as an abuse of power, but that civilians are willing to overlook and even accept these abuses in limited circumstances. These findings comport with the quantitative evidence presented above. They also comport with the lack of a relationship between recent banditry and procedural trust in the static models: in both cases, civilians report a sense of resentment due to the roadblocks or tribute schemes on their own.

B.8 Robustness Tests

B.8.1 Replacing *Territoire* Fixed Effects with Ethnic Group Fixed Effects

Because of the ongoing violence in eastern DRCongo, ethnicity is salient and an organizing cleavage when negotiating protection from armed groups. Armed groups negotiate with local leaders, especially local chiefs, to arrange the tribute systems. These local chiefs draw their support from their relative status within their local ethnic community.

In the main text, I use geographic fixed effects to capture unobservable variation in context. In Table B.1, I re-run the models in Tables 3.3 and 3.4 and replace geographic fixed effects with ethnic group fixed effects.[4] The results are robust to this alternative specification.

	Dependent variable:								
	Perceptions of Security								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pay *Lala Salama* * Banditry (Normalized)	6.285**			6.730**			1.473		
	(2.729)			(2.804)			(1.575)		
Pay *Salongo* * Banditry (Normalized)		1.240			−0.296			1.258	
		(1.437)			(1.574)			(1.440)	
FARDC Roadblock Monopoly * Banditry (Normalized)			2.426**			2.071**			1.534
			(1.017)			(1.011)			(0.991)
Pay *Lala Salama*	0.053			0.032			−0.139		
	(0.224)			(0.221)			(0.187)		
Pay *Salongo*		−0.203			0.429***			−0.237	
		(0.150)			(0.165)			(0.149)	
FARDC Roadblock Monopoly			−0.310***			−0.370***			−0.075
			(0.104)			(0.103)			(0.103)
Banditry (Normalized)	−1.078**	−0.935*	−2.071**	−1.006**	−0.400	−1.490	−1.039**	−1.066**	−1.238
	(0.491)	(0.494)	(0.943)	(0.482)	(0.502)	(0.939)	(0.488)	(0.493)	(0.921)
Constant	1.147*	0.261	13.483	1.168**	1.138***	13.377	0.307	0.290	−12.221
	(0.597)	(0.528)	(525.751)	(0.593)	(0.181)	(525.722)	(0.530)	(0.530)	(319.198)
Observations	2,904	2,882	4,385	2,927	2,927	4,401	2,913	2,907	4,401
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ethnicity Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Survey Wave Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Groupement Clustered Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓

Results from OLS regressions. Each model controls for employment status, gender, age, displacement status, proximity to MONUSCO base, strategic roadblocks, and levels of generalized trust *p<0.1; **p<0.05; ***p<0.01

Table B.1: Relationship between payment of taxes and perceptions of FARDC Legitimacy

[4]Ethnicity and administrative units are related but not synonymous in eastern DRCongo.

B.8.2 Replacing Perceptions of Security with Trust in FARDC

In the main text, I analyze civilian perceptions of their own security. It is possible that perceptions of security improve, but that these are for reasons other than the protection racket. In this section, I use an alternative outcome, perceptions of (and more specifically, trust in) FARDC. Doing so enables me to demonstrate whether the improved perceptions also results in improved perception of the actor providing the security locally. I can only do this for FARDC, as the surveys do not ask questions on perceptions of non-state armed groups for security reasons.

To measure civilian perceptions of and trust in FARDC, I use responses to a battery of five questions. The battery was designed to capture respondents trust in FARDC's administrative competence and procedural justice, each of which are key tenets of institutional trust and legitimacy [101].

To measure administrative competence, each respondent reports if they trust FARDC[5] to ensure their security, protect them from armed groups, and to protect them from bandits.[6] These questions capture the multifaceted nature of a security provider's responsibilities and the variety in threats that civilians face in eastern DRCongo. To capture respondent's perceptions of FARDC's procedural justice, respondents are also asked whether they agree or disagree with the statements that local FARDC soldiers would provide them help when needed and whether they take into consideration the needs of those most vulnerable. Principle components analysis confirmed that the five items capture two distinct but closely related concepts. As such, if the respondent responds affirmatively to any of the questions for the administrative competence, they are coded as trusting FARDC to carry out its core security provision mandate ("FARDC Security"). Likewise, if they answer either of the procedural justice questions affirmatively, they are coded as trusting FARDC's procedural justice ("Procedural Trust"). If a respondent is coded as trusting both FARDC's administrative competence and its procedural justice, I create a third measure that captures a general trust of FARDC ("FARDC Security & Procedural Trust").

[5] These are yes/no questions with an option to refuse to answer. Less than 4% refuse to answer each of the questions.

[6] Armed Groups and bandits have separate meanings in the Congolese context that are well understood. Banditry represents looting and crime, while armed groups are formal rebel groups.

First, I analyze whether directly paying *lala salama* or *Salongo* tribute payments to local FARDC soldiers is associated with improved perceptions of FARDC, conditional on the demand for security due to previous instances of looting and banditry. As noted above, paying *lala salama* or *Salongo* taxes are indicative of FARDC acting as a local stationary bandit, not necessarily that civilians paying the tax view FARDC as legitimate or that they trust FARDC as an organization. Indeed, paying *lala salama* itself is not significantly positively correlated with any of the measures of FARDC legitimacy. Although implemented by the same umbrella organization and used for the same purpose (to collect tribute from those who they protect), *lala salama* tribute payments are predictable while *Salongo* are relatively unpredictable, allowing me to isolate the relative impact that predictability has on perceptions while comparing similar levels of recent banditry.

In Table B.2, I run six logistic regressions. The dependent variables are trust across three dimensions: the combined trust FARDC measure (Models 1 and 2), competence (Models 3 and 4) and procedural justice (Models 5 and 6). The independent variables of interest are the interaction of recent experiences with banditry and whether the respondent reported paying *lala salama* (Models 1, 3, and 5) or *Salongo* (Models 2, 4, and 6). All models in Table B.2 restrict the sample to male respondents because men typically pay both forms of tribute and the questions ask respondents to report their own payments. Each model includes a vector of controls, clusters standard errors at the *groupement*, and includes *Territoire* and survey wave fixed effects to account for unobserved heterogeneity in context.

The results in Table B.2 provide evidence that paying *lala salama* is not itself a function of existing trust. However, the results in Table B.2 also indicate circumstances under which the presence of a stationary bandit that uses predictable extortion schemes to generate revenue can be seen as acceptable by civilians: when the stationary bandit also fills a security void. In Models 1 and 2, the interaction term Pay *lala salama* $*$ Previous Banditry is positive and significantly correlated with perceptions of trust broadly and perceptions of competence especially. When respondents live in areas that experienced banditry, predictable security tribute payments can become palatable and build trust in FARDC. But this result does not extend to procedural justice, indicating that

	Dependent variable:					
	FARDC Security & Procedural Trust		FARDC Security Trust		FARDC Procedural Trust	
	(1)	(2)	(3)	(4)	(5)	(6)
Pay *lala salama* * Banditry (Normalized)	6.867**		7.232**		1.371	
	(2.836)		(2.890)		(1.602)	
Pay *Salongo* * Banditry (Normalized)		0.201		−0.296		−0.039
		(1.459)		(1.574)		(1.467)
Pay *lala salama*	0.009		−0.003		−0.105	
	(0.230)		(0.225)		(0.189)	
Pay *Salongo*		−0.037		0.429***		−0.045
		(0.155)		(0.165)		(0.155)
Banditry (Normalized)	−0.876*	−0.746	−0.794	−0.400	−0.899*	−0.824
	(0.510)	(0.520)	(0.498)	(0.502)	(0.509)	(0.517)
Constant	1.404***	0.259	1.187***	1.138***	0.552***	0.558***
	(0.193)	(0.170)	(0.179)	(0.181)	(0.168)	(0.170)
Observations	2,913	2,891	2,936	2,927	2,922	2,916
Controls	✓	✓	✓	✓	✓	✓
Territoire Fixed Effects	✓	✓	✓	✓	✓	✓
Survey Wave Fixed Effects	✓	✓	✓	✓	✓	✓
Groupement clustered errors	✓	✓	✓	✓	✓	✓

Each model controls for employment status, age, displacement status, proximity to a strategic roadblock, proximity to MONUSCO base, and levels of generalized trust. Sample is restricted to male respondents.*p<0.1; **p<0.05; ***p<0.01

Table B.2: Reported Security Tribute Payments to FARDC and Perceptions of Trust

civilians come to trust security providers to carry out their core function, civilians also recognize that FARDC does not necessarily behave fairly.

In contrast, paying *Salongo* shares no such conditional relationship with the likelihood that a respondent expresses trust in FARDC. Even when FARDC is filling a security void, unpredictable tribute schemes such as *Salongo* are not associated with an increase in trust for the institution. Since the core difference between the security tribute systems is their level of predictability, the divergence in the results in Table B.2 suggest that the predictability of the security tribute systems drives the results in Models 1, 3, and 5, so long as a security void is being filled.

Next, because directly paying taxes via *lala salama* or *Salongo* is not the only way to receive the positive security benefit from a stationary bandit and this relationship is potentially endogenous with a number of other factors that may influence an individual's propensity to trust, I analyze proximity to FARDC roadblocks. Roadblocks do not provide (observable) variation in the predictability of the tribute payment, but civilians generally consider the roadblock payments predictable. By analyzing roadblocks, I am not restricted to only those who self-report paying directly into the tribute systems and thus expand the sample to both men and women.

In Table B.3, I interact a dichotomous variable indicating whether each respondent lives both

1) within 5km of at least one FARDC roadblock and 2) no other armed groups operate a roadblock within that zone, indicating that the local FARDC unit has a local monopoly as a stationary bandit ("FARDC Roadblock Monopoly"), with the banditry measure. As in Table B.2, I include a vector of controls, cluster standard errors at the *groupement*, and add *Territoire* and survey wave fixed effects to account for unobserved heterogeneity in context.

	Dependent variable:		
	FARDC Security & Procedural Trust	FARDC Security Trust	FARDC Procedural Trust
	(4)	(5)	(6)
FARDC Roadblock Monopoly * Banditry (Normalized)	2.364**	2.220**	0.859
	(1.105)	(1.096)	(1.069)
FARDC Roadblock Monopoly	−0.083	−0.156	0.017
	(0.113)	(0.111)	(0.111)
Banditry (Normalized)	−2.130**	−1.745*	−0.863
	(1.048)	(1.041)	(1.020)
Observations	4,394	4,410	4,410
Controls	✓	✓	✓
Territoire Fixed Effects	✓	✓	✓
Survey Wave Fixed Effects	✓	✓	✓
Groupement clustered errors	✓	✓	✓

Each model controls for employment status, gender, age, displacement status, proximity to MONUSCO base, strategic roadblocks, and levels of generalized trust. *p<0.1; **p<0.05; ***p<0.01

Table B.3: Proximity to FARDC Roadblock Monopoly and Trust in FARDC

The results in Table B.3 again indicate that roadblock presence is not itself indicative of trust in FARDC. But the demand for protection and the presence of FARDC as a stationary bandit together is significantly associated with trust in FARDC's overall and competence. The magnitude of the relationship is much smaller than in Table B.2, which is likely due to the fact that roadblocks encapsulate everyone who lives in the area, not just those who directly pay security tribute. As such, the consistency between Table B.2 and Table B.3 suggest that the *lala salama* results expand beyond those who directly participate in the security tribute system to those who live in areas with FARDC acting as a stationary bandit generally. However, the positive trust windfall does not extend to the procedural justice measure, again suggesting that civilians evaluate the concepts of procedural justice and whether they trust the institution to fulfill its core mandate – security provision – separately.

My theory explicitly highlights the fluidity of protection schemes in the absence of a centralized state. Amidst this fluidity, civilians make judgments about new security providers, which they consistently re-evaluate over time and with updated expectations that may differ as the relationship evolves. In Tables B.2 and B.3, I could not distinguish between relatively new stationary bandits and more established ones, which could mask important variation at the initial stages of penetration.

To account for temporal change, I leverage changes in local political dynamics between the two survey waves. Although the survey data is not a panel (i.e. the same respondents are not re-interviewed), the surveys do provide representative coverage at the *groupement* level in both waves. *Groupements* are the second smallest administrative unit in eastern DRCongo and typically include 10-20 villages.[7] Both the 2018 and 2019 waves sample all 180 *groupements* in North and South Kivu. Incorporating these temporal changes also help alleviate concerns that the above results are driven by respondents in areas where FARDC has had a relatively long and stable presence. 21% of 2019 respondents live in a *groupement* where *lala salama* taxation rose more than 10% since 2018, indicating that FARDC units only recently began behaving as stationary bandits.

In Table B.4, I create a binary indicator for whether each survey respondent lives in a *groupement* that experienced more than 10% growth in respondents reporting that they recently paid either *lala salama* or *Salongo* taxes to FARDC, signaling a relatively new stationary bandit. I then run same models as Table 1, but interact the indicator of recent expansion of the stationary bandit with both a binary indicator of whether the response is from the 2019 survey wave and a binary indicator of whether they experienced banditry in the recent past.

The triple interaction term of interests in all models (*FARDC Expansion >10% * 2019 Wave * Recent Banditry*) are positive and significant at least at the $p<0.05$ level. This is suggestive evidence that new stationary bandits receive the same legitimacy windfall by creating predictable taxation schemes and filling a demand for security as above. A crucial difference, however, is that the Procedural Trust result becomes both significant and positive, in contrast to the static models where the Procedural Trust results were not significant. This is indicative – although not conclusive evidence – that civilians being more willing to trust recent stationary bandits across all domains at

[7] I do not aggregate to villages because the sampling strategy is not designed to be representative at the village level.

the very early stages of penetration. The results in Tables B.2 and B.3 suggest that civilians update these perceptions over time and become more discerning (or demanding) over time, in line with recent results on the expansion of taxation [171].

	Dependent variable:		
	FARDC Security & Procedural Trust	FARDC Security Trust	FARDC Procedural Trust
	(7)	(8)	(9)
FARDC Expansion >10% * 2019 Wave * Recent Banditry	0.686^{**}	1.131^{***}	1.941^{***}
	(0.329)	(0.318)	(0.320)
FARDC Expansion >10% * 2019 Wave	-0.834^{***}	-0.686^{***}	-0.706^{***}
	(0.152)	(0.151)	(0.155)
FARDC Expansion >10% * Recent Banditry	0.100	-0.248	-0.797^{***}
	(0.255)	(0.244)	(0.241)
2019 Wave * Recent Banditry	-0.197	-0.256	-0.293^{*}
	(0.169)	(0.158)	(0.156)
Constant	-0.614^{***}	-0.338^{***}	0.205^{*}
	(0.115)	(0.112)	(0.114)
Observations	5,794	5,827	5,795
Controls	✓	✓	✓
Territoire Fixed Effects	✓	✓	✓
Survey Wave Fixed Effects			
Groupement Clustered Errors	✓	✓	✓

Change is operationalized as aggregated difference between the 2019 and 2018 waves at the *groupement* level. Each model controls for employment status, gender, age, displacement status, proximity to MONUSCO base, and levels of generalized trust. They also include *Territoire* fixed effects and *groupement* clustered standard errors *p<0.1; **p<0.05; ***p<0.01

Table B.4: Interacting Recent FARDC Expansion in *Groupement*, Survey Wave, and Recent Experiences with Banditry

The results presented in Table B.4 merit important caveats, however. While these results demonstrate that the expansion of predictable security tribute is correlated with institutional trust when filling a security void, the aggregated data I analyze only captures relative change over one year, severely limiting my ability to draw inferences on the magnitude or sustainability of these changes. For example, because I can only capture change over a single period, I cannot capture whether changes in perceptions of FARDC changed prior to the expansion of the extortion schemes. Moreover, as described above, the civilian-armed group dynamics I analyze play out at levels below – typically at the village level – the unit of aggregation employed here. Despite these important limitations, the results compliment the core results analysis by incorporating as much temporal variation as possible in both the independent and dependent variables at a relatively local level.

APPENDIX C

Appendix: Seeing Blue Helmets is Believing: Exposure to Peacekeepers and Civilian Perceptions of UN PKOs

C.1 Descriptive Statistics

We provide descriptive statistics for the main variables in our models. The Ns vary because each question allowed respondents to not answer and NAs are omitted from the summary statistics. We present the statistics for the Regular sample (Table C.1) and MONUSCO Base sample (Table C.2) separately.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Exposure to MONUSCO	9,439	0.266	0.442	0.000	0.000	1.000	1.000
Trust (Security)	10,028	0.170	0.334	0	0	0	1
Trust (Stabilization)	10,028	0.174	0.354	0	0	0	1
Contribution (Security)	10,028	0.328	0.183	0.000	0.200	0.457	1.000
Contribution (Stabilization)	10,028	0.329	0.203	0.000	0.200	0.400	1.000
Age	10,027	36.361	13.459	18.000	26.000	45.000	91.000
Sex	10,027	1.500	0.500	1.000	1.000	2.000	2.000
Education	10,028	0.571	0.495	0	0	1	1
AccessBasicNeeds	10,028	19.692	4.635	0	17	23	35
ExposureViolence	10,028	0.241	0.633	0	0	0	3
EthnicMajority	9,035	1.224	0.417	1.000	1.000	1.000	2.000
GovTrust	10,028	10.276	3.118	0	8	12	20
Survey Wave	10,028	2,018.485	0.500	2,018	2,018	2,019	2,019

Table C.1: Summary Statistics: Regular Sample

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Exposure to MONUSCO	3,512	0.447	0.497	0.000	0.000	1.000	1.000
Trust (Security)	3,704	0.159	0.324	0	0	0	1
Trust (Stabilization)	3,704	0.122	0.302	0	0	0	1
Contribution (Security)	3,704	0.302	0.149	0.000	0.200	0.400	0.943
Contribution (Stabilization)	3,704	0.301	0.169	0.000	0.200	0.400	1.000
Age	3,704	37.023	14.296	18	25	46	84
Sex	3,704	1.502	0.500	1	1	2	2
Education	3,704	0.401	0.490	0	0	1	1
AccessBasicNeeds	3,704	18.330	4.590	7	15	21	35
ExposureViolence	3,704	0.527	0.921	0	0	1	3
EthnicMajority	3,024	1.232	0.422	1.000	1.000	1.000	2.000
GovTrust	3,704	10.314	3.131	4	8	12	20
Survey Wave	3,704	2,018.584	0.493	2,018	2,018	2,019	2,019

Table C.2: Summary Statistics: MONUSCO Base Sample

C.2 Sampling Strategy and Administrative Units in DRCongo

The data analyzed in this paper are part of a long term survey project in eastern DRCongo. In this section, we provide additional details on the sampling structure for this project. Our sampling strategy relies on administrative units within DRCongo. We begin by focusing on three provinces in eastern Democratic Republic of Congo: Ituri, North Kivu, and South. These provides are filled in red and labeled in white in Figure C.1.

Within these three provinces, we use lower level administrative units to guide our sampling strategy. We graphically represent the administrative unit structure in Figure C.2. DR Congo is subdivided into 26 provinces. Below the province, jurisdictions are divided into either cities or territories, with differing subsequent paths depending on whether it is an urban or rural jurisdiction. Cities (*villes*) are further subdivided into *communes*, which are then subdivided into *quartiers* or *groupements*. In contrast, areas outside major cities) are first split into *territoires* and further subdivided into *communes*, *sectors*, and *chefferies* (chiefdoms), before being further subdivided into *groupements* and then villages. Our sampling strategy relies on provinces, territoires (or villes), and then groupements (or quartier), and finally villages. We provide a visual representation of the sampling procedure for the project in Figure C.3.

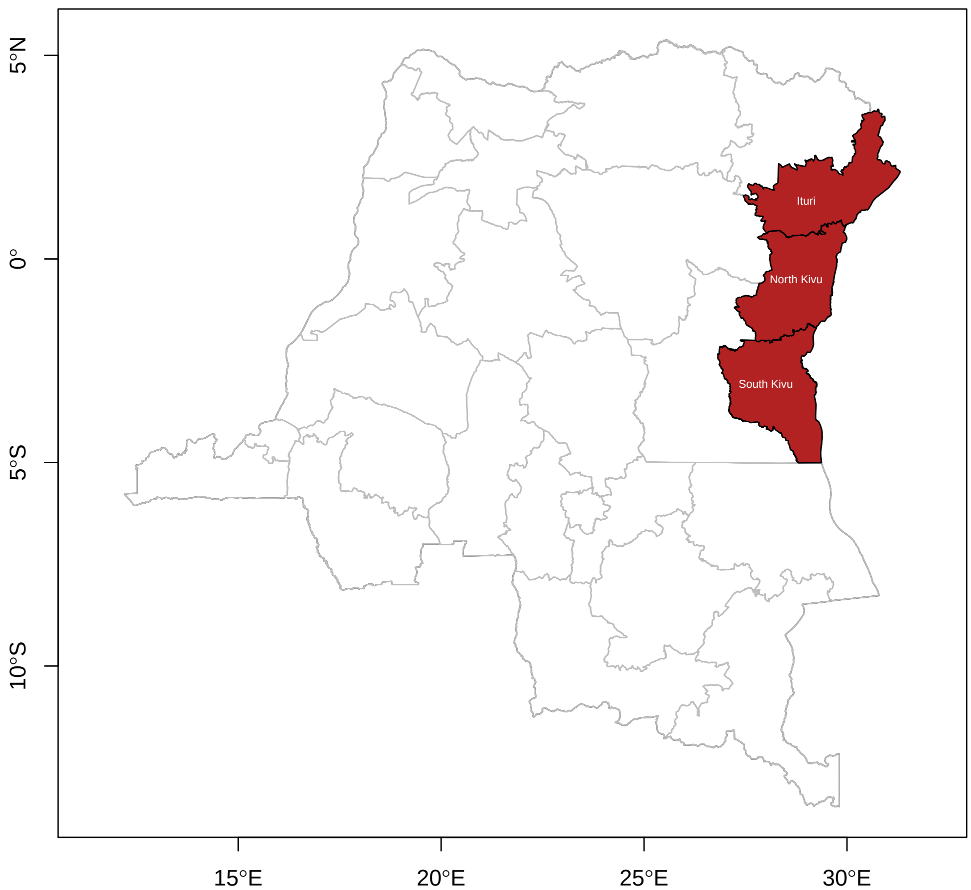


Figure C.1: Provinces analyzed

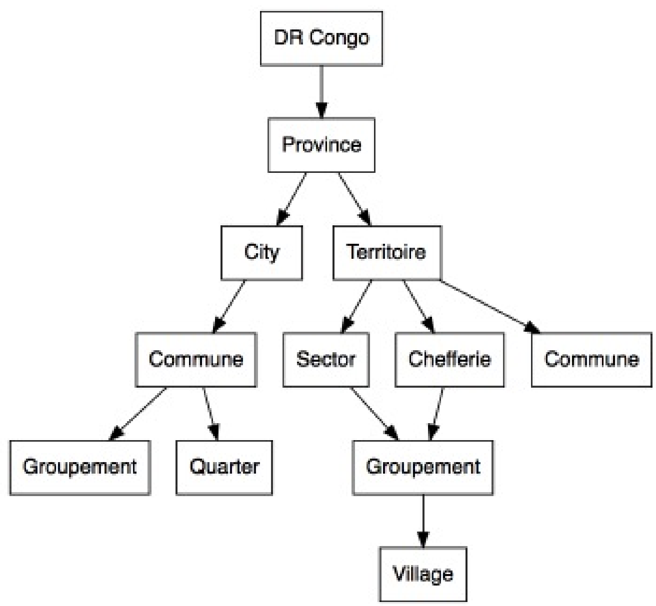


Figure C.2: Structure of administrative units in DRC

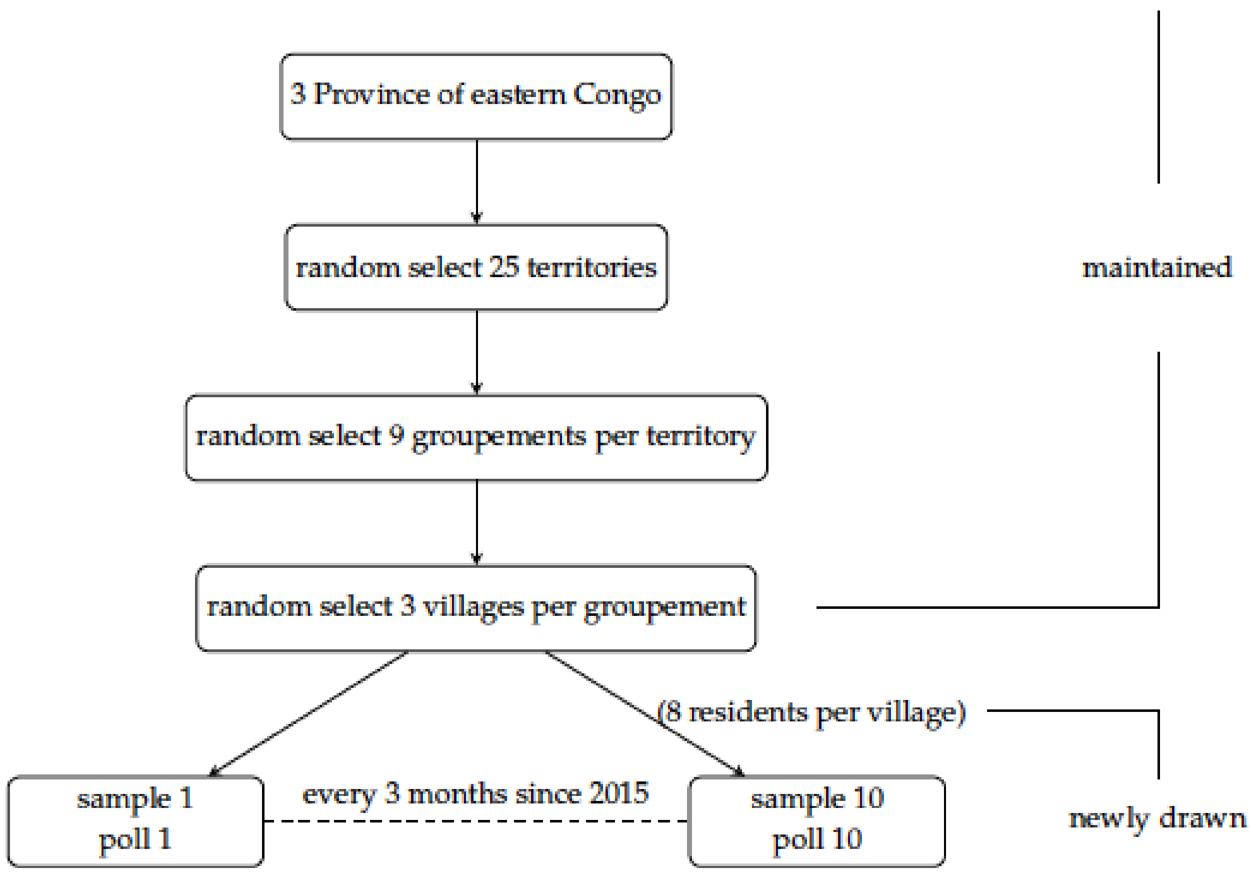


Figure C.3: Multi-Stage Sampling Process for General Sample

C.3 Additional Details on the COB Survey Sampling and Bases

The COBs were randomly selected from a list of all bases located in the three provinces of Ituri, South Kivu and North Kivu. Bases located within proximity to another base were excluded from the sampling frame so that only stand-alone bases were selected. In addition to interviewing peacekeepers, we also conducted surveys with randomly selected local inhabitants in the *groupements* surrounding the eight selected bases. Two waves of data collection were undertaken: one in June-July 2018, and another in July-September 2019.

The results of this survey are based 3,489 face-to-face interviews with randomly selected Congolese adults (of which 50% were women) over two waves of data collection in June and July 2018 and between July and September 2019. A multi-stage cluster sample was used to obtain data representative at the *groupement* level.

Two bases surveyed in 2018 – Oicha and Luna - were closed in 2019 and were substituted with surveys in Boikene and Mayi-Moya respectively. Oicha, Luna and Boikene were all led by Malawian FIB forces. Mayi-Moya was a South African base. Although Boikene and Mayi-Moya were chosen because of their proximity to Oicha and Luna respectively, the Areas of Responsibility are not exactly congruent.

Province	**Territoire**	**Groupement**	**N Surveyed**	**MONUSCO Base**	**TCC**	**FIB**
North Kivu	Masisi	Bashali-Mokoto	201	Kitchanga	India	
	Rutshuru	Binza	216	Nyamilima	India	
	Beni	Batangi-Mbau	216	Oicha	Malawi	✓
		Bambumba Kisiki	229	Luna TOB	Malawi	✓
South Kivu	Walungu	Kamanyola	216	Kamanyola	Pakistan	
	Kalehe	Kalima	218	Bunyakiri	Pakistan	
Ituri	Irumu	Boloma	221	Aveba	Bangladesh	
		Bandiamusu	218	Komanda	Bangladesh	

Table C.3: 2018 MONUSCO Base Sample

Province	**Territoire**	**Groupement**	**N Surveys**	**MONUSCO Base**	**TCC**	**FIB**
North Kivu	Masisi	Bashali-Mokoto	208	Kitchanga	India	
	Rutshuru	Binza	239	Nyamilima	India	
	Beni	Batangi-Mbau	248	Mayi-Moya	South Africa	✓
		Bambumba Kisiki	216	Boikene	Malawi	✓
South Kivu	Walungu	Kamanyola	215	Kamanyola	Pakistan	
	Kalehe	Kalima	210	Bunyakiri	Pakistan	
Ituri	Irumu	Boloma	208	Aveba	Bangladesh	
		Bandiamusu	210	Komanda	Bangladesh	

Table C.4: 2019 MONUSCO Base Sample

C.4 MONUSCO's Spatial Footprint

Figure C.4: MONUSCO's April 2018 Spatial Footprint

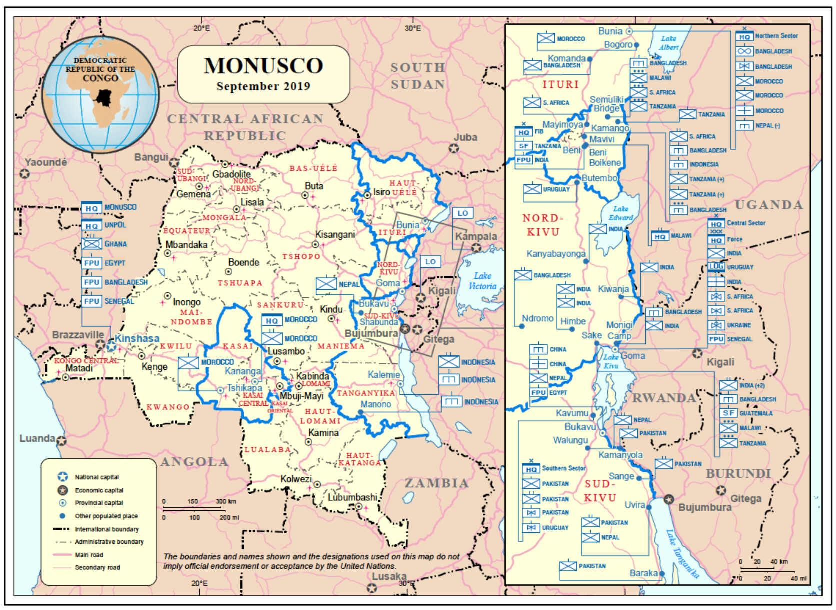


Figure C.5: MONUSCO's Sept 2019 Spatial Footprint

C.5 Quality of Exposure

In the main text, we analyze whether self-reported exposure is associated with perceptions of the mission. We use three questions in which the respondent does not report the quality of that exposure to construct our measure of exposure. Of course, not all exposure is similar; it is possible that a negative exposure or a positive exposure is differentially associated with perceptions of the mission.

In this section, we analyze whether the quality of exposure is differentially related with perceptions of the mission. We use respondent answers to whether they were personally assisted by MONUSCO (positive) and whether they were a victim of misbehavior by MONUSCO (negative) to construct variables that enable us compare whether the quality of the interaction is also important. We re-run the models in the main paper in Tables C.5 (General Sample) and C.6 (MONUSCO Base Sample). We find that, in the General Sample, self-reported victims of MONUSCO misbehavior are not statistically significantly likely to report higher or lower perceptions of MONUSCO. We find that those who self-report personally assisted by the mission, however, is significantly associated with higher perceptions of the mission across each measure. These patterns are reflected in the MONUSCO Base sample as well, with the exception of Model 3, which shows that trust in the stabilization objectives of the mission is positively associated with misbehavior.

	Dependent variable:							
	Trust (Security)		Trust (Stabilization)		Contribution (Security)		Contribution (Stabilization)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Victim MONUSCO Misbehavior	-0.030		-0.005		-0.039		0.006	
	(0.047)		(0.020)		(0.048)		(0.025)	
Personally Assisted by MONUSCO		0.226^{***}		0.165^{***}		0.213^{***}		0.154^{***}
		(0.035)		(0.016)		(0.040)		(0.018)
Observations	8,695	8,716	8,695	8,716	8,695	8,716	8,695	8,716
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Territoire FE	✓	✓	✓	✓	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the General Sample; Models 5-8 use the MONUSCO base sample. Models 1-4 include *Territoire* fixed effects. Models 5-8 include MONUSCO base fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table C.5: Relationship between quality of exposure and perceptions of mission (General Sample)

	Dependent variable:							
	Trust (Security)		Trust (Stabilization)		Contribution (Security)		Contribution (Stabilization)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Victim MONUSCO Misbehavior	−0.025		0.069**		−0.001		−0.011	
	(0.039)		(0.034)		(0.017)		(0.020)	
Personally Assisted by MONUSCO		0.301***		0.306***		0.166***		0.155***
		(0.033)		(0.029)		(0.015)		(0.017)
Observations	2,919	2,980	2,919	2,980	2,919	2,980	2,919	2,980
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
COB Base FE	✓	✓	✓	✓	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-9 use the COB Sample and include COB Base fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table C.6: Relationship between quality of exposure and perceptions of mission (COB Sample)

C.6 Heterogeneous Effects

In the main text, we analyze the survey data in aggregate. In this section, we unpack potential heterogeneous effects by salient characteristics of respondents and of the mission.

C.6.1 Gender

Blue Helmets have a long and troubling history of abuse against civilians, which is often gendered [88, 174]. In light of this, it is possible that exposure to Blue Helmets may create differential reactions for women than me. To explore this possibility, we subset our samples by gender (samples are all gender balanced) and re-run the core models from the main text. Table C.7 uses the men in the General Sample, Table C.8 uses women in the General Sample, Table C.9 uses men in the MONUSCO Base sample, and Table C.10 uses women in the MONUSCO Base sample.

Across each model in the General Sample, results are positive and significant for each perceptions measure in both genders. There is, however, a noticeable difference in the magnitude of the relationship between genders, with the magnitude much larger for men than women.

In the MONUSCO Base sample, all four models are positive and significant in the male sample. Magnitudes are similar to those in the General sample. We do find some differences within the female sample, though: neither contribution measure is statistically significant.

	Dependent variable:			
	Trust (Security)	Trust (Stabilization)	Contribution (Security)	Contribution (Stabilization)
	(1)	(2)	(3)	(4)
Exposure to MONUSCO	0.118***	0.099***	0.108***	0.110***
	(0.013)	(0.006)	(0.013)	(0.007)
Observations	4,311	4,311	4,311	4,311
Controls	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓
Territoire FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the the General Population Sample, restricted to men, and include *Territoire* fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table C.7: Relationship between exposure and perceptions of mission (Men)

	Dependent variable:			
	Trust (Security)	Trust (Stabilization)	Contribution (Security)	Contribution (Stabilization)
	(1)	(2)	(3)	(4)
Exposure to MONUSCO	0.051***	0.017***	0.065***	0.027***
	(0.009)	(0.005)	(0.010)	(0.006)
Observations	4,418	4,418	4,418	4,418
Controls	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓
Territoire FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the the General Population Sample, restricted to women, and include *Territoire* fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table C.8: Relationship between exposure and perceptions of mission (Women)

	Dependent variable:			
	Trust (Security)	Trust (Stabilization)	Contribution (Security)	Contribution (Stabilization)
	(1)	(2)	(3)	(4)
Exposure to MONUSCO	0.105***	0.072***	0.051***	0.048***
	(0.019)	(0.019)	(0.008)	(0.008)
Observations	1,474	1,474	1,474	1,474
Controls	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓
MONUSCO Base FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the the General Population Sample, restricted to women, and include *Territoire* fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table C.9: Relationship between exposure and perceptions of mission (Men), MONUSCO Base Sample

	Dependent variable:			
	Trust (Security)	Trust (Stabilization)	Contribution (Security)	Contribution (Stabilization)
	(1)	(2)	(3)	(4)
Exposure to MONUSCO	0.066***	0.087***	0.006	0.0001
	(0.024)	(0.023)	(0.009)	(0.010)
Observations	1,474	1,474	1,474	1,474
Controls	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓
MONUSCO Base FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the the General Population Sample, restricted to women, and include *Territoire* fixed effects. Observations are weighted according to the probability of selection at the *territoire* level and standard errors are clustered at the *groupement*.

Table C.10: Relationship between exposure and perceptions of mission (Women), MONUSCO Base Sample

C.6.2 Troop Contributing Country

Beyond differences between the FIB and "regular" contingents of Blue Helmets, there exist important differences within mission composition across space. Peacekeeping missions are constituted of soldiers from different Troop Contributing Countries (TCC), which combine to make a unified force under the UN banner but operate within their own country commands. As such, bases are (primarily) staffed by a single TCC, and different TCCs operate in different geographical areas. A number of studies suggest that the "cultural distance" of TCCs may influence the

In our MONUSCO Base sample, we capture bases staffed by three different TCCs (other than the FIB, which we describe above): Pakistan, India, and Bangladesh. In Table C.11, we re-analyze the main models by interacting the Exposure to MONUSCO variable with indicator variables for whether the respondent is sampled from a MONUSCO base staffed by the given TCC. The interaction terms estimate whether, contingent on exposure to the mission, if exposure to that TCC is significantly associated with perceptions of the mission.

The results are mixed. Contingent on exposure to MONUSCO, exposure to Pakistani peacekeepers is positively correlated with trust in security provision, but is not significantly correlated with any of the other three measures. The interaction term of exposure to Indian peacekeepers, in contrast, is positively and significantly associated with the contribution measures, but not with the trust measures. And the exposure to Bangladeshi peacekeepers interaction terms are negatively associated with trust in security, contribution to security, and contribution to stabilization.

	Dependent variable:											
	Trust (Security)			Trust (Stabilization)			Contribution (Security)			Contribution (Stabilization)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure to MONUSCO	0.088***	0.113***	0.137***	0.097***	0.094***	0.086***	0.057***	0.040***	0.065***	0.052***	0.033***	0.069***
	(0.018)	(0.017)	(0.016)	(0.016)	(0.015)	(0.014)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)	(0.008)
Pakistan	−0.029			−0.056*			−0.051***			−0.072***		
	(0.036)			(0.033)			(0.016)			(0.019)		
India		0.076**			−0.078**			−0.028*			−0.045**	
		(0.037)			(0.033)			(0.016)			(0.019)	
Bangladesh			0.168***			0.091**			0.091***			0.127***
			(0.045)			(0.040)			(0.020)			(0.023)
Exposure to MONUSCO * Pakistan	0.071**			−0.012			−0.004			0.005		
	(0.029)			(0.026)			(0.013)			(0.015)		
Exposure to MONUSCO * India		0.0005			−0.005			0.049***			0.068***	
		(0.030)			(0.027)			(0.013)			(0.015)	
Exposure to MONUSCO * Bangladesh			−0.141***			0.043			−0.058***			−0.091***
			(0.038)			(0.034)			(0.017)			(0.020)
Observations	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246
Note:												*p<0.1; **p<0.05; ***p<0.01

Table C.11: Interaction of exposure, TCC, and perceptions of mission

C.6.3 Force Intervention Brigade

In the main text, we analyze exposure within the MONUSCO Base sample without considering variation in the make-up of the forces that populate the bases we sample around. MONUSCO is unique in that it includes the Force Intervention Bridge, which as we describe in the background section has a unique operational mandate that may present fundamentally different dynamics than standard Blue Helmet interactions with civilians.

In Table C.12, we analyze whether exposure to the FIB is differentially associated with perceptions of the mission than more conventional Blue Helmet bases. Our sampling in the MONUSCO base sample captured FIB bases in addition to standard bases. We run four models in which we interact our Exposure to MONUSCO measure with that respondent being sampled from the jurisdiction around a FIB base.

The estimates from the interaction terms indicate the difference between exposure to a FIB and exposure to a conventional Blue Helmets indicate that interacting with FIBs are only differentially associated with perceptions of the Contribution to stabilization. The interaction term on Model 4 is significant and negative. The rest are not statistically significant.

	Dependent variable:			
	Trust (Security)	Trust (Stabilization)	Contribution (Security)	Contribution (Stabilization)
	(1)	(2)	(3)	(4)
Exposure to MONUSCO	0.101^{***}	0.091^{***}	0.058^{***}	0.060^{***}
	(0.014)	(0.013)	(0.006)	(0.007)
FIB Base	-0.080^{**}	-0.123^{***}	-0.042^{***}	-0.048^{***}
	(0.036)	(0.032)	(0.016)	(0.018)
Exposure to MONUSCO * FIB Base	0.021	-0.014	-0.020	-0.034^{*}
	(0.037)	(0.033)	(0.017)	(0.019)
Observations	2,841	2,841	2,841	2,841
R^2	0.25	0.44	0.14	0.19
Controls	✓	✓	✓	✓
MONUSCO Base FE	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the MONUSCO Base Sample and include MONUSCO Base and Survey Wave fixed effects.

Table C.12: Interaction of exposure to FIB and perceptions of mission

C.7 Propensity Score Matching

One of the biggest empirical challenges we face is the potential endogenous relationship between exposure to Blue Helmets and pre-existing positive perceptions of them or of positive perceptions of institutions in general. If such an endogenous relationship exists, the relationships we present in the main text may not be a function of exposure itself, but instead exposure is a function of trust.

The observational nature of our survey data does not allow us to solve this chicken-and-the-egg problem. We note some of the strategies that we use to alleviate these concerns in the main text – including specifically sampling on the likelihood of exposure based on geography in our MONUSCO base sample – but the correlation-driven analysis is potentially problematic for such a topic. As such, in this section we use a quasi-experimental design to further alleviate such endogeneity concerns. In particular, we employ propensity score matching to maximize the comparability of respondents who were exposed to MONUSCO versus those who were not.

The goal of matching is to achieve covariate balance in order to maximize the similarity between the covariate distributions of the "treated" (exposed to MONUSCO) and "control" (not exposed to MONUSCO) groups. We use matching to estimate the average marginal effect of exposure to MONUSCO on perceptions of the mission. We use 1:1 nearest neighbor propensity score matching without replacement. We estimate the propensity score using logistic regression, with a binary indicator of exposure as the "treatment." This matching yielded sufficient balance, as indicated in Figure C.6. We used the following variables to create the matches: *Sex*, *Age*, *Education*, *Assets Score*, *Access to Basic Needs*, *Member of Minority Ethnic Group*, *Exposure to Violence*, *Trust Gov't*, *Territoire*, and Survey Wave.

To estimate the treatment effect and its standard error, we fit four linear regression model with perceptions of MONUSCO as the outcome and exposure to MONUSCO as the treatment. We include covariates and the matching weights in the estimation. We estimate standard errors using matching stratum membership as the clustering variable. Table C.13 presents the results from the models using the matched General sample data. The results are substantively consistent with the results in the main text: across each measure, exposure to the mission is positively and significantly

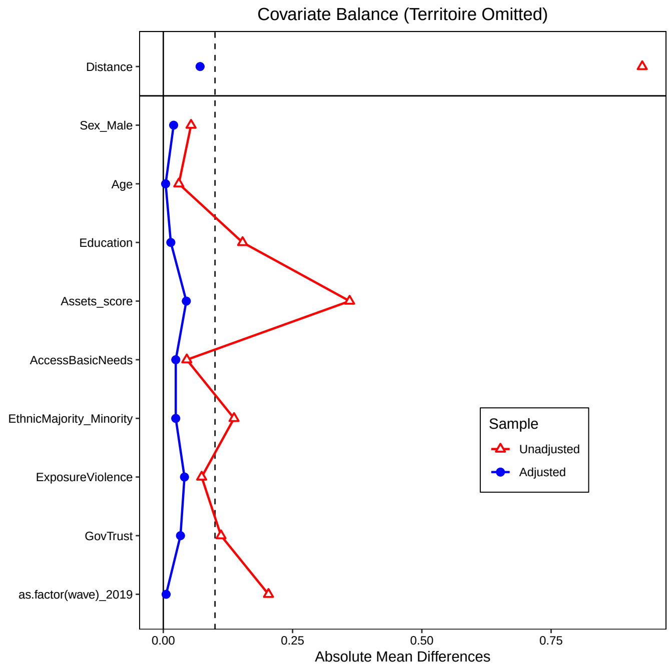


Figure C.6: Balance in the Matched Sample (General Sample)

associated with more positive perceptions of MONUSCO when compared to the most-similar non-exposed respondents.

	Dependent variable:			
	Trust (Security)	Trust (Stabilization)	Contribution (Security)	Contribution (Stabilization)
	(1)	(2)	(3)	(4)
Exposure to MONUSCO	0.113***	0.106***	0.080***	0.076***
	(0.011)	(0.011)	(0.005)	(0.006)
Observations	4,406	4,406	4,406	4,406
R^2	0.122	0.140	0.300	0.258
Controls	✓	✓	✓	✓
Territoire FE	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the the Matched General Population Sample and include *Territoire* and Survey Wave fixed effects.

Table C.13: Relationship between exposure and perceptions of mission, Matched Sample

We repeated the same process for the MONUSCO Base sample. We were unable to achieve sufficient balance using 1:1 nearest neighbor matching in the MONUSCO Base sample, however, so we opted to use full matching instead. Doing so improved the fit of our matches, as plotted in

Figure C.7. We re-run the models from Table C.13 in Table C.14. Consistent with the findings in both the main text and the matched results in the General Sample, the results from Table C.14 are positive and significant across each perception of the mission.

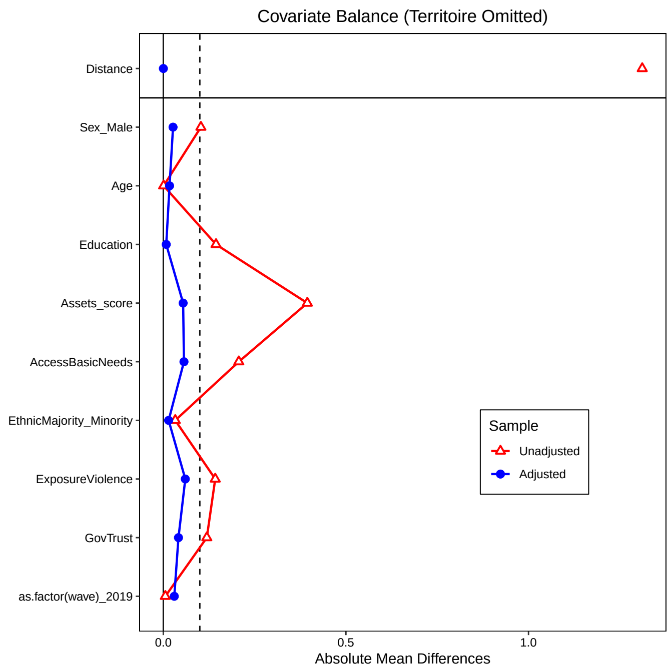


Figure C.7: Balance in the Matched Sample (MONUSCO Base Sample)

	Dependent variable:			
	Trust (Security)	Trust (Stabilization)	Contribution (Security)	Contribution (Stabilization)
	(1)	(2)	(3)	(4)
MONUSCO_exposure_general	0.108***	0.106***	0.054***	0.051***
	(0.011)	(0.010)	(0.005)	(0.006)
Observations	2,841	2,841	2,841	2,841
R^2	0.086	0.073	0.138	0.108
Controls	✓	✓	✓	✓
MONUSCO Base FE	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-4 use the the Matched MONUSCO Population Sample and include MONUSCO Base fixed effects and Survey Wave fixed effects.

Table C.14: Relationship between exposure and perceptions of mission, Matched Sample (MONUSCO Base)

C.8 De-constructing Exposure Measure

In the main text, our explanatory variable is a composite measure of exposure that combines three different types of exposure into a single binary measure. In this section, we de-construct this measure and analyze each of its component parts individually. We re-run the same models as the main text, but replace our composite exposure measure with each of its component parts, which we then use our explanatory variable. We present the results from the models using the General Sample in Table C.15 and the models using the MONUSCO Base Sample in Table C.16.

The results are consistent with the results in the main text. Across each specification, each of the measures of exposure is positively and significantly correlated with positive perceptions of MONUSCO. The magnitudes are relatively similar for MONUSCO bases nearby and Direct Contact. Seeing MONUSCO more frequently has the smallest magnitude in both the General and MONUSCO Base samples.

	Dependent variable:											
	Trust (Security)			Trust (Stabilization)			Contribution (Security)			Contribution (Stabilization)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MONUSCO Base Nearby	0.195***			0.107***			0.195***			0.103***		
	(0.019)			(0.009)			(0.021)			(0.011)		
MONUSCO Direct Contact Last 6m		0.126***			0.114***			0.117***			0.120***	
		(0.023)			(0.011)			(0.025)			(0.013)	
MONUSCO Frequency Seen			0.061***			0.047***			0.055***			0.044***
			(0.006)			(0.003)			(0.006)			(0.003)
Observations	8,515	8,693	9,035	8,515	8,693	9,035	8,515	8,693	9,035	8,515	8,693	9,035
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Territoire FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-12 use the the General Population Sample and include *Territoire* and Survey Wave fixed effects.

Table C.15: Deconstructing Exposure Measure (General Sample)

	Dependent variable:											
	Trust (Security)			Trust (Stabilization)			Contribution (Security)			Contribution (Stabilization)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MONUSCO Base Nearly	0.102***			0.074***			0.031***			0.026***		
	(0.014)			(0.013)			(0.006)			(0.007)		
MONUSCO Direct Contact Last 6m		0.181***			0.175***			0.086***			0.080***	
		(0.026)			(0.023)			(0.011)			(0.013)	
MONUSCO Frequency Seen			0.054***			0.040***			0.036***			0.036***
			(0.006)			(0.005)			(0.003)			(0.003)
Observations	2,869	2,916	3,024	2,869	2,916	3,024	2,869	2,916	3,024	2,869	2,916	3,024
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MONUSCO Base FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Survey Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1-12 use the the MONUSCO Base Sample and include *Territoire* and Survey Wave fixed effects.

Table C.16: Deconstructing Exposure Measure (MONUSCO Base Sample)

C.9 Alternative Measures of Perceptions of MONUSCO

In the main text, we measure civilian perceptions of MONUSCO using trust in the mission and perceptions of MONUSCO's contribution to carry out core mandate-related tasks. These are two manifestations that we believe are the most appropriate to capture broad civilian perceptions in the mission. They are, however, limited in their specificity and do not allow us to measure less direct perceptions of MONUSCO as a whole.

In this section, we use three additional measures of perceptions of MONUSCO to add such nuance to our analysis. In particular, we use respondent answers to questions that ask their perceptions of the implications of MONUSCO's departure from the province, the frequency that you think MONUSCO must leave, and the likelihood that you would seek out MONUSCO in hypothetical scenarios. We present these variables in Table C.17. We create binary indicators for the *Departure Effect*, which takes a value of 1 if the effect on security if MONUSCO left is negative, and *Must Leave*, which takes a value of 1 if respondents respond never. We create an additive scale based on the Likert scale for each respondents answers to the *Seek Out* questions. Higher scores indicate that respondents are more likely to seek out MONUSCO's help in more hypothetical scenarios.

It is important to note that the questions presented here are not directly comparable to the questions analyzed in the main text. In particular, the questions on *Departure Effect* and *Must Leave* do not measure evaluations of MONUSCO's core behavior or capacity as the questions in the main text do. Instead, they capture broader perceptions of the desire for the mission to remain in eastern DRCongo. The *Seek Out* measure is the most directly comparable to the questions analyzed in the main text, with the major difference being that these questions are more *behavioral* in nature. Instead of asking for opinions on the mission, we ask the conditions under which they would act on their perceptions of the mission and actively seek it out.

We re-run the core models from the main text, but replace the Trust and Contribution measures as our outcomes with *Departure Effect*, *Must Leave*, and *Seek Out* in Table C.18. The independent variable of interest in each of the 6 models is the same *Exposure to MONUSCO* variable as in the main text. Models 1, 3, and 5 use the General Sample and Models 2, 4, and 6 use the MONUSCO

Perception Concept	Dimension	Question	Respondent Options
Implications of MONUSCO departure	Security	What would be the effect on your security if MONUSCO left?	Positive, Negative, None
	General	Think MONUSCO must leave	Always/sometimes/never
Seek out MONUSCO	Security	For information on safety, for example before traveling	5p Likert
		If you have a problem with an armed group, such as if there has been an abduction	
		If you have a problem with the police	
		If you are the victim of a crime such as a burglary or theft	
		In case of threat or attack	

Table C.17: Measuring Perceptions of MONUSCO

Base sample. We include the same battery of controls as the main text, Survey Wave fixed effects, *Territoire* fixed effects when analyzing the General Sample, MONUSCO Base fixed effects when analyzing the MONUSCO Base sample.

The results in Table C.18 are broadly consistent with the findings from the main text. In the general sample, exposure to MONUSCO is associated with perceptions that MONUSCO leaving would be bad (estimate: 11%, 95% CI: 8.6% – 14.8%). Interestingly, we do not find a significant relationship in the MONUSCO base sample, however. Exposure to MONUSCO is not significantly associated in either direction with perceptions that MONUSCO must leave. The most directly comparable questions to those analyzed in the main text are the most consistent with the findings in the main text. In both the General and MONUSCO Base sample, exposure to MONUSCO is associated positively and significantly with the likelihood that respondents report they would seek out MONUSCO in response to a series of hypothetical scenarios. It is important to note that the magnitudes in both the General Sample (estimate: 5.8% 95% CI: 4.91% – 6.67%) and the MONUSCO Base Sample (estimate: 2.8%, 95% CI: 1.85 – 3.66) are smaller than those we find in the main text. We believe this reflects the fact that seeking out MONUSCO is an irregular behavior relative to more passive evaluations of the mission.

	Dependent variable:					
	Departure Effect		Must Leave		Seek Out	
	General	*MONUSCO Base*	*General*	*MONUSCO Base*	*General*	*MONUSCO Base*
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to MONUSCO	0.117***	0.009	−0.042	0.039	0.058***	0.028***
	(0.016)	(0.016)	(0.028)	(0.034)	(0.005)	(0.005)
Observations	7,250	2,514	7,615	2,515	8,489	2,841
Controls	✓	✓	✓	✓	✓	✓
Territoire FE	✓		✓		✓	
MONUSCO Base FE		✓		✓		✓
Survey Wave FE	✓	✓	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, , $^{\dagger}p < 0.1$ Results from OLS models. Unit of analysis is individual survey respondent. Battery of controls include: *Gender*, *Age*, *Education*, *Household Assets Ethnic Minority*, *Trust Gov't*, and *ExposureViolence*. Models 1, 3, and 5 use the General Sample and Models 2, 4, and 6 use the MONUSCO Base sample. Models 1, 3, and 5 use *Territoire* fixed effects. Models 2, 4, and 6 use MONUSCO base fixed effects. All models include Survey Wave fixed effects.

Table C.18: Relationship between exposure and alternatives measure of perceptions of mission

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