Wildlife and Conflict: The Cost of Protecting Biodiversity

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Abstract

Scientific evidence shows that we are going through the first human-induced mass extinction, and as such, conservation policies are widely discussed among policymakers. However, there is little research on the harmful externalities of such policies. This paper combines global georeferenced data on wildlife habitats (including both animal and tree genera) with information on armed conflict to estimate the violent externalities generated by international trade restrictions on wildlife products aimed at conserving biodiversity. An event-study specification shows that the imposition of trade restrictions increases the risk of conflict in affected areas. Two-stage least squares estimates for elephant ivory show that trade restrictions increase prices, which in turn increase the likelihood of conflict. Accounting for the spatial distribution of elephants, the implied effect size exceeds that of well-documented industrial conflict minerals. For precious trees, remote sensing analysis suggests that, once restrictions are in place, production shifts from states with high institutional capacity to those with low capacity, generating local windfall rents that fuel additional violence. A distance analysis shows that armed groups positioned to capture these rents expand operations into new areas and become more likely to gain territorial control, supporting the "feasibility" mechanism whereby windfall gains relax their budget constraints and enable violence. A quantitative social planner general equilibrium model shows that a targeted policy restricting trade in states with both high institutional capacity and relatively small stocks of precious trees could improve welfare. The findings document a previously overlooked conflict-related cost of conservation policy and suggest a mitigation strategy.

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1 Introduction

Policymakers have often used trade restrictions to protect scarce resources and minimise market activities associated with harmful externalities. However, anecdotal evidence suggests that this approach often shapes incentives in ways that can generate other externalities, raising questions about the overall welfare effects of such policies. For instance, the Prohibition era and the war against the Mexican drug cartels are notorious for their associated increases in violence (Miron, 1998; Angrist and Kugler, 2008; Dell et al., 2014), and many states have legalised cannabis due to the inability to enforce black-market trade effectively (The Economist, 2001). This paper examines the violent externalities of trade restrictions aimed at protecting wildlife from overconsumption.

The exploitation of wildlife resources is a prominent example in which social and private valuations appear to diverge, warranting government intervention. Given the mounting scientific evidence documenting that we are experiencing, for the first time, a human-induced mass extinction of species (Ceballos et al., 2015), a common approach to protect biodiversity against excess consumption is by restricting trade in wildlife products (Brondízio et al., 2019).[1] For instance, in 1976 and 1989, the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) implemented restrictions on international trade in parts of rhinos and elephants, respectively. Since then, trade restrictions under CITES have expanded considerably, and the convention now protects over 6,610 animal and 32,100 plant species.

Concurrently, illegal wildlife trade has been recognised as the third-largest transnational illicit activity, with illicit markets for wild animals and timber estimated at $23 billion and $157 billion annually, respectively—surpassed only by counterfeiting ($923 billion) and the drug trade ($426 billion) (UNODC, 2024). Anecdotal evidence also links this trade to the activities of armed groups. A 2013 UN investigation described the ivory trade as a major source of funding for the Lord's Resistance Army, an armed group based in Uganda (UNE, 2014), while others (EIA, 2020; BBC, 2024) have highlighted how the rosewood trade in

[1] This study follows the broad definition of wildlife, including wild animals, wild plants, and other organisms that are not domesticated or cultivated and exist in their natural environments (Brondízio et al., 2019).

Senegal and Mozambique has financed local armed groups. Despite its importance—both as a conflict-linked commodity and as a public good (Frank and Sudarshan, 2024)—wildlife trade and biodiversity protection policies have been largely overlooked in economic research, possibly due to challenges related to data availability and measurement.

1.1 Results Preview and Policy Implications

This paper empirically documents the armed-conflict externalities of biodiversity protection policies that regulate wildlife trade under the CITES international treaty—the main global mechanism to protect wildlife from overexploitation—highlighting the cost of conservation-motivated trade restrictions. First, using georeferenced habitat data for seven genera of endangered wild animals and 24 genera of endangered precious trees, I show that CITES trade restrictions—restrictive supply-side policies—are associated with increases in both wildlife confiscations and prices.[2] On average across resources and years, the policy is associated with increases of approximately 0.7 and 1.03–1.17 log points in confiscations and prices, respectively. Then, to estimate the conflict effect of the policy, I construct a global geo-referenced grid ($0.5^\circ \times 0.5^\circ$), with data on wildlife habitat, policy dates, and conflict indicators from three different conflict datasets (ACLED, UCDP, GTD). An event-study specification shows that CITES policies increase the likelihood of conflict and terror events in the habitat of the affected wildlife by about 2.6 percentage points (46% of the baseline risk). The estimates are comparable to the industrial minerals shock (Berman et al., 2017), and, when accounting for the spatial distributions of wildlife and industrial minerals, exceed them. This finding is robust to alternative specifications, disaggregation levels, coding options, conflict definitions, exclusion of specific resources and regions from the sample, and inclusion of various potential confounders.

Inspecting the mechanism suggests that the policy generates windfall gains through two distinct channels. First, focusing on the African elephant ivory market and particular supply-side policies that, importantly, did not change the legal status of ivory trade but only its supply, I show, using 2SLS, that the policy affects conflict through prices. Second, I overlay remote-sensing deforestation (Hansen et al., 2013) with genus-level habitat distributions (aggregated from species maps) (Senula et al., 2019) to proxy harvesting at

[2]Throughout the paper, I use "taxa" to refer to the units listed under CITES, which may be at the genus or species level. I refer to "genera" (plural of genus) when aggregating species-level data, and to "species" when policies apply specifically at that level. I use "wildlife" broadly to encompass both wild animals and wild trees, and I use "animal" and "tree" as shorthand when referring to those subsets.

the genus level. Using this proxy, I estimate a synthetic control event study (Ben-Michael et al., 2021), showing that the policy is effective in reducing harvesting in states with high institutional capacity, but harvesting in low institutional capacity states increases following the policy and is associated with the increase in conflicts. The analysis suggests that, following the policy, armed groups that are likely to benefit from the windfall, tend to initiate one-sided attacks against civilians or protective village militias, fight farther away from their previous locations, and are more likely to win battles. Altogether, this suggests that the windfall gains make attacks by armed groups financially feasible.

The study's findings have several policy implications. First, they highlight a potential trade-off between restriction-based environmental conservation policies and armed conflict. As in the case of drugs (Becker et al., 2006; Angrist and Kugler, 2008; Dell et al., 2014; Castillo et al., 2020), restrictive trade policies can fuel violence, not only because trade becomes illegal but also because restrictions raise wildlife product prices and shift production to weak states with limited enforcement capacity. Second, the analysis shows that differences in state capacity and stock of precious trees shape the conflict externality—factors that policymakers could explicitly consider when seeking to mitigate unintended costs. Third, the findings are important for peace-building efforts by uncovering a source of variation that helps explain armed conflict.

1.2 Related Literature

This paper contributes to three strands of the academic literature. First, it contributes to the literature on conservation policies, which has largely focused on estimating their effectiveness (Assunção and Gandour, 2019; Assunção et al., 2020; Hsiao, 2021; Da Mata and Dotta, 2021; Assunção et al., 2023; Frank and Oremus, 2023), identifying the drivers of environmental degradation (Burgess et al., 2012; Greenstone and Jack, 2015; Burgess et al., 2015, 2017; Couttenier et al., 2022), and examining the implementation challenges of conservation efforts, particularly in low-capacity states (Balboni et al., 2021b; Glennerster and Jayachandran, 2023; Harstad, 2023). However, these studies have paid relatively little attention to the harmful externalities of restrictive conservation policies, particularly in the context of international treaties, biodiversity protection, and the interaction of non-state armed actors with the environment.

Second, the paper contributes to the literature on the drivers of conflict and the financing of armed groups by identifying a novel source of variation—income shocks related to wildlife

and biodiversity—as a determinant of conflict. Related work has examined commodity shocks (Dube and Vargas, 2013; Bazzi and Blattman, 2014; Berman and Couttenier, 2015; Berman et al., 2017; Ciccone, 2018), the financing of armed groups and militias (Shapiro and Siegel, 2009; Bueno de Mesquita, 2013; Limodio, 2019; Battiston et al., 2022), and climate shocks (Harari and Ferrara, 2018; McGuirk and Nunn, 2020; Eberle et al., 2020).

Finally, the paper contributes to the empirical trade literature by documenting the price effects (Huber, 1971; Bernhofen and Brown, 2004; Irwin, 2014) and production relocation (Flaaen et al., 2020) associated with trade restrictions, and by linking these to the broader externalities of trade policy and government intervention in markets, in a setting with external validity. Specifically, existing studies examine the effects of trade restrictions, government intervention, and restrictive supply-side policy shocks on conflict and violence (Becker et al., 2006; Angrist and Kugler, 2008; Dell et al., 2014; Castillo et al., 2020), but typically focus on the cocaine trade, adopt a domestic lens with limited external validity, and rely primarily on administrative data at the political-unit level. The study most closely related to this paper is Chimeli and Soares (2017), who focus on the Mahogany export ban in Brazil. However, they adopt a domestic approach, do not use georeferenced data on violence and resources, and do not identify a specific economic mechanism.[3]

Outline. The remainder of the paper is organised as follows. Section 2 reviews CITES policies, wildlife trade, and their links to armed group activity. Section 3 presents the data. Section 4 discusses the identification strategy, reports the baseline results for the global sample, and provides robustness checks. Section 5 focuses on Africa and examines the mechanism. Section 6 outlines the theoretical model and proposes mitigation strategies, and Section 7 concludes.

2 Conceptual Framework

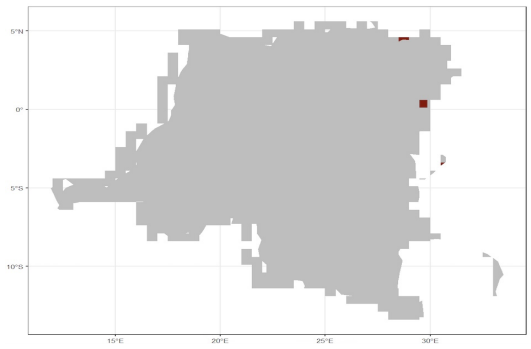
This section starts with a motivating example illustrating the effect of CITES policies on conflicts. It then describes the CITES convention, its mandate, policies, and legal scope. It also discusses the market for wildlife and its industrial organisation. Finally, it provides anecdotal evidence linking wildlife trade to armed group activity.

[3]Furthermore, Chimeli and Soares (2017) rely on police-reported violence, which is distinct from armed conflict and political violence.

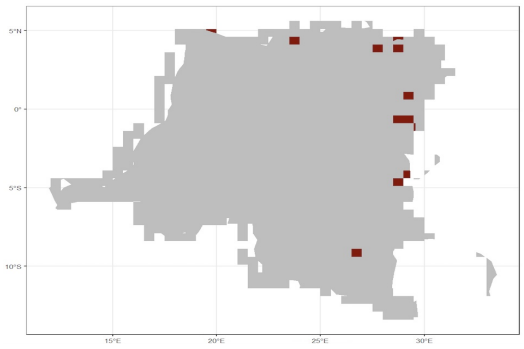
2.1 Trade Restrictions and Wildlife Conflict: A Motivating Example

Figure 1 provides anecdotal evidence of a relative increase in conflicts in rosewood habitat areas following the 2016 CITES trade restrictions. The top row shows UCDP conflict events in the Democratic Republic of the Congo during 2014-2015—just before the restrictions—inside and outside rosewood cells. The bottom row displays conflict events from 2016-2017, immediately after the policy. While rosewood locations experience a 350% increase in conflict events, non-rosewood locations experience a 33% reduction. Although anecdotal, this illustrates the conflict effects induced by the CITES restrictions.

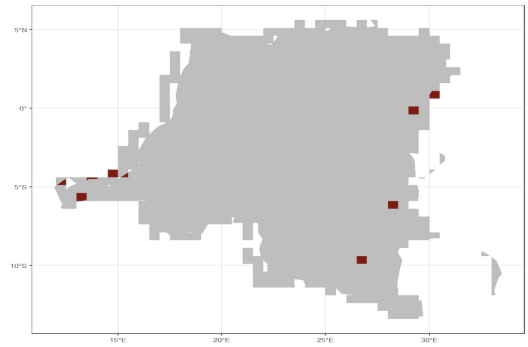
Figure 1: CITES Trade Restrictions and Rosewood (*Dalbergia*) Conflicts in the Democratic Republic of the Congo



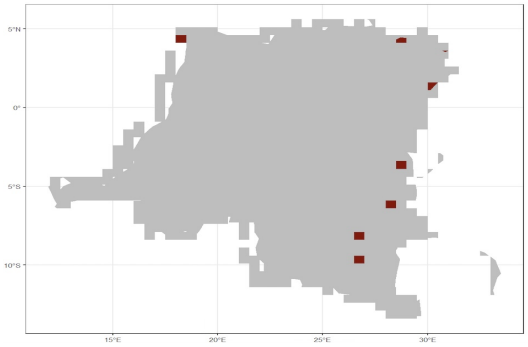
(a) Pre-Restriction Rosewood



(b) Pre-Restriction No Rosewood



(c) Post-Restriction Rosewood



(d) Post-Restriction No Rosewood

Notes: The figure shows conflict events before and after the imposition of the CITES rosewood (*Dalbergia*) trade restriction in 2016, separately for rosewood and non-rosewood regions. Panels (a) and (b) show UCDP conflict events for 2014–2015 in rosewood and non-rosewood regions, respectively. Panels (c) and (d) show UCDP conflict events for 2016–2017 in rosewood and non-rosewood regions, respectively.

2.2 CITES' Mandate

The Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) is an international agreement aimed at conserving wildlife by regulating international trade, ensuring that the trade does not cause species extinction. Established in 1973 and entering into force in 1975—with the leadership of the United States and other Western countries—CITES was created in response to growing concerns about the threat global trade poses to endangered species. Today, it has 184 member countries.

The main purpose of CITES is to foster international cooperation in environmental protection, primarily in response to three key challenges: (i) the global interconnectedness of ecosystems, where environmental degradation in one country can have cross-border consequences; (ii) the institutional weakness of some of the most ecologically rich countries, limiting their capacity to safeguard biodiversity; and (iii) misaligned incentives between resource-rich countries that may be tempted to exploit natural assets and others that prioritise conservation.

CITES lists wildlife taxa—at the species or genus level—in three Appendices according to conservation status. Appendix I includes taxa at risk of extinction (e.g., rhinos), with trade allowed only in rare cases such as for scientific purposes. Appendix II includes taxa that could become endangered if trade is not regulated (e.g., hippopotamus). Appendix III includes taxa protected within specific countries that have requested international assistance in controlling trade (e.g., South African abalone).

CITES Parties meet approximately every three years at the Conference of the Parties to update listings of wildlife taxa and revise policies. Each Party is responsible for implementing and enforcing CITES regulations at all border crossings—ports, airports, and land borders.

At its launch, CITES listed about 500 taxa (predominantly species). By 2023, more than 38,000 taxa were regulated under CITES, most of them insects, small plants, and marine life.

Countries that do not comply with CITES may face trade bans on legal wildlife products, lose access to technical and financial conservation support, and come under diplomatic pressure from other member states. For example, in 2017, China banned domestic trade in antique ivory following CITES threats of suspension from legal wildlife trade. Additionally, in 2023, CITES imposed trade sanctions on Mexico, suspending all commercial trade in CITES-listed species due to non-compliance with obligations to protect the critically en-

dangered vaquita.[4] The sanctions affected a wide range of wildlife products (e.g., crocodile leather, reptile skins, reptiles and exotic pets, orchids, and cacti).

2.3 The Industrial Organisation of Wildlife Markets

2.3.1 Demand

Contemporary demand for wildlife products largely originates from Asia, particularly China, reflecting a combination of cultural, economic, and medicinal factors (Zhu, 2020). Traditional medicine remains a major source of demand for products such as rhino horn, tiger bones, and pangolin scales (Mainka and Mills, 1995), while luxury markets value elephant ivory, rosewood, sandalwood, crocodile skin, and exotic furs for their aesthetic and status appeal (Zhu, 2022; Sosnowski and Petrossian, 2020). Rosewood, in particular, has signified elite status since the Qing dynasty and is increasingly treated as an investment asset (Ding and Yin, 2024).

The recent surge in demand is closely tied to the rising economic power of China and other Asian countries, where growing incomes have fuelled consumption of goods perceived as luxury items, status symbols, or components of traditional medicine (UNODC, 2020). This trend is reinforced by a broader state-led revival of traditional Chinese culture and heritage, initiated under Hu Jintao (2002-2012) and intensified under Xi Jinping (2012-present) (Zhu, 2020).

2.3.2 Supply

The supply of wildlife products has long been dominated by armed groups, predating formal trade restrictions (RUSI, 2015; TRAFFIC, 2015; WWF, 2015; EIA, 2017). UNODC (2020) describes how armed groups facilitate poaching by providing resources and retaining the majority of profits. Local brokers then collect wildlife products and transport them to urban storage centres, from which intermediaries—often foreign nationals originating from major destination markets—export the goods by bribing officials to evade customs enforcement.[5] For example, EIA (2014) documents how the Shandong cartel used legal agricultural trade as a cover to smuggle ivory, bribing local politicians in the process. Finally, wholesalers

[4] Other recent examples include Thailand (2013), Belize (2013), Guinea (2013), Lao PDR (2016), the Democratic Republic of Congo (2018), and Nigeria (2022).

[5] Exporters are often nationals of the destination country, as this helps mitigate trust issues inherent in cross-border illegal trade.

and retailers distribute the products within destination markets.

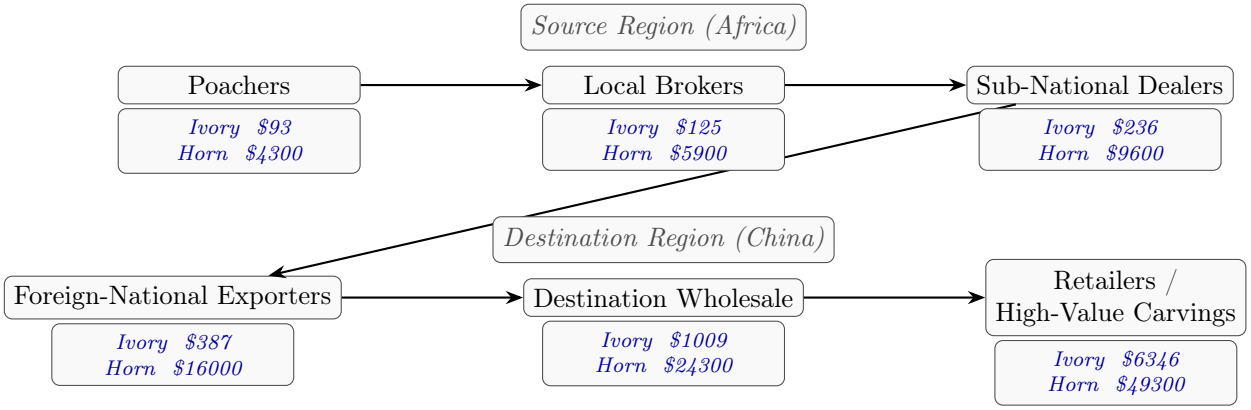
The Rosewood Trade and Northern Mozambique's Conflict. The insurgencies in northern Mozambique's Cabo Delgado and Nampula provinces since 2017 have been linked to the illicit trade in rosewood (*Dalbergia*), listed under CITES Appendix II since 2016. According to BBC News (2023), demand from China has fueled illegal logging operations that are exploited by the al-Shabab insurgent group. A Mozambique government report cited by BBC News (2023) states that "*al-Shabab insurgents have taken advantage of the illicit timber trade to fuel and finance the reproduction of violence,*" and further notes that "*the insurgents involvement in the smuggling of fauna and flora products, including wood, and the exploitation of forest and wildlife resources is contributing to a very high level of fundraising for the insurgency group.*" The same report estimates that "*its revenue from these activities amounted to 1.9 million USD a month.*" Mozambique analyst Joe Hanlon adds that "*it has also gained enough funds to recruit in neighbouring provinces further south.*" There have also been reports of firms paying a "*10% protection fee*" to the armed group in exchange for permission to carry out illegal logging in forest areas. These dynamics underscore the significant role the high-end illegal timber trade plays in financing conflicts across Africa.

Ivory Trade and Armed Groups' Activity in Africa. Several organisations have documented links between the ivory trade and armed groups' activities. According to United Nations Security Council (2013) "*The Lord's Resistance Army (LRA), an armed group originating in Uganda, is known to have poached elephants in Garamba National Park (Democratic Republic of Congo) and trafficked ivory through South Sudan into Sudan, where it is exchanged for arms and supplies.*" Similarly, an investigation by INTERPOL (2014) reveals that "*Kony–the LRA leader–ordered his fighters to collect ivory, which was used to barter for food, weapons, and cash*" and that "*the LRA's operations in Garamba have decimated local elephant populations and created an illicit supply route from Congo through South Sudan.*" In Chad and the Central African Republic, the Janjaweed group has targeted parks such as Zakouma National Park. According to Enough Project (2015) "*Heavily armed horsemen conducted cross-border poaching raids, massacring hundreds of elephants in a matter of days. The ivory was transported north, reportedly taxed or protected by military and rebel networks.*" According to Global Initiative Against Transnational Organized Crime (2017) "*ivory, along with gold and diamonds, became a resource exploited by the Seleka and Anti-Balaka armed factions in the Central African Republic, who used it to fund military operations.*"

The Supply Chain of Ivory. Poachers typically earn about 10% of the final raw ivory price. For an adult African elephant, whose tusks can weigh up to 100 kg (Milliken et al., 2000), this can make poaching an attractive source of income. As tusks move through the supply chain, their price can increase by 200–300% at multiple stages, and again after being carved into high-value artifacts.

The supply chain for elephant ivory and rhino horn trade is illustrated in Figure 2

Figure 2: The Supply Chain of Ivory and Rhino Horn



Notes: The figure illustrates the supply chains of elephant ivory and rhino horn, from poachers in source countries to final retailers in destination markets. Estimated prices are per kilogram, based on UNODC (2020).

2.3.3 Further Anecdotal Evidence

Data from the African Elephant Database—a pan-African aerial census conducted every 5 to 10 years—offers further support for the armed groups-poaching link. During the Chadian Civil War (2005–2010), major fighting occurred near Am Timan and Mongo. In early 2005, a census in Zakouma Park near Am Timan counted 3,885 elephants. By 2014, only 443 remained—a 90% decline. Similarly, Lake Fitri near Mongo had 200 elephants in 2005 and only 70 in 2015, a 65% drop. In the Democratic Republic of the Congo, the Kivu civil wars (2004–2013) took place near Maiko and Kahuzi-Biega National Parks. In 1992, Maiko and surrounding areas had an estimated 6,500 elephants; by 2015, only 100 remained. In Kahuzi-Biega, the population fell from 1,150 in 2002 to 70 in 2015. These represent declines of 94–98%. Although descriptive, the analysis suggests armed groups involvement in poaching.

3 Data

This section discusses the data sources, the different conflict datasets, variable definitions, and measurements. I also provide various statistics describing the data.

3.1 Data Sources

The sample consists of a global grid divided into 0.5×0.5 degree units (approximately 55×55 kilometers at the equator), with the unit of analysis being the cell-year. The main outcome variable is a conflict indicator, with wildlife habitat and trade restriction dates as the key explanatory variables. I use wildlife prices and deforestation data to explore the mechanism.

3.1.1 Conflict

To maximise spatial and temporal coverage, I use georeferenced conflict data from all main sources: UCDP (Sundberg and Melander, 2013), ACLED (Raleigh et al., 2010), and GTD (LaFree and Dugan, 2007). Each source has its own strengths and limitations. UCDP covers conflicts since 1989 with at least 25 battle-related deaths and requires at least one organised actor, potentially omitting relevant events just below the threshold. ACLED, starting in 1997 (Africa), 2010 (Asia), and 2017 (Latin America), imposes no fatality threshold and captures a broader range of events, though it may include less relevant incidents. The GTD has been available globally since 1970 and focuses solely on terrorism.

All three datasets draw on news, media, NGO, and government reports. Compared to ACLED, UCDP's strict fatality threshold and GTD's narrow event definition help reduce measurement error and media bias. These concerns are mitigated using cell and country-year fixed effects. In ACLED, I follow Berman et al. (2017) in coding "battles," "violence against civilians," and "protests and riots" as conflict events, and I also conduct a separate analysis by subcategory.

3.1.2 Habitats

In constructing genus-level habitat measures for wildlife taxa (wild animals and trees), I first select the relevant taxa. I do so by first selecting only taxa that are discussed in Groves and Rutherford (2023) and UNODC (2024) as heavily traded in illicit markets and protected under CITES. Second, due to econometric identification requirements, I focus

solely on taxa with well-defined, mappable habitats.[6] Given this, the full sample includes seven genera of endangered wild animals along with 24 genera of endangered trees.

Animal habitat data are sourced from the IUCN, the leading scientific conservation organisation specialising in wildlife monitoring. These are typically species-level range maps, which I use directly or aggregate to the genus as needed. For trees, there is no single source providing habitat suitability measures for endangered tree taxa. To overcome this limitation, I gather georeferenced observations of tree species surveyed by the Global Biodiversity Information Facility (GBIF). To minimise measurement error, I disregard the time dimension of these surveys and treat the observations as a time-invariant proxy for species presence at each location. Following established methods in the quantitative ecology literature Phillips et al. (2006); Senula et al. (2019), I use these observations as inputs to a Maximum Entropy algorithm to construct species-level habitat suitability estimates based on bioclimatic and geographical features. I then aggregate these species-level surfaces to the genus to obtain genus-level habitat distributions, which I use as proxies for the spatial distribution of precious tree genera.

3.1.3 Policies

Policy change dates are sourced from the CITES website and summarised in Appendix Table A.1. Most wild animal *taxa* are listed under Appendix I, with exceptions such as abalone, hippopotamus, and crocodiles. All tree *taxa*—typically listed at the genus level—except *Dalbergia nigra* (Appendix I) are listed under Appendix II, with zero commercial trade quotas—effectively constituting a trade ban. Unless stated otherwise, policies are enforced 90 days after announcement.

3.1.4 Prices

Due to the illicit nature of the wildlife trade, there is no official source of wildlife prices. Of the 31 genera in the sample, I obtained price data for six. Price data for three tree genera—*Dalbergia* and *Pterocarpus* (2009–2020), and *Diospyros* (1997–2021)—were sourced from China's largest domestic wholesale raw wood market, the Yuzhu International Timber Market (Ding and Yin, 2024). Rhino horn prices were obtained from surveys of retail markets in Hong Kong (IUCN, 1990).

[6] For instance, some exotic birds and snakes are known to be traded in illicit markets but do not have well-defined habitat maps.

For elephant ivory and Nile crocodile skin, I follow Farah and Boyce (2019) and Hauenstein et al. (2019) in using prices of close substitutes. Nile crocodile skin prices are proxied using American alligator skin prices, and post-ban elephant ivory prices are proxied using mammoth ivory.[7]

To validate the adequacy of the mammoth ivory price series, I use three alternative sequences as part of the sensitivity checks. First, Do et al. (2021) and Sosnowski et al. (2019) estimate ivory prices from confiscation data, controlling for various fixed effects, but their series end in 2013 and 2016, respectively. Second, I scrape and aggregate ivory transaction data from auction-house websites for the period 2012–2021, when antique ivory could still be legally sold in the UK. Both alternative sequences are highly correlated with mammoth ivory prices (correlation coefficient = 0.82–0.85; t = 5.68–6.64), and the main estimates remain robust when either is used.

To summarise, for two of the six product categories—elephant ivory and Nile crocodile—I use close substitutes. For the remaining four—*Dalbergia*, *Diospyros*, *Pterocarpus*, and rhino horn—prices are sourced from Chinese markets, the primary destination for these products.

3.1.5 Deforestation of Tree Species

Official statistics on traded quantities of trees are not available at the species or genus level. Moreover, many of these taxa are traded through illicit markets. To estimate changes in harvested quantities of protected trees following the policy, I combine remote-sensing deforestation data (Hansen et al., 2013) with species-level habitat maps—aggregated to the genus—on a $0.15^\circ \times 0.15^\circ$ grid. This yields a proxy for genus-level harvesting quantities.

The deforestation measure of Hansen et al. (2013) is based on Landsat imagery. Tree cover loss is defined as a stand-replacement disturbance, or the complete removal of tree canopy, at the pixel level. The dataset provides annual estimates of tree cover loss relative to year-2000 forest cover, at a spatial resolution of 1 arc-second (30×30 meters).

[7] Discovered in Siberia in 1992, mammoth ivory has been legally exported from Russia—primarily to Hong Kong. Its prices, sourced from Comtrade, reflect wholesale values and are less prone to measurement error compared to other ivory price sequences derived from surveys and confiscation data.

3.1.6 Industrial Minerals

For the location and type of industrial minerals, I use data from Berman et al. (2017), which covers 14 minerals across Africa. I extend their dataset until 2024 by merging it with updated price series for the respective minerals.

3.2 Descriptive Statistics

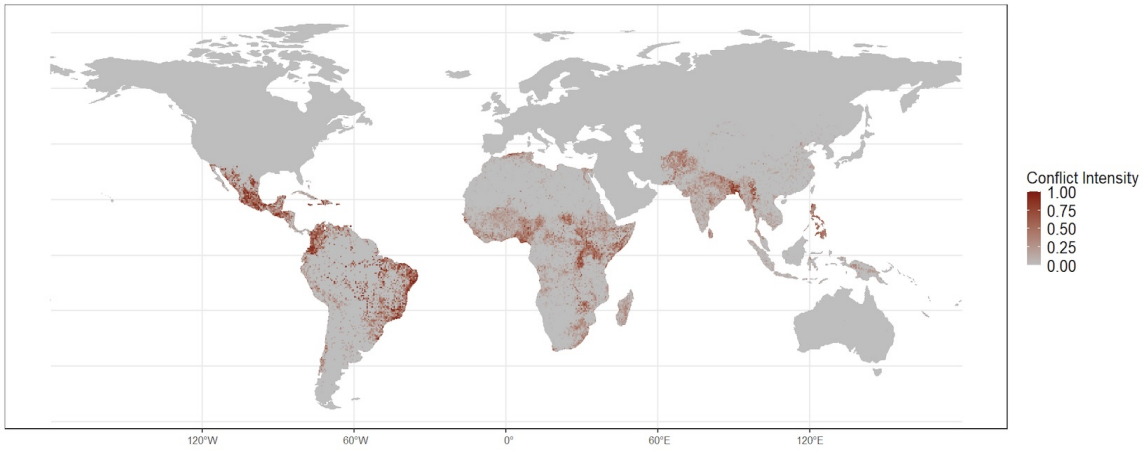
The final sample consists of 176 countries, of which 172 experienced at least one conflict or terror event across all datasets. A total of 149 countries have some form of resource presence—59 with wild animals and 149 with different species of wild trees.

The sample includes 96,440 unique cells, covering the periods 1997–2024 (ACLED), 1989–2023 (UCDP), and 1970–2021 (GTD). Overall, 16.5% of cells (15,916) experienced at least one conflict event during the sample period. Unconditional conflict probabilities are 5.5% (ACLED), 1.2% (UCDP), and 0.82% (GTD). Resource cells exhibit higher conflict probabilities, with ACLED estimates of 0.104 for wild animal areas, 0.118 for wild tree areas, and 0.161 for mineral areas, compared to the overall sample average of 0.056. This may reflect unobserved characteristics, highlighting the importance of including cell and country-year fixed effects in the analysis.

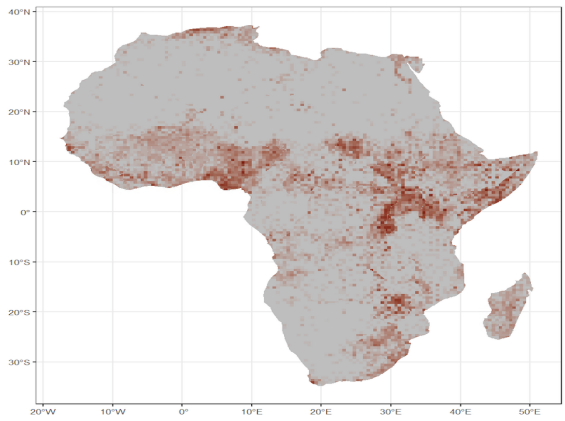
Figure 3 displays the global distribution of conflict events recorded in ACLED.[8] Most events are clustered in the Great Lakes region of Africa, extending through Middle Africa toward the West Coast. Additional clusters appear along the Southeast coast and in the Horn of Africa. Outside Africa, notable clusters are observed along Brazil's East Coast, in Central America, and in Central Asia. Appendix Table A.4 reports pairwise correlations across conflict datasets, indicating that conflict events are spatially correlated across the three sources. ACLED records the highest number of events, and GTD the lowest.

[8] Appendix Figure A.1 shows the distribution of events based on UCDP and GTD.

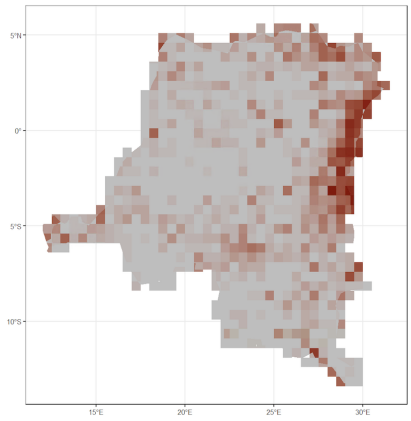
Figure 3: Spatial Distribution of ACLED Conflict Events



(a) ACLED Conflicts



(b) Africa ACLED Conflicts



(c) DRC ACLED Conflicts

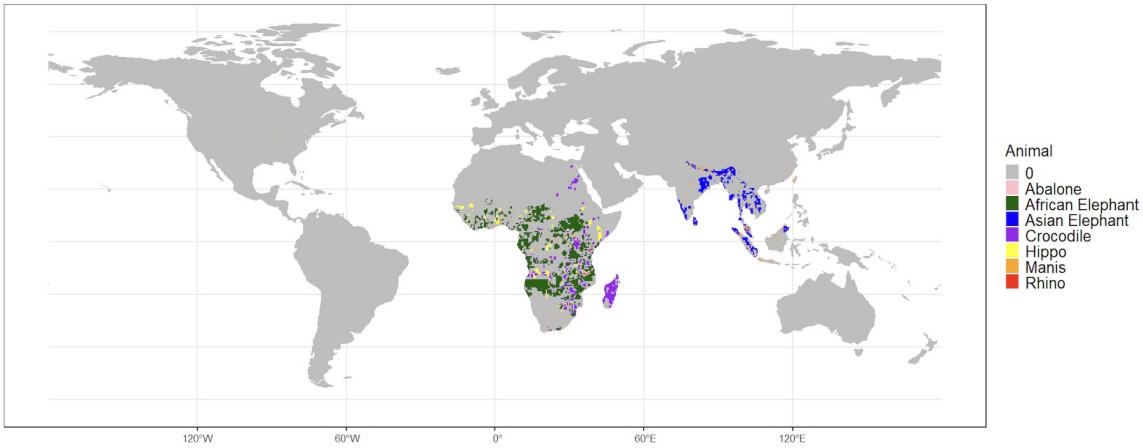
Notes: Panel (a) shows the spatial distribution of ACLED (1997–2024) conflict events; darker shading indicates a higher proportion of years with at least one recorded incident. Panels (b) and (c) show regional conflict maps for Africa and the Democratic Republic of Congo (DRC), respectively.

Overall, 5% of cells are suitable for wild animals and 10% for trees. Elephants (African and Asian) have the largest animal habitat, covering 2.8% of cells, while *Dalbergia* is the most widespread tree genus, covering 4.5% of cells. Figures 4 and 5 show the spatial distributions of wild animals and trees included in the sample: animals are concentrated primarily in Sub-Saharan Africa and Asia, while trees are concentrated in Sub-Saharan Africa, Southeast Asia, and Latin America.

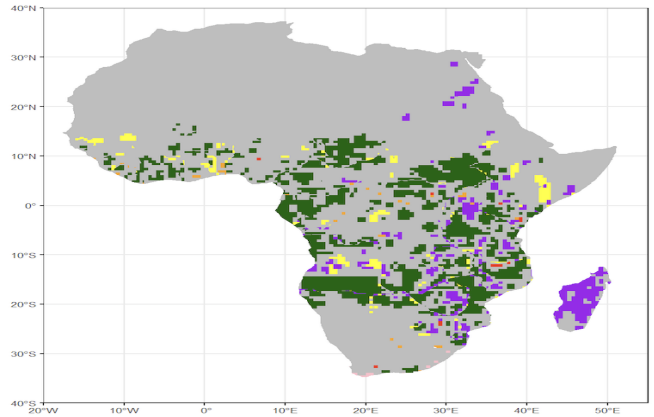
5% of habitat cells are suitable for more than one taxon. I address this issue using

two approaches. First, I assign a primary taxon to each cell based on estimated market size (UNODC, 2024).[9] Second, I exclude cells with multiple taxa from the sample. I supplement the graphical analysis with descriptive statistics of the main variables of interest in Appendix Table A.2.

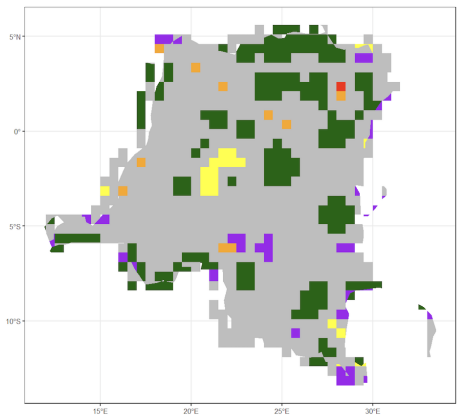
Figure 4: Spatial Distributions of Wild Animals



(a) Global Distribution of Wild Animal Habitat



(b) Wild Animal Habitat Across Africa

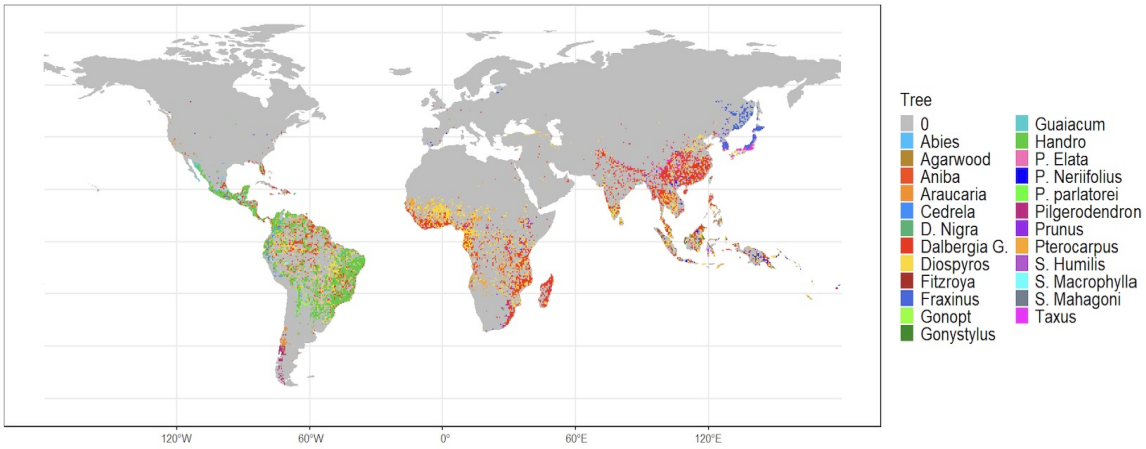


(c) Wild Animal Habitat in the DRC

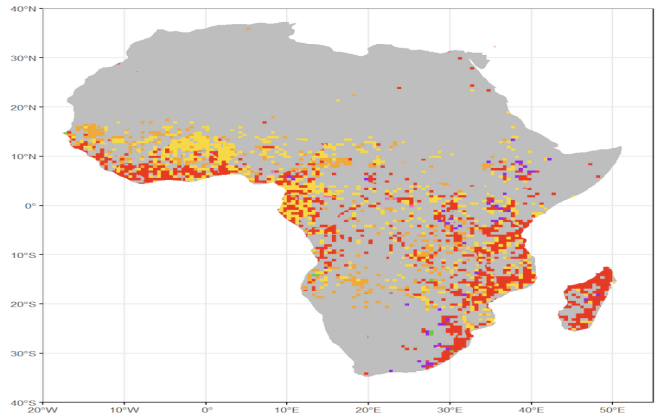
Notes: Panel (a) shows the spatial distribution of areas suitable for wild animals. Panels (b) and (c) show regional habitat distributions for Africa and the Democratic Republic of Congo (DRC), respectively.

[9]For example, elephant ivory and *Dalbergia* (rosewood) represent the largest illicit markets for wild animals and timber, respectively.

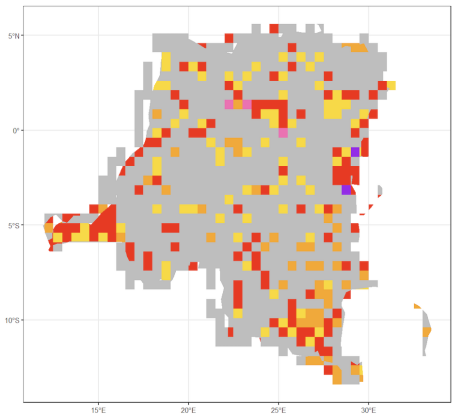
Figure 5: Spatial Distribution of Conflict and Wildlife Resources



(a) Global Distribution of Wild Tree Habitat



(b) Wild Tree Habitat Across Africa



(c) Wild Tree Habitat in the DRC

Notes: Panel (a) shows the spatial distribution of areas suitable for wild trees. Panels (b) and (c) show regional habitat distributions for Africa and the Democratic Republic of Congo (DRC), respectively.

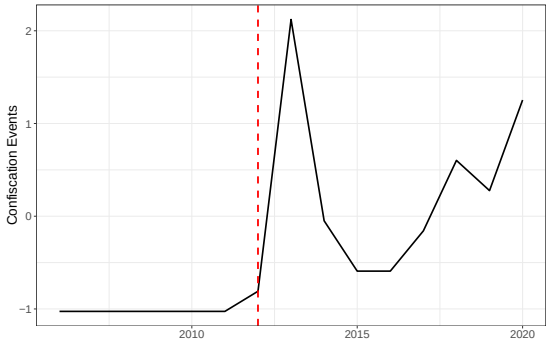
3.2.1 Prices and Confiscations

CITES restricts exports from source countries and imposes no sanctions on consumers. These restrictions are enforced at both exporters' and importers' borders. This subsection presents evidence that CITES restrictions are associated with reduced wildlife supply, as reflected in increased confiscations and higher prices.

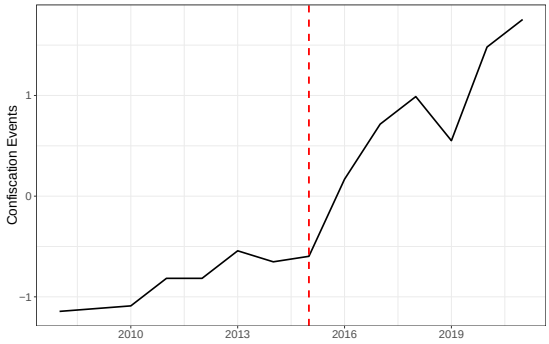
Confiscations. Figure 6 displays the number of confiscation events against the policy

timing for blackwood (*Diospyros*), rosewood (*Dalbergia*), and elephant ivory, where all series exhibit jumps following the policy. Appendix Table C.1 reports the corresponding difference-in-differences estimates.[10]

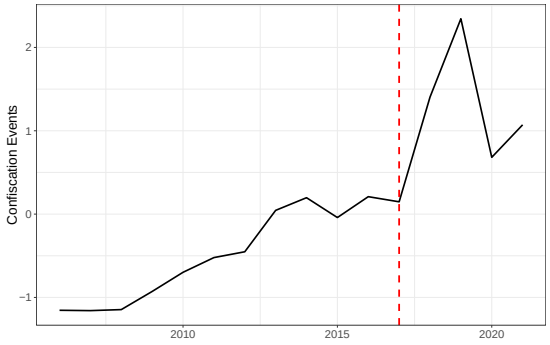
Figure 6: Wildlife Trade Restrictions and Conflict Likelihood



(a) Ebony (*Diospyros*)



(b) Rosewood (*Dalbergia*)



(c) Elephant Ivory

Notes: The figure depicts standardised sequences of wildlife confiscation events, alongside policy changes (in red) for blackwood (2013), rosewood (2016), and the Chinese ban on elephant ivory (2017).

Prices. To estimate the statistical association between the policy and wildlife prices, I construct a wildlife-year panel and estimate an event study specification, using prices as the outcome and policy indicators as explanatory variables.[11] I use precious metals as a control

[10] I opt to use confiscation events rather than total confiscation weights, as most events lack this information.

[11] Appendix Figure A.3 shows detrended prices before and after trade restrictions for the six wildlife products for which I have data: elephant ivory, rhino horn, crocodile skin, Dalbergia, Pterocarpus, and Diospyros.

group for wild animals, and World Bank hardwood timber price indices for Cameroon and Indonesia as a control group for wild trees. Given the staggered timing of the policy, I use the imputation estimator proposed by Borusyak et al. (2024).

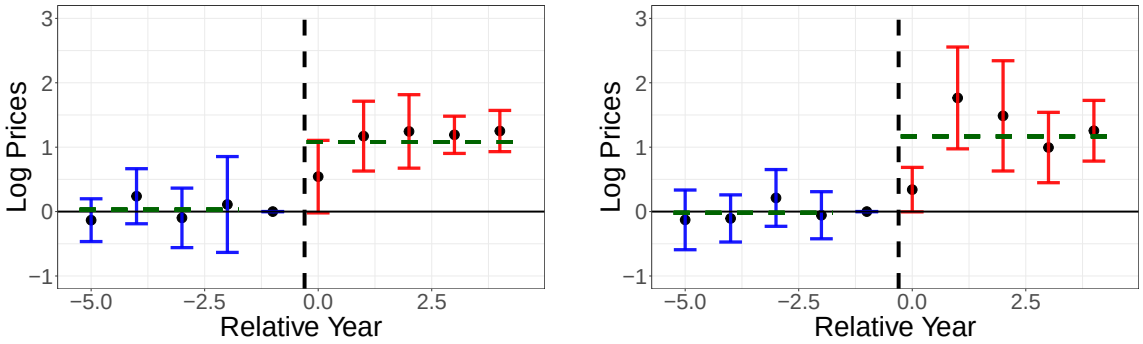
I estimate the following specification:

$$\ln(p_{w,t}) = \sum_{z=\Gamma^-}^{-2} \beta_z D_{w,t+z} + \sum_{j=0}^{\Delta^+} \gamma_j D_{w,t+j} + \delta_w + \lambda_t + \epsilon_{w,t} \tag{1}$$

Where $\ln(p_{w,t})$ is the log-transformed and standardised price of wildlife/resource w in year t, $D_{w,t+z}$ and $D_{w,t+j}$ indicate the timing of the policy relative to treatment, and δ_w and λ_t represent wildlife/resource and year fixed effects, respectively. To mitigate concerns about serial correlation, standard errors are clustered at the unit level.

Figure 7 presents event study estimates for wild animals (left) and wild trees (right). Appendix Table C.2 reports the difference-in-differences estimates, showing that the effect of the policy on wildlife prices is positive, statistically significant, and is about 1.117 and 1.03 standard deviations for wild animals and wild trees, respectively.

Figure 7: Trade Restrictions and Wildlife Prices



(a) Wild Animals **(b)** Wild Precious Trees

Notes: The figure presents estimates using the staggered event study imputation estimator suggested by Borusyak et al. (2024). Each observation corresponds to a resource-year. The wild animal sample includes 386 observations, and the wild trees sample includes 549 observations. The estimates are based on equation 1, with the interaction term $Wildlife \times Policy$, an indicator explaining log standardised prices, and include category and year fixed effects. The omitted period is the year prior to the policy announcement. The control group for wild animals is precious metals (gold, silver, and platinum), and for wild precious trees it is the World Bank hard tropical timber index. Error bars indicate 95% confidence intervals, with standard errors clustered to allow for arbitrary serial correlation.

4 Empirical Analysis

This section details the empirical strategy. Then it presents the main estimates and assesses their robustness using a series of alternative specifications.

4.1 Identification Strategy

To assess how international trade restrictions on wildlife products affect local conflict likelihood, I estimate an event study specification. I use a binary conflict indicator as an outcome and an interaction between policy timing and habitat suitability as the main explanatory variable. This identification strategy—interacting a global shock with local cell-level characteristics—follows recent advances in the conflict literature (Miguel et al., 2004; Dube and Vargas, 2013; Berman et al., 2017). Concerns about potential confounders and omitted variables are mitigated through a rich set of fixed effects. A key advantage of this empirical strategy is that data on habitat and policy timing is available for all wildlife in my sample. The core logic is to test whether conflict likelihood changes in habitat areas following a global shock to the trade of a specific wildlife.[12] Since CITES meetings occur on a predetermined three-year schedule and policies take effect within 90 days, I code the announcement year as the event start ($t = 0$).

Using the imputation event study estimator (Borusyak et al., 2024), I estimate the following equation separately: for wild animals and for precious trees.

$$Y_{k,t} = \sum_{z=-\Gamma^-}^{-2} \beta_z D_{w,t+z} \times M_{k,w} + \sum_{j=0}^{\Delta^+} \gamma_j D_{w,t+j} \times M_{k,w} + \lambda_k + \delta_{c,t} + \epsilon_{k,t} \tag{2}$$

$Y_{k,t}$ is a binary indicator for conflict in cell k and year t; $D_{w,t}$ indicates whether trade in wildlife taxon w is restricted in year t; and $M_{k,w}$ is a time-invariant indicator for the suitability of cell k for taxon w. The specification includes cell and country-year fixed effects to control for time-invariant factors (e.g., geography) and time-varying country-level shocks (e.g., domestic policies). Thus, the coefficients of interest, γ_j, are identified from within-cell variation in CITES trade restrictions over time. To mitigate concerns about serial correlation, I cluster standard errors at a spatial radius of 500 kilometre, which yields

[12] An alternative approach would follow Berman et al. (2017) in using variation in international prices as a continuous treatment. However, due to the illegal nature of the trade, consistent price data is difficult to obtain. Nonetheless, Appendix Table B.1 presents analogous estimates for the six species for which I do have price data.

the most conservative estimates.

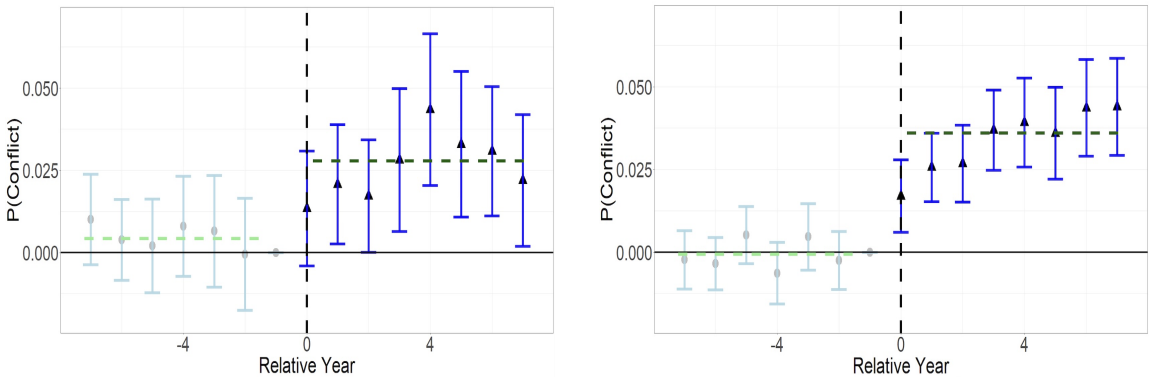
4.2 Baseline Results

Figure 8 displays event study estimates (Equation 2) using the ACLED conflict outcome. Panel (a) presents estimates for wild animals. The parallel trends assumption holds, and the estimated effect is positive and statistically significant, showing an average increase of 2.6 percentage points (corresponding to 35% from the baseline risk) in the likelihood of conflict in cells with wild animals following the policy. The effect intensifies up to the fifth post-policy period and then diminishes.

Panel (b) presents estimates for wild precious trees. The parallel trends assumption appears to hold, and the estimated effects are positive, statistically significant, and immediate. On average, the policy leads to a 3.54 percentage points (corresponding to 46% from the baseline risk) increase in the likelihood of conflict in cells suitable for wild precious trees, with the effect increasing monotonically over time. The lower standard errors of the wild precious trees estimates are likely driven by more accurate spatial data on tree distribution.

Table 1 reports difference-in-differences estimates using ACLED, UCDP, and GTD conflict outcomes, all consistent with the event study findings. Importantly, the UCDP estimates—capturing large conflict events with a death threshold above 25—are also positive and statistically significant (for animals: 1.29 percentage points and a 42% rise from the baseline conflict risk; for trees: 0.8 percentage points and a 27% rise from the baseline conflict risk). The GTD estimates, which also capture events from the 1970s and 1980s, are similarly consistent, showing positive and statistically significant effects (for animals: 1.5 percentage points and an 86% increase from the baseline conflict risk; for trees: 1.4 percentage points and an 80% increase from the baseline conflict risk).

Figure 8: Wildlife Trade Restrictions and Conflict Likelihood



(a) Wild Animals **(b)** Wild Precious Trees

Notes: The figure reports LPM estimates using the staggered event study imputation estimator suggested by Borusyak et al. (2024). Each observation corresponds to a cell-year (1,430,970 for wild animals and 1,435,230 for wild trees). The estimates are based on equation 2, with the interaction term $Habitat \times Policy$, an indicator explaining conflict probability. The omitted period is the year prior to the policy announcement. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the ACLED dataset. Error bars indicate 95% confidence intervals, with standard errors that are spatially clustered to allow for spatial and temporal correlation within a 500 km radius of each cell's centroid.

Table 1: Wildlife Trade Restrictions and Conflict Likelihood: Difference in Differences

	Dep. Var.: Conflict (0/1)					
	Wild Animals			Wild Trees		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
	(1)	(2)	(3)	(4)	(5)	(6)
Habitat × *Policy*	0.0265***	0.0129***	0.0151***	0.0354***	0.0082***	0.0139***
	(0.0068)	(0.0046)	(0.0040)	(0.0042)	(0.0029)	(0.0023)
	[0.0028]	[0.0014]	[0.0008]	[0.0017]	[0.0008]	[0.0009]
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	1,430,970	3,338,930	4,960,696	1,435,230	3,348,870	4,975,464
Dep. Var. Mean	0.0757	0.0302	0.0173	0.0757	0.0302	0.0173
Dep. Var. SD	0.2645	0.1712	0.1306	0.2645	0.1712	0.1306

Notes: The table reports LPM estimates using the Borusyak et al. (2024) imputation difference-in-differences estimator. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife species w at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. Standard errors reported in square brackets are clustered at the country-year and cell levels, allowing for within-country spatial correlation and infinite serial correlation within a cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

4.3 Sensitivity Analysis

In this subsection, I discuss sensitivity checks.

Exogeneity of Policy. Although the parallel trends assumption is satisfied, there may still be concerns about potential endogeneity, specifically whether CITES responds to poaching crises linked to conflict or targets conflict-affected regions. This is unlikely given how CITES operates. While scientific recommendations inform CITES decisions, the final outcome is political and requires a two-thirds majority vote among member countries. Frank and Wilcove (2019) show that there are often long delays—averaging 10 years—in implementing trade bans on threatened species, reflecting the slow and unpredictable nature of the political process. In addition, a text analysis of CITES protocols reveals no explicit mention of armed conflict or armed groups in official meetings.

To further address concerns about policy endogeneity, Appendix Figure D.1 confirms

that the estimates remain robust when iteratively excluding different continental subregions, reducing concerns that CITES systematically targets conflict-prone regions.

Measurement Error. Another concern with using wildlife habitat classification as a proxy for treatment exposure is the potential for measurement error. I implement two exercises to address this. First, Appendix Table D.2 reports country-level, shift-share style estimates, using policy years as shifts and the total number of habitat cells as a proxy for each country's wildlife stock as shares. This aggregation helps reduce the risk of local-level measurement errors. Second, Appendix Tables D.3 and D.4 report estimates using a $0.25° \times 0.25°$ and $1° \times 1°$ grid resolutions to test robustness to cell-size.

Potential Confounders. Due to the large spatial coverage of wildlife habitat, another concern is that its distribution may overlap with other valuable resources—such as gold, minerals, or crops—potentially confounding the estimates. To mitigate this concern, I exclude all cells geologically suitable for gold production (Girard et al., 2022), as well as those that overlap with precious mineral deposits (Berman et al., 2017).[13] To further ensure that spatial confounders are not driving the estimates, I divide the sample into above- and below-median groups based on urban areas, crop production, human footprint, and population density, and replicate the ACLED estimates from Table 1 for each subsample. Following Eberle et al. (2020), I also exclude all Sahel countries. Estimates are reported in Appendix Table D.5. Although coefficient magnitudes vary, likely due to reduced sample sizes, the estimates remain robust across all specifications.

Different Control Groups. The global approach—necessary for external validity and to capture a wide range of resources and policy shocks—raises concerns about the adequacy of the control group. To mitigate this concern, I estimate a staggered event study specification using the augmented synthetic control estimator from Ben-Michael et al. (2021), which constructs control groups that perfectly match the pre-trends of treated units. Estimates are reported in Appendix Figure D.2 and Appendix Table D.6. Furthermore, in Table D.7, I pool wild animals and wild trees, defining treatment as CITES restrictions on either category.

Alternative Conflict Outcomes. Conflict is a complex and difficult-to-measure phenomenon. To reduce measurement error, the common approach in the conflict literature is to estimate a linear probability model with a binary conflict outcome (Bazzi and Blattman, 2014; Ciccone, 2018). Appendix Table D.8 reports estimates using the total number of

[13] Although the geological suitability map from Girard et al. (2022) is specific to gold, it covers approximately 43% of African cells and likely captures other artisanal mining areas as well.

conflict events and total number of deaths in a given cell-year. Appendix Table D.9 reports estimates using conflict onset instead of conflict incident.[14]

Alternative Estimators. Appendix Table D.10 shows estimates using the estimators from Callaway and Sant'Anna (2021) and Sun and Abraham (2021), which are consistent with those reported in Table 1.

5 Mechanism

This section examines the mechanism through which restrictions on wildlife trade increase conflict, drawing on the commodity-conflict literature (Becker et al., 2006; Angrist and Kugler, 2008; Fearon, 2008; Dube and Vargas, 2013; Berman et al., 2017) emphasising the role of resource windfalls in fueling violence.

First, focusing on the harvesting of endangered precious trees, I show that harvesting activity shifted from strong, more compliant states to weak states, where most of the conflict effect originates. Second, given the evidence showing that the policy affects wildlife prices (Figure 7 and Appendix Figure A.3), I focus on the ivory market, where I can estimate the price effect of CITES policies on conflict. Additionally, I aggregate the estimates by spatial and population exposure and compare it to the effect of the industrial minerals shock studied by Berman et al. (2017). After establishing the conflict-windfall nexus, I explore how armed groups' fighting dynamics and winning likelihood have changed following the policy.

5.1 Evidence of Windfall Gains

5.1.1 Quantities

While CITES policy is global, countries vary in their local capacity to enforce it. Because the policy restricts supply, it can generate windfall gains in some regions by increasing production at the expense of areas where enforcement is strong. To identify this channel empirically, I focus on Africa and on protected precious trees, for which I can estimate harvested quantities using remote-sensing data combined with habitat suitability.[15] In particular, for the assessment, I combine remote-sensing deforestation data from Hansen et al.

[14] Following Berman et al. (2017), I define conflict onset as the first post-peace conflict event in a given cell and exclude all subsequent events within the same cell.

[15] Data on wild animal poaching are limited in spatial coverage and subject to selection and reporting biases.

(2013) with species-level habitat suitability. CITES is likely to target taxa experiencing high harvesting pressure and therefore exhibiting different pre-trends. To address this, I use a staggered event-study synthetic control estimator (Ben-Michael et al., 2021). With this approach, I estimate the change in deforestation in locations suitable for precious trees following CITES trade restrictions. I restrict the sample to Africa and split it into two subsamples—countries with relatively high state capacity and those with relatively low capacity.

I estimate the following synthetic staggered event-study specification:

$$Y_{w,k,t} = \sum_{z=-\Delta^-}^{-2} \beta_z D_{w,k,t+z} + \sum_{j=0}^{\Gamma^+} \gamma_j D_{w,k,t+j} + \lambda_k + \delta_{c,t} + \eta_w + \epsilon_{w,k,t}. \tag{3}$$

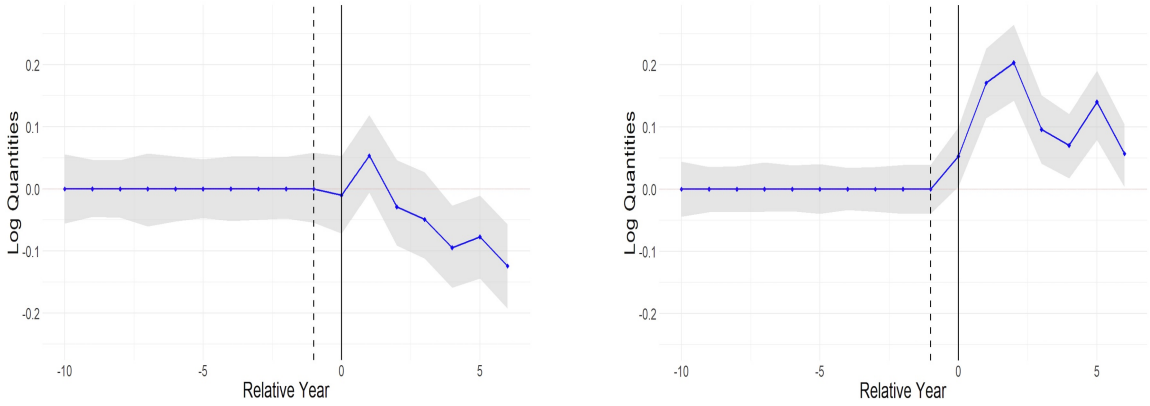
$Y_{w,k,t}$ denotes the log harvested quantity of protected tree taxon w (species or genus) in grid cell k at time t. The policy variable $D_{w,k,t}$ indicates whether trade in taxon w is restricted in grid cell k at time t. The specification includes grid-cell, country–year, and taxon fixed effects. Standard errors are computed using the wild bootstrap, following the procedure for synthetic control estimators in Ben-Michael et al. (2021).

To assess whether the quantity windfall is associated with an increase in conflict, I re-estimate the conflict event-study specification for trees (akin to Equation 2), but splitting the sample into countries with high and low state capacity.

Figure 9, panel (a), shows a decrease of about 9.7% in harvesting in strong states following the policy, while panel (b) shows an increase of about 5.5% in weak states. On average, in the African sample, the policy reduced harvesting by 0.5% (Appendix Table C.3), suggesting that nearly all conservation benefits were offset by increased harvesting in weak states.

Figure 10 shows that the policy–conflict relationship is primarily driven by weak states, with an average increase of 3.3 percentage points in conflict likelihood, compared to only 0.15 percentage points in strong states, which is statistically insignificant (Appendix Table C.4). Appendix Table C.5 reports the difference-in-differences coefficient for the entire African sample, showing an average increase of 5.3 percentage points in conflict likelihood. This suggests that differences in production elasticity—driven by variation in enforcement capacity across states—underlie the windfall heterogeneity and are associated with the policy–conflict relationship.

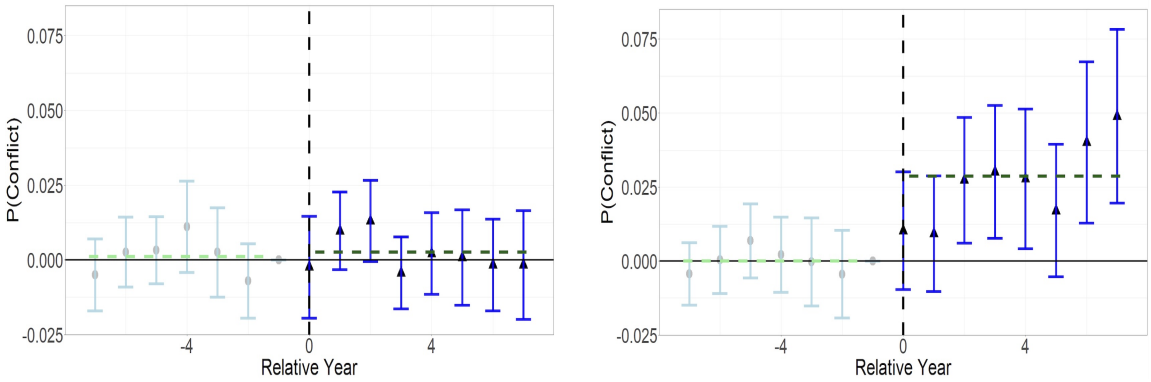
Figure 9: Trade Restrictions and Harvesting of Protected Precious Trees by State Capacity: Synthetic Control Estimates



(a) High State Capacity **(b)** Low State Capacity

Notes: The figure displays staggered event-study synthetic control estimates (Ben-Michael et al., 2021) for harvesting of precious trees in African countries with above (a) and below (b) median state capacity. Each observation corresponds to a cell-year, where cell size is $0.15° \times 0.15°$. The sample is restricted to Africa and includes 423,016 (881,298) observations for the high- (low-) capacity state sample. The dependent variable is the log of harvested quantities of trees, based on remote sensing estimates (Hansen et al., 2013). The main explanatory variable is an interaction between *policy* and *habitat* indicators, capturing the location and timing of species/genus protected by CITES. Standard errors are computed using the wild bootstrap, following the procedure for synthetic control estimators in Ben-Michael et al. (2021).

Figure 10: Trade Restrictions on Protected Precious Timber and Conflict by State Capacity



(a) High State Capacity **(b)** Low State Capacity

Notes: The figure reports LPM estimates using the staggered event study imputation estimator suggested by Borusyak et al. (2024). The left (right) chart reports estimates for African countries with above- (below-) median state capacity. Each observation corresponds to a cell-year (131,663 for high-capacity and 191,137 for low-capacity states). The estimates are based on equation 2, but for split—high- and low-capacity—samples, with the interaction term $Habitat \times Policy$, an indicator explaining conflict probability. The omitted period is the year prior to the policy announcement. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the ACLED dataset. Error bars indicate 95% confidence intervals, with standard errors that are spatially clustered to allow for spatial and temporal correlation within a 500 km radius of each cell's centroid.

5.1.2 Prices

The African elephant ivory market provides a suitable setting to estimate the effect of the policy on conflict via prices. To estimate this effect I use three policy-driven supply shocks, which, importantly, did not change the legal status of ivory. In 1998 and 2007, CITES approved organised sales of ivory from South Africa, Botswana, Namibia, and Zimbabwe to China and Japan. The rationale behind this policy was to suppress prices and reduce poaching incentives (Kremer and Morcom, 2000; UNODC, 2016). Additionally, in 2017, China–the largest market for ivory–under pressure from CITES, shut down its secondary antique ivory market. I categorise the first two supply shocks as expansionary and interpret the China ban as a contractionary supply shock. Using these three shocks as instruments, I estimate a 2SLS specification, linking the policies to conflict through prices.

Importantly, for the exclusion restriction to hold, the policy shocks—ivory sales and the China ban—must affect local conflicts across Africa only through their impact on prices, and not through any other channel. To mitigate this concern, I exclude the four African

countries that participated in the sales from the sample.[16] Given that all policy decisions were made either by CITES or by China—under pressure from CITES—and were outside the control of the remaining African countries in the sample, the validity of this assumption appears plausible.

I estimate the following 2SLS specification:

$$\ln(p_t) \times M_k = \gamma_1(Expan_t \times M_k) + \gamma_2(Contract_t \times M_k) + \lambda_k + \delta_{c,t} + \nu_{k,t} \tag{4}$$

$$Y_{k,t} = \beta \left(\widehat{\ln(p_t) \times M_k} \right) + \lambda_k + \delta_{c,t} + \epsilon_{k,t} \tag{5}$$

$Expan_t$ ($Contract_t$) is an indicator variable for the expansionary (contractionary) policies in the ivory market at time t. I define the announcement year and the subsequent year as a treatment window to capture the policy shock, and interact it with the indicator variable M_k, which equals one if cell k is designated as elephant habitat.[17] $\ln(p_t)$ denotes the price of elephant ivory. To mitigate concerns about other confounders—such as geographic variation, domestic policies, or shocks to other commodities—the specification includes cell and country–year fixed effects, as well as controls for the industrial minerals shock (Berman et al., 2017).

Table 2 reports the 2SLS estimates. Columns (1)–(3) of Panel A present aggregated results for ACLED, UCDP, and GTD, respectively. The ACLED and UCDP coefficients show increases in conflict likelihood of 1.7 and 1.3 percentage points, corresponding to 23% and 45% relative to the baseline risk. The GTD coefficient is smaller—0.5 percentage points, or 33% from the baseline risk—and less precisely estimated, though it points in the same direction. Comparing across shocks, column (1) suggests that the mineral shock (Berman et al., 2017) has a stronger effect on ACLED conflict events compared to the ivory shock (0.032 compared to 0.017). In contrast, column (2) shows that the mineral shock has a weaker effect on UCDP large-scale conflict events (0.002 compared to 0.014). Panel B reports the first-stage estimates, with associated F-statistics that are above conventional thresholds for instrument strength. Panel C presents the reduced-form estimates, showing that contractionary shocks reduce conflict while expansionary shocks increase it, and Panel

[16] Appendix Table D.13 reports 2SLS estimates obtained by iteratively excluding each of Africa's five continental subregions.

[17] I code the shocks as follows: CITES 1st sale as 1998 and 1999; CITES 2nd sale as 2007 and 2008; and the China ban as 2017 and 2018.

D compares OLS and 2SLS estimates. The 2SLS coefficients are approximately 1.5 to 2 times larger, which likely reflects attenuation bias in OLS due to price endogeneity—for example, if some large producing locations act as price makers. Finally, Panel E reports population-weighted least squares (WLS) estimates, showing the average partial effect for a person-weighted cell. The coefficients on the ivory and industrial-mineral shocks are larger in magnitude than their OLS counterparts.

Table 2 columns (4)–(6) report the ACLED violence decomposition estimates. Columns (4)–(5) of Panel A show that most of the ivory conflict effect is driven by one-sided violence, defined as events where a recognised armed group attacks civilians or small unrecognised militias. In contrast, most of the mineral shock effect is driven by battles between armed groups. Column (6) reports placebo estimates testing the effect of the ivory shock on protests and riots; the coefficients are statistically insignificant. Appendix Tables D.12, D.13, and D.14 present placebo exercises supporting the exogeneity assumption of the policies with regard to ivory-related conflicts. Appendix Table D.14 reports estimates using three alternative ivory price sequences.

In summary, Table 2 provides evidence of a direct link between CITES supply-side policies, induced price changes, and the likelihood of local conflict events.

Table 2: Policies, Price Shocks and Conflict Likelihood in the Elephant Ivory Market: 2SLS

	Dep. Var.: Conflict (0/1)					
	Aggregated			ACLED Sub-Categories		
	ACLED	UCDP	GTD	One-Sided Violence	Battles	Protests/Riots
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV Estimates						
$\widehat{Habitat \times Price}$	0.0171***	0.0137***	0.0058*	0.0083***	0.0037	0.0024
	(0.0055)	(0.0047)	(0.0031)	(0.0036)	(0.0037)	(0.0030)
$Mineral \times Price$	0.0322***	0.0018	0.0022	0.004**	0.0066***	0.0354***
	(0.0066)	(0.0032)	(0.0022)	(0.0020)	(0.0024)	(0.0063)
Panel B: First Stage						
$Habitat \times Expansionary\ Shock$	−0.8291***	−0.7703***	−0.7703***	−0.8291***	−0.8291***	−0.7703***
	(0.0861)	(0.0842)	(0.0842)	(0.0861)	(0.0861)	(0.0842)
$Habitat \times Contractionary\ Shock$	0.7663***	0.8250***	0.8250***	0.7663***	0.7663***	0.8250***
	(0.1495)	(0.1469)	(0.1469)	(0.1495)	(0.1495)	(0.1469)
F-Stat	42,369	68,934	68,934	42,369	42,369	68,934
Panel C: Reduced Form						
$Habitat \times Expansionary\ Shock$	−0.0147***	−0.0105***	−0.0017	−0.0042	−0.0102***	−0.0015
	(0.0051)	(0.0035)	(0.0016)	(0.0032)	(0.0034)	(0.0014)
$Habitat \times Contractionary\ Shock$	0.0151***	0.0113*	0.0083*	0.0131***	0.0018	0.0025
	(0.0068)	(0.0061)	(0.0048)	(0.0048)	(0.0056)	(0.0052)
Panel D: OLS						
$Habitat \times Price$	0.0124***	0.0058**	0.0029	0.0051***	0.0067***	0.0012
	(0.0034)	(0.0028)	(0.0018)	(0.0017)	(0.0024)	(0.0018)
$Mineral \times Price$	0.0322***	0.0017	0.0021	0.004**	0.0066***	0.0354***
	(0.0066)	(0.0032)	(0.0022)	(0.0020)	(0.0024)	(0.0063)
Panel E: WLS						
$Habitat \times Price$	0.0168***	0.0112**	0.0036	0.011**	0.0033	0.0029
	(0.0058)	(0.0045)	(0.0023)	(0.0043)	(0.004)	(0.0035)
$Mineral \times Price$	0.0414***	0.0005	0.0031	0.0068**	0.0073***	0.041***
	(0.0071)	(0.0027)	(0.0027)	(0.0024)	(0.0021)	(0.0073)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Dep. Var. Mean	0.0757	0.0302	0.0173	0.0324	0.0332	0.0232
Dep. Var. SD	0.2645	0.1712	0.1306	0.1613	0.1734	0.1508
Observations	305,312	836,992	836,992	276,256	276,256	276,256

Note: The table reports 2SLS estimates for African elephants. Each observation corresponds to a cell-year, and the sample is restricted to Africa. Panel A reports the main 2SLS estimates, where the variable *Habitat* is an indicator measuring the suitability of cell k for African elephants, and *Price* denotes the log price of ivory at time t. The estimates are based on the first-stage equation 4. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell-year, based on the conflict dataset mentioned in the title. Panel B reports the first-stage estimates, in which policies explain the price shocks. *Expansionary Shock* is an indicator for policy-driven increases in ivory supply, while *Contractionary Shock* reflects policy-induced supply reductions. Panel C reports reduced-form estimates of the effects of these policies on the conflict indicator. Panel D presents OLS estimates from regressing the conflict indicator on the interaction term *Habitat* × *Price*. Panel E presents population-weighted least squares (WLS) estimates. Columns 1–3 report estimates for aggregated conflict variables, whereas Columns 4–6 report disaggregated categories, excluding state-related violence. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid.* significant at 10%; ** significant at 5%; *** significant at 1%.

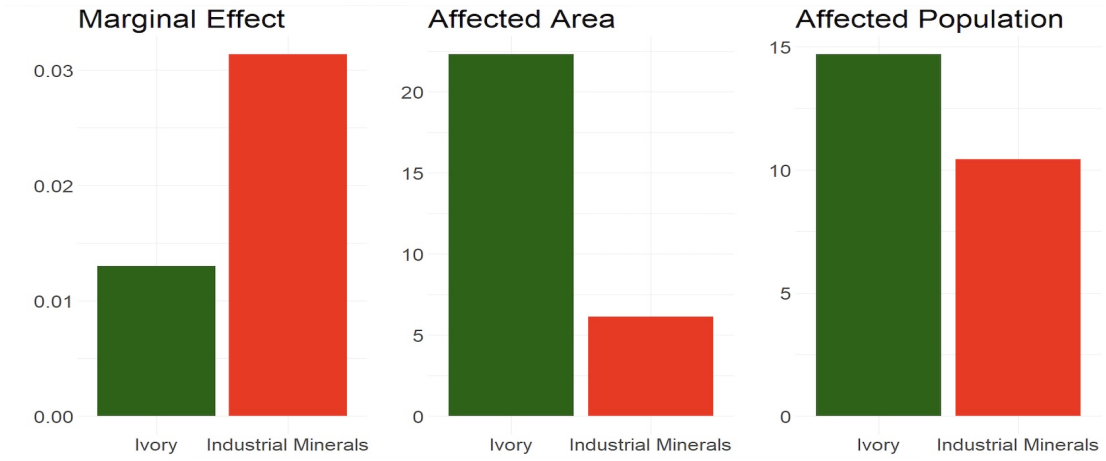
Aggregation. Although the industrial minerals shock (Berman et al., 2017) has a larger marginal effect on conflict than the wildlife shock (0.0322 versus 0.0124 in the OLS specification), the total conflict impact also depends on resource distribution and population exposure. Shocks to scarce, geographically concentrated resources affect fewer people and locations, whereas widely distributed resources can be more devastating. Only 195 grid cells contain industrial minerals, compared to 1,717 cells suitable for African elephants. For example, based on the Berman et al. (2017) industrial mining sample, Uganda has no industrial mining activity, yet approximately 15% of its land area is suitable for elephants. The broad spatial distribution of wildlife habitat and its lower marginal effect on conflict, compared to the concentrated presence and greater marginal impact of industrial minerals, may explain why the wildlife shock has been overlooked in the literature.

First, to account for differences in spatial distribution, I use the OLS estimates reported in Table 2, Panel D, column (1), and multiply them by the number of grid cells that are suitable for or contain each resource.[18] Second, to account for population exposure, I use the population-weighted least squares (WLS) estimates reported in Table 2, Panel E, Column (1). I then multiply the coefficient estimates by the number of cells containing each resource and by the average population of the corresponding wildlife or mineral grid cells to approximate total population exposure.

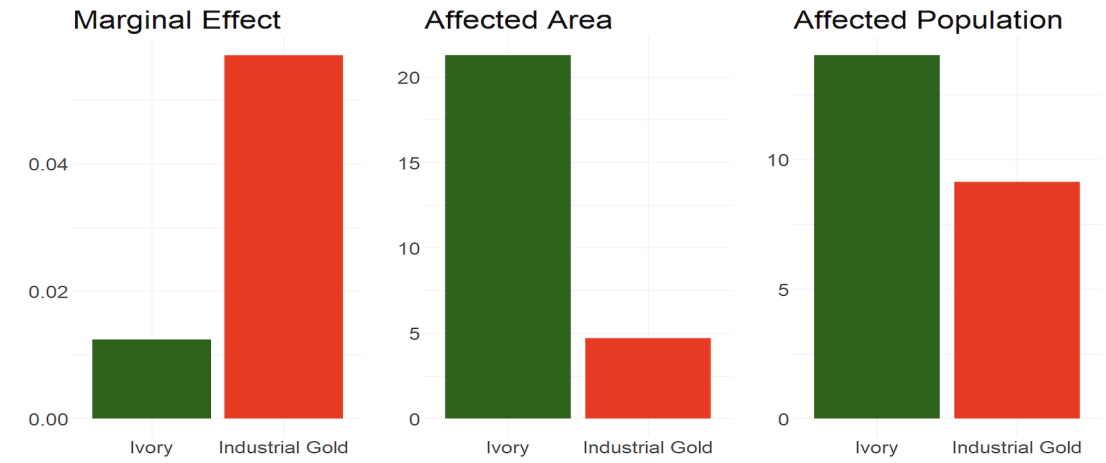
Figure 11 displays aggregate conflict estimates for a one–standard deviation price shock to ivory, industrial minerals, and industrial gold. In the *Affected Area* panels, the y-axis represents the expected increase in number of grid cells with at least one conflict event following a price shock, computed as the OLS coefficient (Panel D, column (1)) multiplied by the number of resource-suitable/containing cells. In the *Affected Population* panels, the y-axis represents the expected increase in number of people—measured in units of 100,000—living in conflict zones following a price shock, computed as the WLS coefficient (Panel E, column (1)) multiplied by the total population in the relevant resource cells. Although the marginal per-cell effects are larger for industrial minerals and industrial gold, ivory is more consequential on an aggregate basis when weighting by affected area or population exposure.

[18] The OLS coefficients in Panel D provide the most conservative estimates of the wildlife shock.

Figure 11: Aggregate Price-Conflict Estimates by Geographic and Population Exposure: Elephant Ivory, Industrial Minerals, and Industrial Gold



Aggregated Conflict Estimates for Ivory and Industrial Minerals



Aggregated Conflict Estimates for Ivory and Industrial Gold

Notes: The figure depicts conflict exposure to ivory, industrial minerals, and industrial gold shocks using three aggregation approaches: marginal effect, total exposed area, and affected population. These measures are based on the estimates reported in Table 2, Panel D, column (1) (OLS), and Panel E, column (1) (WLS). The top panel displays the estimates for ivory and industrial minerals, while the bottom panel displays the estimates for ivory and industrial gold. The left chart shows the marginal effects, derived from the baseline model coefficients; the middle chart shows the estimates aggregated by the number of cells containing each resource class; and the right chart shows the weighted least squares estimates, further aggregated by exposed population. The *Affected Population* y-axis is scaled in units of 100,000.

5.2 Mechanism: Armed Groups Dynamics

This subsection examines how armed groups' fighting dynamics have changed following the windfall gains arising from CITES trade restrictions.

The literature (Blattman and Miguel, 2010; Bazzi and Blattman, 2014; Berman et al., 2017; Jaimovich and Toledo, 2021) discusses several mechanisms through which windfall gains can fuel conflict. First, by easing financing constraints for armed groups, they increase the feasibility of rebellion and the likelihood of attacks. Second, by raising the expected returns from capturing resource-rich areas, they incentivise territorial competition among armed actors. Third, they exacerbate grievances and social instability by making certain groups feel relatively disadvantaged. Fourth, by altering local migration patterns and reshaping the size and composition of the population, they may contribute to ethnic tensions and conflict.

This subsection provides two empirical tests. The first helps to disentangle the competition and feasibility channels. The second examines how the winning likelihood of different groups—those likely to benefit from the windfall with those who were not—changed following CITES policies. Due to the lack of anecdotal evidence linking grievances or migration to the wildlife trade or CITES policies, I focus solely on the feasibility and competition channels.

5.2.1 Distance Analysis

To assess which channel—competition or feasibility—is empirically dominant, I examine the spatial distribution of armed clashes, that is, how far groups operate from their pre-policy strongholds after the policy shock. If competition is stronger, I expect groups outside wildlife habitat (who likely did not receive windfalls) to move toward resource-rich areas to contest rents; consequently, clashes should concentrate nearer to the territories of windfall-exposed groups. Given that the outcome measures distance to each group's own centroid, this implies that, relative to rivals, windfall groups will appear to fight closer to baseline. If feasibility is stronger, I expect the windfall-exposed groups (those with pre-policy territory overlapping habitat) to expand outward and fight farther from their previous battlegrounds.

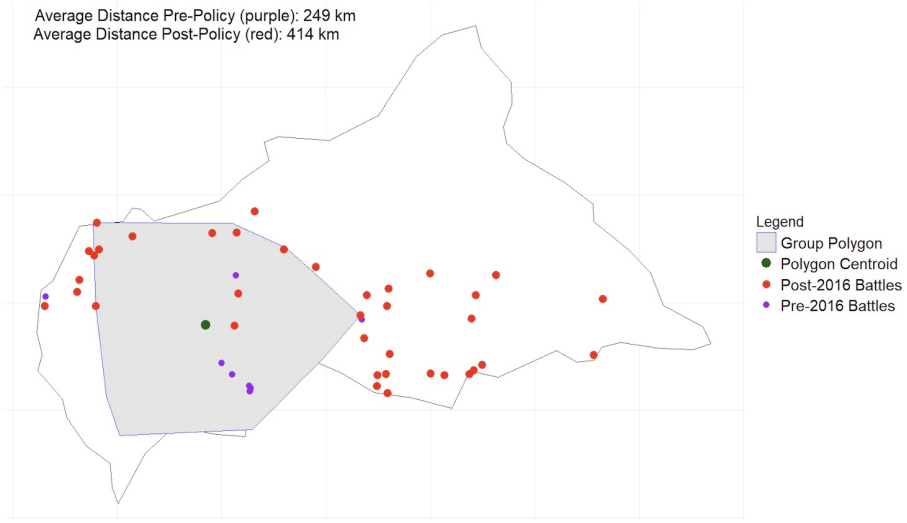
To implement this test, I proceed as follows. First, I analyse the 2016 rosewood ban and the 2017 China ban on domestic ivory trade in separate samples. Second, I select well-recognised armed groups that fought in at least three distinct locations from the start of the sample up to three years before the relevant policy, and I construct a

group–battle–location–year panel.[19] Third, for each group I draw a convex hull around pre-policy conflict locations and compute the polygon's centroid, which I treat as the group's central location. Fourth, using these pre-policy polygons, I classify groups as "ivory" or "rosewood" according to the share of polygon area overlapping elephant or rosewood habitat (*Dalbergia* and *Pterocarpus*). I label as "wildlife" those in the upper half of the overlap distribution and the remainder as "non-wildlife." Fifth, I restrict the sample to the two years before and after each policy, with 2014–2017 for rosewood and 2015–2018 for ivory. Sixth, I define the outcome as the log distance between each conflict event and the group's centroid, computed as the geodesic distance in kilometres, and I estimate the effect of the interaction between a post-policy indicator and the group's wildlife classification. A positive coefficient indicates feasibility, meaning windfall groups fight farther post-policy. A negative coefficient indicates competition, meaning rivals move toward windfall territories, which makes windfall groups appear closer in relative terms.

Figure 12 illustrates the logic of the empirical test by examining the fighting dynamics of the Anti-Balaka group in the Central African Republic. Based on the overlapping-polygon classification, the group is classified as a "rosewood" group likely to benefit from the rosewood windfall. The grey-blue polygon marks the group's territory, derived from battles between 1997 and 2013, and the green dot indicates the centroid of that polygon. Purple dots represent the group's battle locations in 2014–2015—just before the CITES ban on rosewood—while red dots represent battle locations in 2016–2017—just after the ban. On average, the purple battles occurred 249 kilometers from the centroid, while the red battles averaged 414 kilometers.

[19] At least three locations are required to construct a convex hull, which I use as a proxy for pre-policy territory.

Figure 12: Anti-Balaka Battles and Territory in the Central African Republic



Notes: The figure shows the fighting dynamics of Anti-Balaka—classified as a "rosewood" group—in the Central African Republic, before and after the 2016 CITES *Dalbergia* ban. The grey-blue polygon delineates the group's fighting territory based on battles from 1997–2013, and the green dot marks its centroid. Purple dots represent battles in 2014–2015, while red dots represent battles in 2016–2017 (after the ban).

To test whether the dynamic described in Figure 12 is anecdotal or systematic, I estimate the following difference-in-differences specification:

$$Distance_{g,b,k,t} = Policy_t \times WildlifeGroup_g + \eta_g + \lambda_k + \delta_{c,t} + \epsilon_{g,b,k,t} \tag{6}$$

$Distance_{g,b,k,t}$ is the (log) kilometre distance between battle b, fought by group g in location k at time t, and the group's centroid, defined based on its pre-sample conflict locations. $Policy_t$ is a post-policy indicator, and $WildlifeGroup_g$ is an indicator for whether the group's polygon overlaps with either elephant or rosewood habitat and falls in the upper half of the distribution. The specification includes group, cell, and country-year fixed effects to account for group- and location-specific heterogeneity, as well as national-level shocks occurring in the same year. Following Eberle et al. (2020) I cluster standard errors at the group and country-year levels.[20]

Table 3 reports the estimates. Both ivory- and rosewood-linked groups fought significantly farther (on average, approximately 20%) from their baseline locations in the post-policy period, relative to non-wildlife groups.[21] These findings suggest that the fea-

[20] I also experiment with clustering at the spatial radius of 500 kilometre of each battle location.
[21] In each regression, I exclude the other resource-linked category of groups to isolate the treatment effect.

sibility channel is empirically stronger: wildlife-heavy armed groups, likely to benefit from the windfall, appear to have used it to expand their territorial reach. Appendix Table C.1 presents event-study estimates and indicates parallel pre-trends.

Table 3: Trade Restrictions and Armed Groups' Battle Distance

	Dep. Var.: log(Distance$_{g,b,k,t}$)					
	Elephant Ivory Groups			Rosewood Groups		
	(1)	(2)	(3)	(4)	(5)	(6)
Elephant Ivory Group × *Policy*	0.1632***	0.1395*	0.1842***			
	(0.0692)	(0.073)	(0.081)			
	[0.0667]	[0.073]	[0.0789]			
Rosewood Group × *Policy*				0.1675***	0.1438***	0.1666**
				(0.0372)	(0.052)	(0.0684)
				[0.0334]	[0.05]	[0.0656]
Group FE	Y	Y	Y	Y	Y	Y
Location FE	N	Y	Y	N	Y	Y
Country-Year FE	N	N	Y	N	N	Y
Observations	9,302	9,302	9,302	24,429	24,429	24,429
Dep. Var. Mean	5.7449	5.7449	5.7449	5.7183	5.7183	5.7183
Dep. Var. SD	0.8010	0.8010	0.8010	0.7557	0.7557	0.7557

Notes: The table reports OLS estimates of changes in log battle distance for wildlife-heavy groups following CITES trade restrictions, relative to non-wildlife-heavy groups. Each observation corresponds to a group-battle-location-year. Locations are assigned based on a $0.5^\circ \times 0.5^\circ$ grid. The sample is restricted to African countries and to events in which at least one side is an armed group that had fought three or more battles by 2013. The dependent variable—log distance—measures how far battle b, fought by group g in location k at year t, occurred from the group's pre-sample centroid, calculated based on a polygon of its earlier conflict locations. *Elephant Ivory Group* and *Rosewood Group* equal one for armed groups whose territory overlaps with elephant or rosewood habitat above the median share, and *Policy* is a post-policy indicator. Columns 1-3 present estimates for elephant-heavy groups (excluding rosewood-heavy groups); Columns 4-6 present estimates for rosewood-heavy groups (excluding elephant-heavy groups). Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. Standard errors reported in square brackets are two-way clustered by country-year and group, allowing for within-country spatial correlation and serial correlation within groups. * significant at 10%; ** significant at 5%; *** significant at 1%.

5.2.2 Winners and Losers of the Wildlife Windfall

This subsection presents suggestive evidence on whether wildlife-heavy armed groups are more likely to win battles following wildlife windfall gains. For clashes between armed groups or against the government, ACLED records which actor gains territory. I use this information to construct a win-loss indicator for each battle, and use this as an outcome vari-

able. I construct a group–battle–location–year panel, using battles involving non-wildlife-heavy groups against the government as a control group. The analysis focuses on the 2016 rosewood and 2017 ivory trade restrictions. In each case, I drop groups linked to the other wildlife category, interact a "wildlife-heavy" indicator with a "post-policy" indicator, and restrict the sample to the two years before and after each policy. I view this analysis as suggestive, as following the policy, groups or the government might strategically engage in battles, confounding causal inference.

I estimate the following specification:

$$Win_{g,b,k,t} = Policy_t \times WildlifeGroup_g + \eta_g + \lambda_k + \delta_{c,t} + \epsilon_{g,b,k,t} \tag{7}$$

$Win_{g,b,k,t}$ is an indicator variable for whether group g, fought battle b in location k at time t, gained territory. $Policy_t$ is a post-policy indicator, and $WildlifeGroup_g$ is an indicator for whether the group's polygon overlaps with either elephant or rosewood habitat and falls in the upper half of the distribution. The specification includes group, cell, and country-year fixed effects to absorb group- and location-specific heterogeneity and contemporaneous national-level shocks. Standard errors are two-way clustered at the group and country-year levels or at a spatial radius of 500 kilometre of each battle location.

Table 4 reports the estimates, showing that wildlife-heavy armed groups are more likely to gain territory following CITES policies, with the probability of winning increasing by 59 and 41 percentage points for ivory and rosewood groups, respectively.

Table 4: Trade Restrictions and Winning Likelihood

	Dep. Var.: $Win_{g,b,k,t}$ (0/1)					
	Elephant Ivory Groups			Rosewood Groups		
	(1)	(2)	(3)	(4)	(5)	(6)
Elephant Ivory Group × *Policy*	0.2899*	0.3570*	0.5966***			
	(0.158)	(0.191)	(0.1641)			
	[0.1619]	[0.1974]	[0.1692]			
Rosewood Group × *Policy*				0.2585**	0.4590***	0.4161***
				(0.132)	(0.087)	(0.074)
				[0.124]	[0.091]	[0.0592]
Group FE	Y	Y	Y	Y	Y	Y
Location FE	N	Y	Y	N	Y	Y
Country-Year FE	N	N	Y	N	N	Y
Observations	5,924	5,924	5,924	6,468	6,468	6,468
Dep. Var. Mean	0.4132	0.4132	0.4132	0.4499	0.4499	0.4499
Dep. Var. SD	0.4925	0.4925	0.4925	0.4975	0.4975	0.4975

Notes: The table reports LPM estimates obtained via OLS. Each observation corresponds to a group-battle-location-year. Locations are assigned based on a $0.5^\circ \times 0.5^\circ$ grid. *Elephant Ivory Group* and *Rosewood Group* are indicators equal to one for armed groups whose territory overlaps with wildlife habitat (elephant or *Dalbergia*) above the median share, and *Policy* is a post-policy indicator. The dependent variable is a dummy equal to one if the group gains territory in a given battle, serving as a proxy for victory. The sample includes only clashes between well-recognised armed groups, either with each other or with the government, and is restricted to Africa. Columns 1-3 report estimates for ivory-heavy groups (excluding *Dalbergia*-heavy groups), whereas Columns 4-6 report estimates for *Dalbergia*-heavy groups (excluding ivory-heavy groups). Standard errors reported in square brackets are two-way clustered by country-year and group, allowing for within-country spatial correlation and serial correlation within groups. * significant at 10%; ** significant at 5%; *** significant at 1%.

6 Conclusion

In 1973, under the leadership of the United States and the United Kingdom, governments around the world came together to increase global cooperation in protecting biodiversity and established the CITES convention. Since then, more and more countries have joined the Convention–which today has 184 signatories–and an increasing number of trade restrictions on wildlife have been imposed (Brondízio et al., 2019). Concurrently, mounting scientific evidence has shown that we are experiencing, for the first time, a human-induced mass extinction (Ceballos et al., 2015). While the urgency of protecting biodiversity continues to grow and restrictive conservation policies are being adopted widely (Waldron, 2020), little is known about the harmful externalities associated with many of these policies (Frank and

Oremus, 2023). For instance, they can alter market structures and incentives, potentially leading to unintended consequences.

This paper is the first to document the conflict effects—a negative and harmful externality—of a widely adopted global biodiversity protection mechanism. The paper shows that the policy fuels local conflict and violence, likely by making such activities financially feasible. Moreover, the study reveals several dimensions of heterogeneity that policymakers could exploit to mitigate these harmful side effects and suggests a concrete mitigation strategy using targeted bans.

Importantly, this does not mean that CITES policies are inherently harmful; rather, it highlights the need to evaluate them through a cost-benefit lens, taking their externalities into account. The conflict externality documented in the paper is one example of the potential costs that need to be considered—particularly in light of growing evidence of environmental degradation and the urgent need to allocate resources effectively for conservation. Ultimately, any restriction-based conservation policy has the potential to generate some form of negative externality, underscoring the importance of future research that assesses both the costs and benefits of environmental protection efforts.

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Appendix

Wildlife and Conflict: The Violent Cost of Biodiversity Protection Policies

Guy Pincus

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A Descriptive Statistics

This section reports descriptive statistics related to the main estimates presented in the paper. Table A.1 shows policy dates and the level of imposed restrictions, and Tables A.2 and A.3 provide summary statistics. Figures A.1, A.2, and A.3 show conflict spatial distributions, wildlife spatial distribution in the Democratic Republic of the Congo, and wildlife prices, respectively.

Policy Timeline

Table A.1: Policy Timeline

	Date Announce	Date Enforce	Appendix
Protected Trees			
Luxury			
Swietenia Humilis	1975	1975	II
Pericopsis Elata	1991	1991	II
Dalbergia Nigra	1991	1991	I
Swietenia Mahagoni	1992	1992	II
Prunus	1994	1994	II
Swietenia Macro	1995	1995	II
Agarwood	2004	2004	II
Aniba	2009	2009	II
Diospyros	2013	2013	II
Pterocarpus	2016	2016	II
Dalbergia	2016	2016	II
Industrial			
Abies	1975	1975	II
Araucaria	1975	1975	II
Fitzroya	1975	1975	II
Pilgerodendron	1975	1975	II
Podocarpus P.	1975	1975	II
Podocarpus N.	1975	1975	II
Guaiacum	2002	2002	II
Gonystylus	2004	2004	II
Taxus	2004	2004	II
Gonopterodendron	2010	2010	II
Fraxinus	2014	2014	II
Cedrela	2019	2019	II
Handroanthus	2022	2022	II
Wild Animals			
Crocodile	1975	1975	I
Asian Elephants	1977	1977	I
African Elephants	1977	1977	II
Rhino	1977	1977	I
African Elephants	1989	1990	I
Hippo	1994	1994	II
African Elephants	1998	1999	Stock Release
Pangolin (Manis)	1999	1999	I
Abalone	2006	2006	III
African Elephants	2007	2008	Stock Release
African Elephants	2017	2017	China Ban

Notes: The table reports the dates and levels of trade restrictions imposed on species included in the sample.

Summary Statistics

Table A.2: Descriptive Statistics: Global

	N	Mean	St. Dev.	Control − Treatment
Pr(Conflict > 0) ACLED				
All Cells	784,742	0.0557	0.2294	
If Wild Animals = 0	649,794	0.0457	0.2088	-0.0585^{***}
If Wild Animals > 0	134,948	0.1042	0.3055	(0.0010)
If Wild Trees = 0	627,126	0.0399	0.1957	-0.0788^{***}
If Wild Trees > 0	157,616	0.1188	0.3235	(0.0010)
If Industrial Mine = 0	248,250	0.0770	0.2666	-0.0838^{***}
If Industrial Mine > 0	4,875	0.1608	0.3674	(0.0040)
Pr(Conflict > 0) UCDP				
All Cells	3,375,400	0.0120	0.1088	
If Wild Animals = 0	3,189,060	0.0099	0.0991	-0.0374^{***}
If Wild Animals > 0	186,340	0.0474	0.2124	(0.0001)
If Wild Trees = 0	3,010,000	0.0090	0.0944	-0.0278^{***}
If Wild Trees > 0	365,400	0.0368	0.1882	(0.0001)
If Industrial Mine = 0	248,250	0.0378	0.1908	0.0101^{***}
If Industrial Mine > 0	4,875	0.0277	0.1641	(0.0030)
Pr(Conflict > 0) GTD				
All Cells	5,014,880	0.0082	0.0902	
If Wild Animals = 0	4,738,032	0.0074	0.0858	-0.0144^{***}
If Wild Animals > 0	276,848	0.0218	0.1461	(0.0001)
If Wild Trees = 0	4,472,000	0.0057	0.0752	-0.0233^{***}
If Wild Trees > 0	542,880	0.0290	0.1678	(0.0001)
If Industrial Mine = 0	248,250	0.0244	0.1541	0.0001
If Industrial Mine > 0	4,875	0.0242	0.1537	(0.0001)
Resources Distribution (Cross-Section)				
Wild Animals > 0	5,324	0.0552	0.2284	
Wild Trees > 0	10,440	0.1083	0.3107	
Industrial Mine > 0	195	0.0019	0.1374	

Notes: The table reports conditional and unconditional probabilities of conflict incidence based on the ACLED, UCDP, and GTD datasets, as well as resource distributions.

Table A.3: Descriptive Statistics: Africa

	N	Mean	St. Dev.	Control − Treatment
Pr(Conflict > 0) ACLED				
All Cells	343,952	0.0789	0.2696	
If Wild Animals = 0	269,724	0.0725	0.2593	-0.0297^{***}
If Wild Animals > 0	74,228	0.1022	0.3029	(0.0012)
If Wild Trees = 0	269,612	0.0636	0.2440	-0.0709^{***}
If Wild Trees > 0	74,340	0.1344	0.3411	(0.0013)
If Industrial Mine = 0	339,077	0.0777	0.2677	-0.0831^{***}
If Industrial Mine > 0	4,875	0.1608	0.3674	(0.0053)
High State Capacity	98,980	0.0514	0.2209	-0.0397^{***}
Low State Capacity	241,640	0.0911	0.2878	(0.0008)
Pr(Conflict > 0) UCDP				
All Cells	429,940	0.0338	0.1808	
If Wild Animals = 0	337,155	0.0328	0.1780	-0.0050^{***}
If Wild Animals > 0	92,785	0.0378	0.1906	(0.0007)
If Wild Trees = 0	337,015	0.0306	0.1723	-0.0149^{***}
If Wild Trees > 0	92,925	0.0456	0.2085	(0.0008)
If Industrial Mine = 0	425,065	0.0339	0.1810	0.0062^{***}
If Industrial Mine > 0	4,875	0.0277	0.1641	(0.0024)
High State Capacity	123,725	0.0107	0.1032	-0.033^{***}
Low State Capacity	302,050	0.0437	0.2044	(0.0004)
Pr(Conflict > 0) GTD				
All Cells	638,768	0.0133	0.1145	
If Wild Animals = 0	500,916	0.0131	0.1136	-0.0009^{***}
If Wild Animals > 0	137,852	0.0140	0.1176	(0.0004)
If Wild Trees = 0	500,708	0.0111	0.1046	-0.0103^{***}
If Wild Trees > 0	138,060	0.0213	0.1444	(0.0004)
If Industrial Mine = 0	633,893	0.0132	0.1141	-0.0110^{***}
If Industrial Mine > 0	4,875	0.0242	0.1537	(0.0022)
High State Capacity	183,820	0.0078	0.0884	-0.0078^{***}
Low State Capacity	448,760	0.0156	0.1241	(0.0002)
Resources Distribution (Cross-Section)				
Wild Animals > 0	2,651	0.2158	0.4114	
Wild Trees > 0	2,655	0.2161	0.4116	
Industrial Mine > 0	195	0.0159	0.1250	
State Capacity & Precious Trees				
Wild Trees Distribution| High=1	759,330	0.0587	0.2351	0.017^{***}
Wild Trees Distribution| Low=0	1,346,026	0.0417	0.1999	(0.0003)

Notes: The table reports conditional and unconditional probabilities of conflict incidence based on the ACLED, UCDP, and GTD datasets, resource distributions across Africa, and the distribution of wild trees across high- and low-capacity states.

Conflicts Spatial Distributions

Figure A.1: Spatial Distributions of UCDP Conflict Events

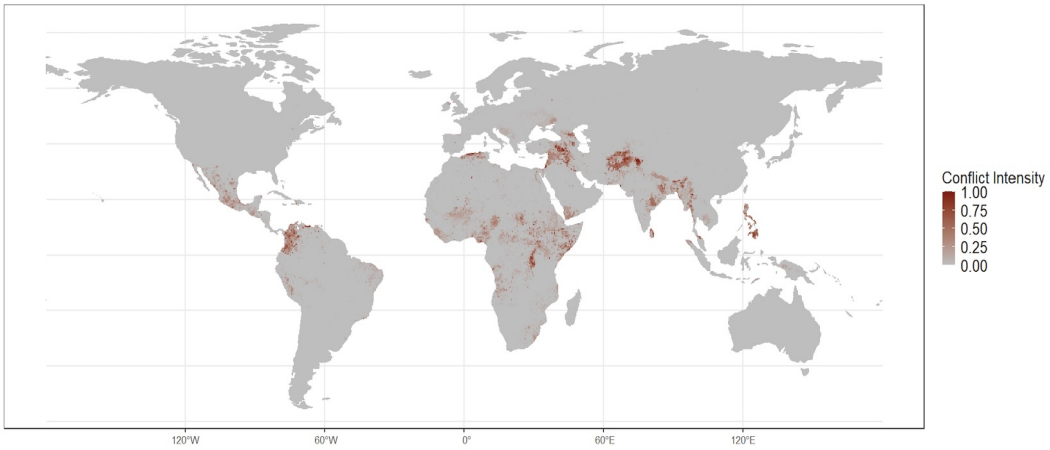
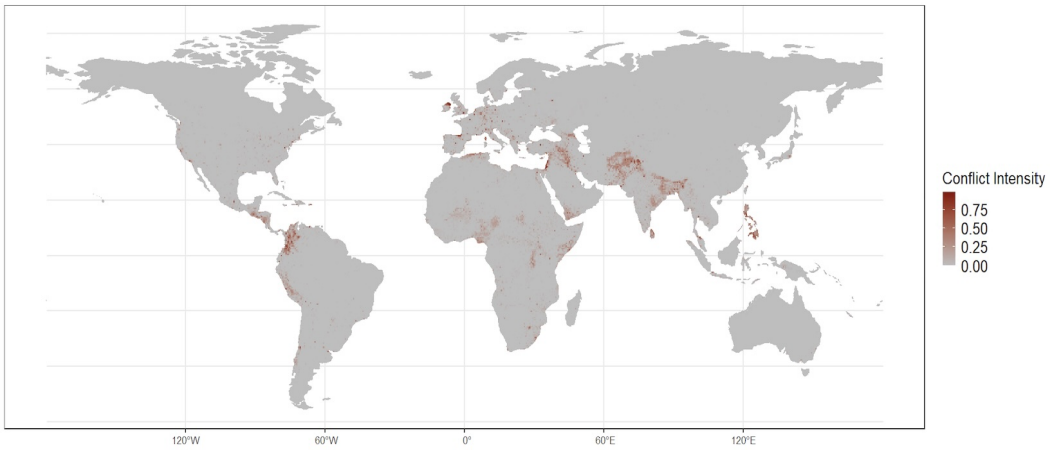


Figure A.2: Spatial Distributions of GTD Conflict Events



Notes: The maps present the spatial distribution of conflict for UCDP (1989–2023) and GTD (1970–2021). Darker shading indicates cells with a higher proportion of years featuring at least one conflict incident.

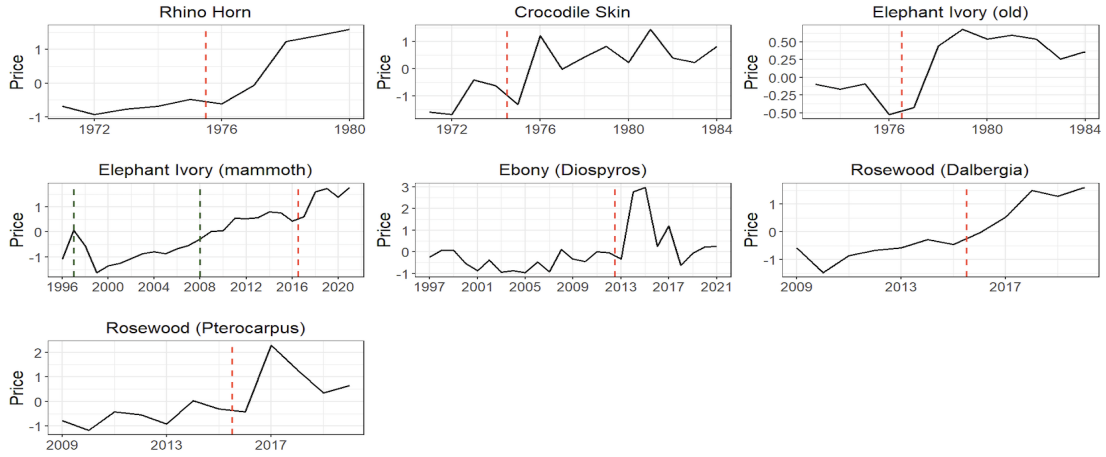
Table A.4: Conflict Correlogram

	ACLED	UCDP	GTD
ACLED	1	0.314***	0.259***
UCDP		1	0.421***
GTD			1

Notes: Entries show pairwise Pearson correlations between conflict datasets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Wildlife Prices

Figure A.3: Trade Restrictions and Wildlife Prices



Wild Animals and Endangered Trees

Notes: The figure depicts detrended wildlife prices alongside policy changes (in red). The top (bottom) row depicts wild animal (tree) prices.

B Further Results

This section reports additional results documented throughout the analysis, shedding more light on the conflict-wildlife nexus. Table B.1 follows the empirical approach of Berman et al. (2017), using wildlife prices as a source of time variation, while Table **??** reports a one-by-one price shock analysis. Table B.3 provides one-by-one long-difference estimates for individual wildlife species.

Table B.4 provides suggestive evidence that the demand for ivory is price-inelastic. I use two partially restrictive policy shocks (in 1977 and 1984) and import data from Hong Kong and Japan to estimate the price elasticity of demand using a 2SLS specification. Total traded volume increased following the shocks.

Figure B.1 provides evidence of substitution between elephant and hippo ivory, showing an increase in reported traded volumes of hippo teeth following restrictive policy in the elephant ivory market.

Table B.5 provides evidence of substitution between ivory-related and mineral-related conflicts. I interact the contractionary policy years in the ivory market with a distance measure between elephant habitat and the nearest industrial mineral site. The positive coefficient implies that in years of reduced conflict in elephant regions, there is an increase in conflict in nearby industrial mineral regions.

Finally, Figure B.2 provides suggestive evidence on the link between organised crime and the ivory trade, and how this nexus evolved over time. I plot the share of large confiscations out of total confiscations, showing a clear increase over time, which suggests that the involvement of criminal syndicates in the trade increased over time.[22]

[22]The analysis relies on the assumption that large-scale smuggling requires logistical capacity that small-scale smugglers do not possess.

Wildlife Price Shocks and Conflict Events

Table B.1: Wildlife Price Shocks and Conflict Likelihood

	Dep. Var.: Conflict (0/1)								
	ACLED			UCDP			GTD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Habitat × *Price*	0.0063***	0.0063***	0.0081***	0.0022***	0.0022***	0.0027***	0.0030***	0.0030***	0.0040***
	(0.0015)	(0.0015)	(0.0017)	(0.0007)	(0.0007)	(0.0009)	(0.0006)	(0.0006)	(0.0008)
	[0.0013]	[0.0013]	[0.0015]	[0.0007]	[0.0007]	[0.0008]	[0.0007]	[0.0007]	[0.0008]
Habitat Around × *Price*			0.0059***			0.0015**			0.0028***
			(0.0011)			(0.0007)			(0.0006)
			[0.0012]			[0.0006]			[0.0006]
Mineral × *Price*		0.0272***	0.0207***		0.0008	0.0004		0.0016	0.0006
		(0.0065)	(0.0060)		(0.0033)	(0.0033)		(0.0025)	(0.0026)
		[0.0059]	[0.0057]		[0.0032]	[0.0032]		[0.0025]	[0.0026]
Mineral Around × *Price*			0.0138***			0.0006			0.0018
			(0.0032)			(0.0032)			(0.0026)
			[0.0023]			[0.0019]			[0.0015]
Dep. Var. Mean	0.0531	0.0531	0.0531	0.0117	0.0117	0.0117	0.0081	0.0081	0.0081
Dep. Var. SD	0.2243	0.2243	0.2243	0.1075	0.1075	0.1075	0.0890	0.0890	0.0890
Cell FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	751,939	751,939	751,939	3,334,380	3,334,380	3,334,380	4,953,936	4,953,936	4,953,936

Notes: The table reports LPM estimates using OLS. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *price* denotes the log price of the corresponding wildlife species w in cell k at time t. The variable *Mineral* × *Price* captures the industrial mineral price shock (Berman et al., 2017). The *Around* variables indicate spatial lags. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column titles. Standardised coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. Standard errors in square brackets are clustered at the country-year and cell levels, allowing for spatial correlation within a country and infinite serial correlation within a cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table B.2: Wildlife Price Shocks and Conflict Likelihood: Disaggregated Estimates

	Dep. Var.: GTD Conflict Indicator (0/1)							
	African Elephant	Asian Elephant	Hippo	Rhino	Crocodile	Dalbergia	Pterocarpus	Diospyros
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Habitat × *Price*	0.0060***	0.0168***	0.0074***	−0.0020***	0.0018***	0.0077***	0.0047***	0.0028***
	(0.0017)	(0.0032)	(0.0030)	(0.0006)	(0.0006)	(0.0011)	(0.0013)	(0.0005)
Around × *Price*	0.0061***	0.0017	0.0082***	−0.0010	0.0011**	0.0029***	0.0012	0.0010
	(0.0018)	(0.0017)	(0.0021)	(0.0011)	(0.0005)	(0.0008)	(0.0008)	(0.0005)
Composite Wildlife Index	0.0032***	0.0035***	0.0030***	0.0030***	0.0027***	0.0026***	0.0028***	0.0042***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0006)	(0.0016)
Dep. Var. Mean	0.0082	0.0082	0.0082	0.0082	0.0082	0.0082	0.0082	0.0082
Dep. Var. SD	0.0902	0.0902	0.0902	0.0902	0.0902	0.0902	0.0902	0.0902
Cell FE	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,507,440	2,507,440	2,507,440	964,400	4,822,000	964,400	964,400	2,411,000

Note: The table reports LPM estimates using OLS separately for the different wildlife species. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *price* denotes the log price of the corresponding wildlife species w in cell k at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the GTD dataset. In each column, the treatment group is restricted to the wildlife referenced in the title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Wildlife Trade Restrictions and Conflicts: One by One Long Difference Estimates

Table B.3: Wildlife Trade Restrictions & Conflict: Difference in Differences One-by-One Estimates

	GTD Conflict (0/1)							
	Crocodile	Asian Elephant	African Elephant	Rhino	Hippo	Pangolin	Abalone	
Panel A: Wild Animals	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
$Habitat \times Post_1$	0.0022***	−0.0006	0.0312***	-0.0011	0.0042*	0.003	0.012	
	(0.001)	(0.0021)	(0.0071)	(0.0013)	(0.0024)	(0.0052)	(0.0254)	
$Habitat \times Post_2$	0.0095***	0.0371***	0.0219***	0.0106	0.0025	0.0322***	-0.0628	
	(0.0023)	(0.0098)	(0.0073)	(0.009)	(0.0032)	(0.0111)	(0.0149)	
Cell FE	Y	Y	Y	Y	Y	Y	Y	
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	
Observations	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	
	S. Humilis	P. Elata	D. Nigra	Prunus	S. Mahagon	S. Macro	Agra	Aniba
Panel B: Wild Luxury Trees	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$Habitat \times Post_1$	0.04***	0.0085	0.0032	0.0401***	0.022	0.0156*	0.0166*	0.001
	(0.0148)	(0.0097)	(0.0033)	(0.01133)	(0.015)	(0.0091)	(0.012)	(0.0027)
$Habitat \times Post_2$	0.0321***	0.0096	−0.0066	0.0209***	0.0098	0.0005	0.0417***	−0.0005
	(0.0121)	(0.0171)	(0.0042)	(0.0115)	(0.0137)	(0.0089)	(0.014)	(0.0087)
Cell FE	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880
	Luxury Trees				Industrial Trees			
	Diospyros	Pterocarpus	Dalbergia		Abies	Araucaria	Fitzr	Pilger
Panel C: Wild Luxury & Industrial Trees	(17)	(18)	(19)		(21)	(22)	(23)	(24)
$Habitat \times Post_1$	0.0017	0.0176***	0.0212***		0.0102	0.0248***	0.0013	−0.0127*
	(0.0019)	(0.0046)	(0.0032)		(0.0104)	(0.0101)	(0.0106)	(0.0073)
$Habitat \times Post_2$	0.0103***	0.0121***	0.0091***		0.0119	0.0201*	0.0054	−0.0178
	(0.0021)	(0.0049)	(0.003)		(0.0157)	(0.0118)	(0.0087)	(0.0118)
Cell FE	Y	Y	Y		Y	Y	Y	Y
Country-Year FE	Y	Y	Y		Y	Y	Y	Y
Observations	5,014,880	5,014,880	5,014,880		5,014,880	5,014,880	5,014,880	5,014,880
Panel D: Wild Industrial Trees	P. Parlatorei	Guaiacum	Gonystylus	Taxus	Gonopter	Fraxinus	Cedrela	
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	
$Habitat \times Post_1$	-0.0105	-0.0016	0.0105	-0.009*	-0.0058	0.0024	-0.0163***	
	(0.0126)	(0.0055)	(0.0177)	(0.0049)	(0.0043)	(0.0029)	(0.0052)	
$Habitat \times Post_2$	-0.0447	0.0013	0.0168	−0.0017	−0.0082	0.0002	−0.0041	
	(0.0254)	(0.0058)	(0.0191)	(0.0025)	(0.0048)	(0.0018)	(0.0048)	
Cell FE	Y	Y	Y	Y	Y	Y	Y	
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	
Observations	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	5,014,880	

Notes: The table reports LPM estimates using difference-in-differences. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and $Post_1$ indicates the three years following the imposition of CITES trade restrictions on wildlife species w. $Post_2$ indicates all subsequent periods, capturing the average long-term effect of the policy on conflicts. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the GTD conflict dataset. Panel A reports estimates for wild animals, whereas the other panels report estimates for different tree species. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Suggestive Evidence on Ivory Demand Elasticity

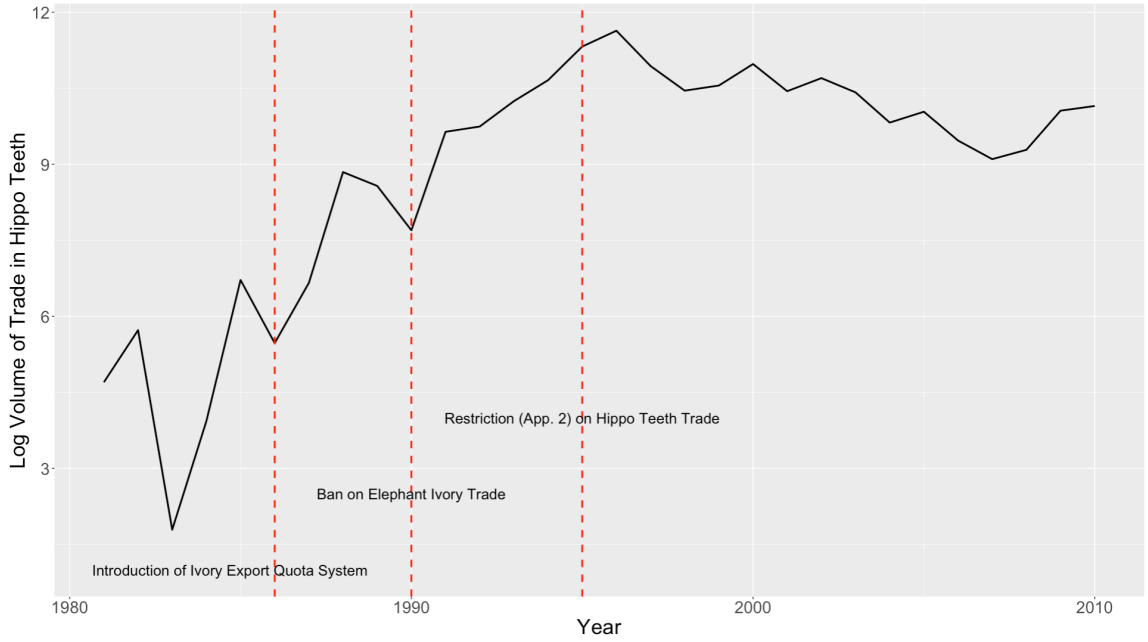
Table B.4: Elephant Ivory Elasticity Analysis Based on Pre-Ban Imports to Japan and Hong Kong: 2SLS

	log(Ivory Revenue)	*log(Ivory Quantity)*
	(1)	(2)
Panel A: 2SLS		
Coefficient	1.3455***	0.3455
Panel B: First Stage		
Policy → Price	1.4556***	1.4556***
F-statistic	24.8	24.8
Panel C: Reduced Form		
Coefficient	1.9585***	0.5029
Panel D: OLS		
Coefficient	1.3246***	0.3246
Country Fixed Effects	Y	Y
Observations	70	70

Notes: The table provides empirical evidence suggesting that the demand for ivory is price-inelastic, based on pre-ban import data from Hong Kong and Japan. Panel A presents 2SLS estimates, using policy shocks as instruments, with the unit of observation being the log of total value and the log of total weight of imported ivory. Specifications include country fixed effects. Panel B shows the first-stage estimates and the F-statistic. Panel C reports the reduced-form estimates, and Panel D shows the OLS results. All standard errors are Newey-West to account for serial correlation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Suggestive Evidence of Substitution between Elephant and Hippo Ivory

Figure B.1: Substitution of Elephant Ivory to Hippo Ivory



Notes: The figure shows the overall (log) export of hippo teeth from African countries to the rest of the world, measured in tonnes. The three vertical lines indicate different policy shocks. The first line marks the introduction of the ivory export quota system in 1984–1985. The second line marks the ban (Appendix I) on international trade in ivory in 1989. The third red line marks CITES's restriction on international trade in hippo teeth (Appendix II).

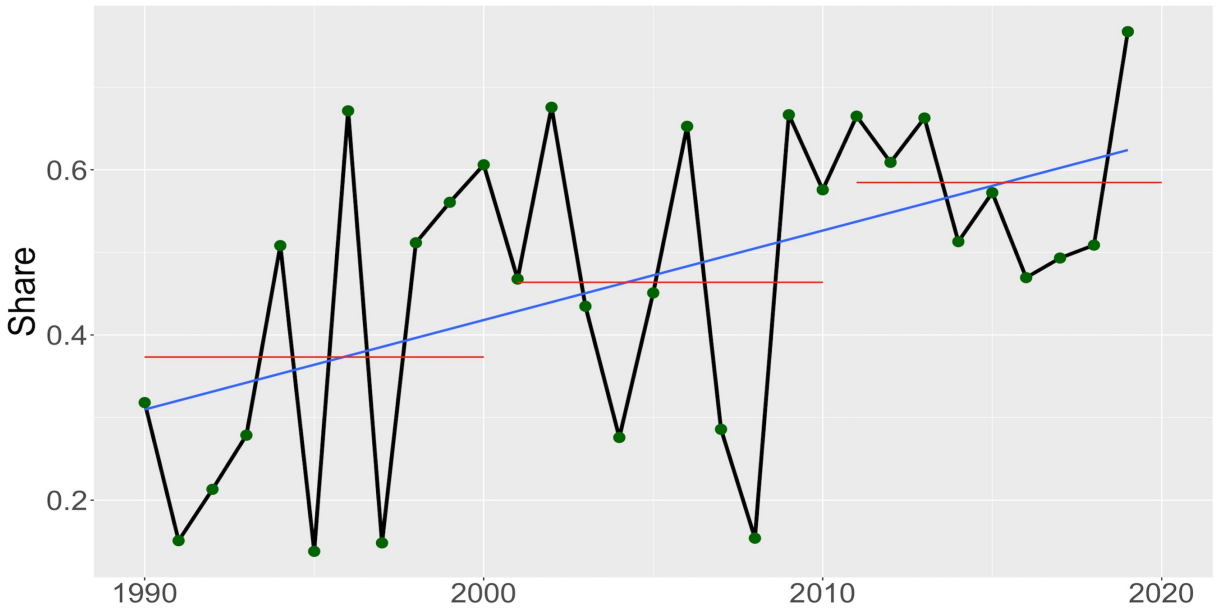
Suggestive Evidence of Conflict Substitution between Elephant Ivory and Industrial Minerals

Table B.5: Substitution between Ivory and Mineral Related Conflict Events in Africa

	ACLED Incident Indicator (1–3)			ACLED Onset Indicator (4–6)		
	(1)	(2)	(3)	(4)	(5)	(6)
Sales × Elephant Cell	−0.023***	−0.015***	−0.015***	−0.012***	−0.009***	−0.009***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Sales × Distance Mine–Elephant	0.005***	0.003***	0.003***	0.002***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p^{Ivory} × Elephant Cell		0.008***	0.016***		0.003	0.007
		(0.005)	(0.006)		(0.003)	(0.004)
p^{Ivory} × Elephant Around Cell			0.017***			0.008***
			(0.006)			(0.004)
p^{Mine} × Mine Cell		0.042***	0.037***		0.023***	0.020***
		(0.006)	(0.007)		(0.004)	(0.004)
p^{Mine} × Mine Around Cell			0.012***			0.007***
			(0.005)			(0.002)
Mean Dep. Var.	0.0788	0.0788	0.0788	0.0451	0.0451	0.0451
SD Dep. Var.	0.264	0.264	0.264	0.208	0.208	0.208
Cell FE	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y
Observations	258,375	258,375	258,375	241,232	241,232	241,232

Notes: The table presents estimates showing substitution by armed groups between industrial minerals and ivory. Outcome variables measure conflict at the cell-year level. Columns 1–3 use an indicator for conflict incidents; columns 4–6 use an indicator for conflict onset. Columns 2 and 5 control for elephant ivory and industrial mineral price shocks (Berman et al. 2017); columns 3 and 6 additionally control for neighbouring areas of elephant habitat and industrial minerals. All specifications include interactions of supply shocks with elephant habitat and a negative distance measure between mining and elephant cells. All models include cell and country-year fixed effects. Standardised coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure B.2: Share of Large Confiscations over Time



Notes: The figure depicts the share of large ivory confiscations (above 0.5 tonnes) from the total amount of confiscations at the annual level. The blue line indicates the relationship between the share and time, and the red horizontal lines indicate decade-level averages.

C Complementary Result Tables

This section presents supplementary tables that support the main results of the paper. Table C.1 reports difference-in-differences estimates for the confiscation analysis, Table C.2 shows difference-in-differences policy-price estimates, Table C.4 reports difference-in-differences policy-conflict estimates for high and low capacity states, and Table C.3 reports precious trees harvested quantities synthetic control estimates. Table C.1 presents event-study estimates for the distance analysis, complementing Table 3.

Table C.1: Trade Restrictions and Wildlife Confiscations

	Dep. Var.: log(# Confiscation Events)		
	(1)	(2)	(3)
Habitat × *Policy*	1.6556***	0.7512**	0.6923***
	(0.2216)	(0.34752)	(0.21442)
Resource FE	Y	N	Y
Year FE	N	Y	Y
Observations	52	52	52

Note: The table reports difference-in-differences estimates for the effect of CITES trade restrictions on wildlife confiscations (*Diospyros* (ebonies), *Dalbergia* (rosewood), and elephant ivory). Standard errors are Newey-West, allowing for infinite-order serial correlation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.2: Trade Restrictions and Wildlife Prices: Difference-in-Differences

	Dep. Var.: Log Prices					
	Wild Animals			Wild Trees		
	(1)	(2)	(3)	(4)	(5)	(6)
$Wildlife \times Policy$	0.582***	1.806***	1.117***	0.125***	1.367***	1.030***
	(0.167)	(0.393)	(0.162)	(0.131)	(0.238)	(0.124)
Resource FE	N	Y	Y	N	Y	Y
Year FE	Y	N	Y	Y	N	Y
Observations	386	386	386	549	549	549

Notes: The table reports estimates using the Borusyak et al. (2024) imputation difference-in-differences estimator. Each observation corresponds to a resource-year (wildlife, and World Bank timber or precious metals prices as controls). $Wildlife \times Policy$ is an interaction of wildlife w with its corresponding policy indicator, indicating the timing of CITES trade restrictions imposed on wildlife w. The control group for wild animals is precious metals (gold, silver, and platinum), and for wild precious trees it is the World Bank hard tropical timber index. Standard errors are Newey-West, allowing for infinite serial correlation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.3: Trade Restrictions and the Harvesting of Precious Trees by State Capacity: A Synthetic Difference-in-Differences Analysis

	Dep. Var.: log(deforestation + 1)		
	Aggregate	High Capacity	Low Capacity
	(1)	(2)	(3)
$Habitat \times Policy$	-0.0058^{**}	-0.097^{***}	0.055^{**}
	(0.008)	(0.031)	(0.025)
Cell FE	Y	Y	Y
Country-Year FE	Y	Y	Y
Observations	1,304,314	423,016	881,298
Dep. Var. Mean	2.13	1.762	2.31
Dep. Var. SD	1.899	1.852	1.896

Note: The table reports synthetic control difference-in-differences estimates using the Ben-Michael et al. (2021) estimator. Each observation corresponds to a cell-year. The variable $Habitat$ is an indicator measuring the suitability of cell k for wild tree species w, and $Policy$ indicates the timing of CITES trade restrictions imposed on wildlife species w at time t. The dependent variable is the annual log of deforested 30×30 cells within a larger $0.15° \times 0.15°$ cell. The sample is restricted to African countries, with column 1 showing aggregate quantities, column 2 showing estimates restricted to above-median-capacity states, and column 3 showing estimates restricted to below-median-capacity states. Coefficients are reported with standard errors which are computed using the wild bootstrap, following the procedure for synthetic control estimators in Ben-Michael et al. (2021).* significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.4: Wild Trees Trade Restrictions and Conflict Likelihood by State Capacity: Difference-in-Differences

	Dep. Var.: Conflict (0/1)					
	High Capacity			Low Capacity		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
	(1)	(2)	(3)	(4)	(5)	(6)
Habitat × *Policy*	0.0015	−0.0061	0.0054*	0.0331***	0.0163***	0.0264***
	(0.0036)	(0.0036)	(0.0030)	(0.0069)	(0.0063)	(0.0057)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	131,663	166,342	250,741	191,137	242,541	367,459
Dep. Var. Mean	0.0199	0.0135	0.0075	0.0516	0.0337	0.0114
Dep. Var. SD	0.1398	0.1154	0.0862	0.2212	0.1805	0.1062

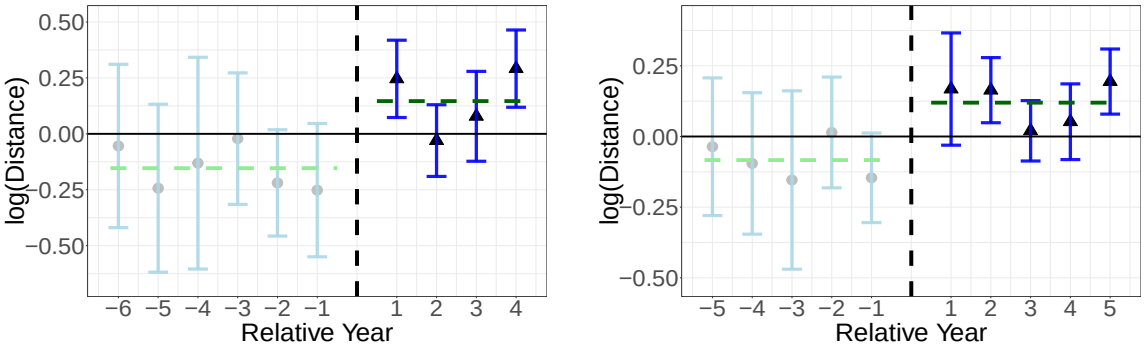
Notes: The table reports LPM estimates using the Borusyak et al. (2024) imputation difference-in-differences estimator. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife species w at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column title. The sample is restricted to African countries, where columns 1–3 are associated with above-median capacity states, and columns 4–6 are associated with below-median capacity states. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.5: Wildlife Trade Restrictions and Conflict Likelihood: Difference-in-Differences

	Dep. Var.: Conflict (0/1)		
	Wild Trees: Only Africa Sample		
	ACLED	UCDP	GTD
	(1)	(2)	(3)
Habitat × *Policy*	0.053***	0.0091	0.0233***
	(0.0063)	(0.0054)	(0.00459)
Cell FE	Y	Y	Y
Country-Year FE	Y	Y	Y
Observations	343,952	429,940	638,768
Dep. Var. Mean	0.0789	0.0338	0.0133
Dep. Var. SD	0.26	0.1808	0.1145

Notes: The table reports linear probability model (LPM) estimates using the imputation-based difference-in-differences estimator of Borusyak et al. (2024), with treatment defined as the imposition of CITES trade restrictions on species, covering only wild trees in Africa. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife species w at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. Standard errors reported in square brackets are clustered at the country-year and cell levels, allowing for within-country spatial correlation and infinite serial correlation within a cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure C.1: Distance Analysis Event Study



(a) Elephant Ivory 2017 Ban **(b)** Rosewood 2016 Ban

Notes: The figure reports a simple fixed-effects event study estimate with log distance as the outcome. Panel (a) presents the estimates for the 2017 ivory ban, and Panel (b) presents the estimates for rosewood. The omitted period is the year prior to the policy announcement. Error bars denote 95% confidence intervals, based on two-way clustered standard errors at the group and country-year levels.

D Sensitivity Checks

This section discusses alternative specifications and assesses the robustness of the paper's main estimates.

Predictive Power of Wildlife Habitat on Country-Level Stocks

One concern with the identification strategy based on wildlife habitat classification,

One concern with identification that relies on habitat data is whether these measures predict observed wildlife abundance. Unfortunately, granular data on wildlife stocks is unavailable. Table D.1 examines whether the country-level count of habitat-suitable grid cells predicts country-level wildlife stocks for the four species with available stock data. The estimates indicate that habitat suitability is a strong predictor of stock.

Table D.1: Wildlife Habitat and Country-Level Wildlife Stock

	Dep. Var.: Log (Country-Level Stocks + 1)			
	Diospyros	Dalbergia	Pterocarpus	Elephant
	(1)	(2)	(3)	(4)
log (# Diospyros cells + 1)	0.0134***			
	(0.0026)			
log (# Dalbergia cells + 1)		0.0297***		
		(0.0047)		
log (# Pterocarpus cells + 1)			0.0485[a]	
			(0.0038)	
log (# Elephant cells + 1)				0.0428***
				(0.0031)
Constant	1.9706***	1.8719***	1.0281***	0.8199***
	(0.2012)	(0.2160)	(0.1447)	(0.1922)
Observations	50	50	50	35
R^2	0.3563	0.4529	0.7748	0.5242
Adjusted R^2	0.3429	0.4415	0.7701	0.5215

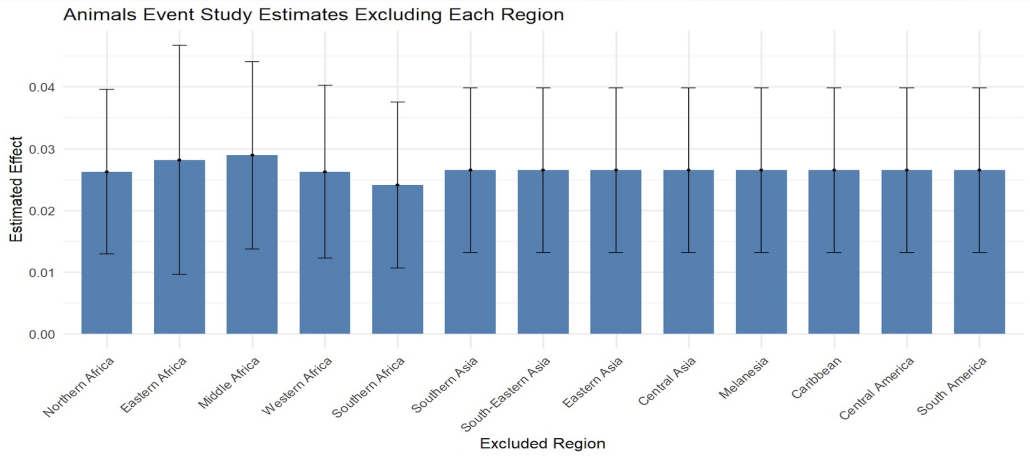
Notes: The table reports OLS estimates showing the correlation of the log number of cells per country suitable for wildlife species w (based on a binary variable), with the country-level stock of that resource. * significant at 10%; ** significant at 5%; *** significant at 1%.

Exogeneity of Policy

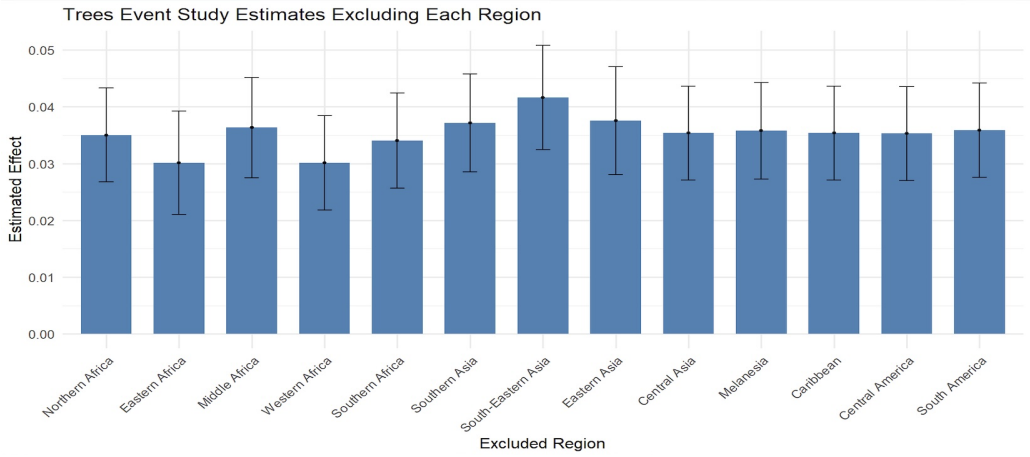
Another identification concern is the exogeneity of the policy with respect to conflicts. Given the way it operates, it is unlikely that CITES intentionally targets conflict regions or specific conflict events in its policies. First, CITES decisions are largely political and require a 66% majority. Second, Frank and Wilcove (2019) documents an average delay of 10 years between species extinction and the imposition of CITES trade restrictions.

Third, CITES meets every three years based on a pre-determined schedule. Fourth, a text analysis of CITES protocols reveals no explicit mention of armed conflict or armed groups in official meeting records. Taken together, these institutional features make the assumption of quasi-exogenous policy timing plausible. To further ensure that the estimates are not driven by any particular region targeted by CITES, I replicate the estimates from Table 1 and iteratively exclude different sub-regions from the analysis. Figure D.1 demonstrates the robustness of the estimates to this exercise.

Figure D.1: Wildlife Trade Restrictions and Conflict Likelihood: Sequential Exclusion of Subregions



(a) Wild Animals



(b) Wild Precious Trees

Notes: The figure reports LPM estimates using the staggered event study imputation estimator (Borusyak et al., 2024). Each bar reports a point estimate, excluding one sub-continental region at a time. Each observation corresponds to a cell-year. The estimates are based on specification 2, with the interaction term $Habitat \times Policy$, an indicator explaining conflict probability. The omitted period is the year prior to the policy announcement. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the ACLED dataset. Error bars indicate 95% confidence intervals, with standard errors that are spatially clustered to allow for spatial and temporal correlation within a 500 km radius of each cell's centroid.

Measurement Error and Sensitivity to Cell-Size

Another concern when using wildlife habitat as a proxy for treatment exposure is the potential for measurement error. Table D.2 reports country-level shift-share style estimates. For each country I sum the total number of cells suitable for a given wildlife, and multiply it by the post-policy years for this wildlife. I then sum this variable across country-year to create a wildlife-weighted country-year level exposure to the policy, and due to the skewness of the distribution, take its log. The outcome variable is country-year log conflict events. Furthermore, to mitigate concerns regarding grid choice, I construct alternative grids, with $0.25° \times 0.25°$ and $1° \times 1°$ degree size. Tables D.3 and D.4 report estimates, consistent with the paper's main results.

Table D.2: Wildlife Trade Restrictions and Conflict Events: Country-Level Estimates

	Dep. Var.: log (# Country-Year Conflict Events + 1)					
	Wild Animals			Wild Trees		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
log (*Policy Exposure* + 1)	0.4533**	0.2229*	0.16359***	0.4362***	0.5172**	0.4695**
	(0.0419)	(0.1285)	(0.0419)	(0.1228)	(0.2065)	(0.1790)
Country FE	Y	Y	Y	Y	Y	Y
Subcontinent Region Year FE	Y	Y	Y	Y	Y	Y
Mean Dep. Var.	1.9861	1.0345	0.7624	1.9861	1.0345	0.7624
SD Dep. Var.	1.5140	1.3993	1.1307	1.5140	1.3993	1.1307
Observations	2,024	3,710	5,512	2,024	3,710	5,512

Notes: The table reports LPM estimates using OLS. Each observation corresponds to a country-year. The variable *Policy Exposure* ranks countries by their total, wildlife-weighted annual exposure to the policy. The outcome is the log number of conflict events in a given country-year, based on the conflict dataset mentioned in the title. Coefficients are reported with two-way clustered standard errors (in parentheses), clustered at the levels of the fixed effects. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table D.3: Wildlife Trade Restrictions and Conflict Likelihood at $0.25° \times 0.25°$ Resolution

	Dep. Var.: Conflict (0/1)					
	Wild Animals			Wild Trees		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
	(1)	(2)	(3)	(4)	(5)	(6)
Habitat × *Policy*	0.0204***	0.0099***	0.0116***	0.0272***	0.0063***	0.0107***
	(0.0053)	(0.0036)	(0.0031)	(0.0033)	(0.0022)	(0.0018)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	5,723,880	13,355,720	19,842,784	5,740,920	13,395,480	19,901,856
Dep. Var. Mean	0.0583	0.0233	0.0134	0.0583	0.0233	0.0134
Dep. Var. SD	0.2037	0.1318	0.1005	0.2037	0.1318	0.1005

Notes: The table reports LPM estimates using the Borusyak et al. (2024) imputation difference-in-differences estimator. Each observation corresponds to a cell-year, with $0.25° \times 0.25°$ cell-size. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife w at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table D.4: Wildlife Trade Restrictions and Conflict Likelihood at 1° × 1° Resolution

	Dep. Var.: Conflict (0/1)					
	Wild Animals			Wild Trees		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
	(1)	(2)	(3)	(4)	(5)	(6)
Habitat × *Policy*	0.0358***	0.0174***	0.0204***	0.0478***	0.0111***	0.0188***
	(0.0092)	(0.0063)	(0.0054)	(0.0057)	(0.0039)	(0.0031)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	357,742	834,732	1,240,174	358,807	837,217	1,243,866
Dep. Var. Mean	0.1022	0.0408	0.0234	0.1022	0.0408	0.0234
Dep. Var. SD	0.3571	0.2311	0.1763	0.3571	0.2311	0.1763

Notes: The table reports LPM estimates using the Borusyak et al. (2024) imputation difference-in-differences estimator. Each observation corresponds to a cell-year, with 1° × 1° cell-size. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife w at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Potential Confounders

Given the broad spatial distribution of wildlife habitat, a potential concern is that it may overlap with other valuable resources—such as gold, minerals, or crops—thereby confounding the estimates. To address this, I exclude all cells geologically suitable for gold production (Girard et al., 2022), as well as those with precious mineral deposits and surrounding areas (Berman et al., 2017).[23] To further mitigate concerns about spatial confounders, I divide the sample into above- and below-median groups based on urban area coverage, crop production, human footprint, and population density, and replicate the difference in differences ACLED estimates within each subsample. Following Eberle et al. (2020), I also exclude all Sahel countries. Estimates are presented in Table D.5. While coefficient magnitudes vary—likely due to reduced sample sizes—the results remain robust across all specifications.

[23] Although the geological suitability map from Girard et al. (2022) is specific to gold, it covers approximately 43% of African grid cells and likely captures other artisanal mining zones as well.

Table D.5: Wildlife Trade Restrictions and Conflict Likelihood: Excluding Potential Confounders

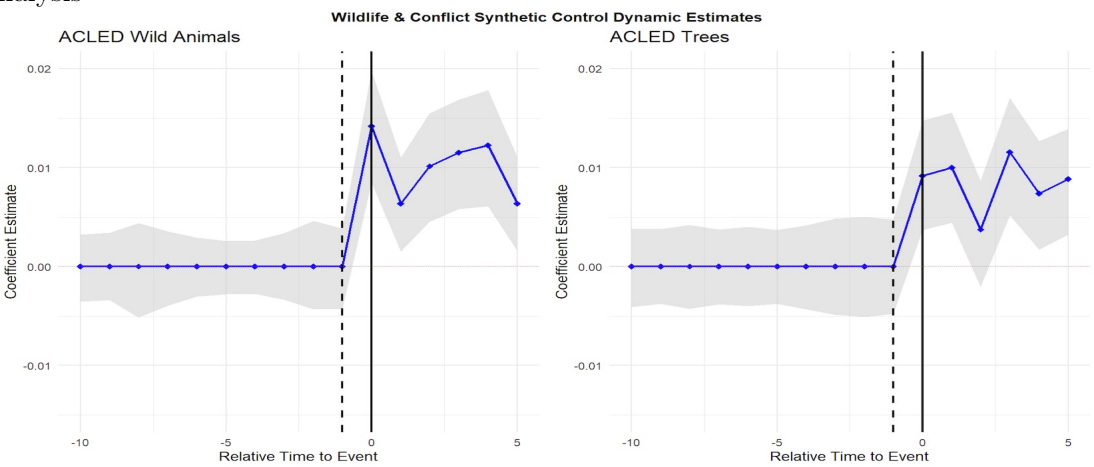
	Dep. Var.: ACLED Conflict (0/1)									
	Built		Crop		Human Footprint		Pop		Gold & Sahel	
	High	Low	High	Low	High	Low	High	Low	Gold	Sahel
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Wild Animals										
Habitat × *Policy*	0.0282***	0.0222***	0.0213***	0.0212***	0.0195**	0.0273***	0.0330***	0.0230***	0.0281***	0.0211***
	(0.0096)	(0.0088)	(0.0077)	(0.0112)	(0.0083)	(0.0095)	(0.0160)	(0.0072)	(0.0088)	(0.0072)
Panel B: Wild Trees										
Habitat × *Policy*	0.0204***	0.0398***	0.0305***	0.0297***	0.0205***	0.0299***	0.0267***	0.0466***	0.0312***	0.0271***
	(0.0049)	(0.0057)	(0.0048)	(0.0058)	(0.0080)	(0.0092)	(0.0047)	(0.0075)	(0.0043)	(0.0042)
Cell FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	261,397	309,042	276,535	299,357	284,670	291,222	241,265	320,450	451,572	436,984
Dep. Var. Mean	0.1142	0.0440	0.1100	0.0441	0.1130	0.0393	0.0936	0.0602	0.0663	0.0792
Dep. Var. SD	0.3180	0.2051	0.3129	0.2052	0.3166	0.1943	0.2912	0.0602	0.2488	0.2701

Note: The table reports LPM estimates using OLS. Each observation corresponds to a cell-year. Each column splits the sample into above- or below-median groups based on the variable indicated in the title. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife w, and *Policy* denotes the timing of CITES trade restrictions imposed on species w. The dependent variable is an ACLED binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and infinite temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Different Control Groups

The global approach—essential for external validity and for capturing a broad range of resources and policy shocks—raises concerns about the adequacy of the control group. To address this, I estimate a staggered event study model using the augmented synthetic control estimator from Ben-Michael et al. (2021), which constructs control groups that exactly match the pre-treatment outcome trends of treated units (Figure D.2 and Table D.6). In Table D.7, I pool wild animals and wild trees, defining treatment as CITES restrictions on either category.

Figure D.2: Wildlife Trade Restrictions and Conflict Likelihood: A Synthetic Control Analysis



Notes: The figure depicts LPM estimates using the staggered event study synthetic control estimator from Ben-Michael et al. (2021). Each observation corresponds to a cell-year. The sample includes 1,430,970 observations for animals and 1,430,970 observations for trees. The estimates are based on specification 2, with the interaction term $Habitat \times Policy$, an indicator explaining conflict probability. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the ACLED dataset. Coefficients are reported with standard errors which are computed using the wild bootstrap, following the procedure for synthetic control estimators in Ben-Michael et al. (2021).

Table D.6: Wildlife Trade Restrictions and Conflict Likelihood: A Synthetic Difference in-Differences Analysis

	Dep. Var.: ACLED Conflict (0/1)	
	Wild Animals	Wild Trees
	(1)	(2)
Habitat × *Policy*	0.005***	0.008***
	(0.001)	(0.002)
Cell FE	Y	Y
Country-Year FE	Y	Y
Observations	1,430,970	1,430,970
Dep. Var. Mean	0.075	0.075
Dep. Var. SD	0.264	0.264

Notes: The figure reports LPM estimates using the staggered event study synthetic control estimator from Ben-Michael et al. (2021). Each observation corresponds to a cell-year. The estimates are based on specification 2, with the interaction term *Habitat* × *Policy* an indicator explaining conflict probability. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the ACLED dataset. Coefficients are reported with standard errors which are computed using the wild bootstrap, following the procedure for synthetic control estimators in Ben-Michael et al. (2021). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table D.7: Wildlife Trade Restrictions and Conflict Likelihood: Difference-in-Differences

	Dep. Var.: Conflict (0/1)		
	Wild Animals and Trees		
	ACLED	UCDP	GTD
	(1)	(2)	(3)
Habitat × *Policy*	0.0391***	0.01***	0.0137***
	(0.004)	(0.0027)	(0.0028)
Cell FE	Y	Y	Y
Country-Year FE	Y	Y	Y
Observations	1,430,970	3,338,930	4,960,696
Dep. Var. Mean	0.0757	0.0302	0.0173
Dep. Var. SD	0.2645	0.1712	0.1306

Notes: The table reports linear probability model (LPM) estimates using the imputation-based difference-in-differences estimator of Borusyak et al. (2024), with treatment defined as the imposition of CITES trade restrictions on species, covering both wild animals and wild trees. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife species w at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. Standard errors reported in square brackets are clustered at the country-year and cell levels, allowing for within-country spatial correlation and infinite serial correlation within a cell. * significant at 10%; ** significant at 5%; *** significant at 1%.

Alternative Conflict Outcomes

Conflict measurement is complex and likely to suffer from measurement error. As such, the literature commonly uses a binary conflict indicator variable (Bazzi and Blattman, 2014; Berman et al., 2017; Ciccone, 2018). The UCDP and GTD conflict outcomes—owing to their narrower definitions—are likely to suffer less from measurement error and yield estimates consistent with those based on ACLED data. Tables D.8 and D.9 report estimates using alternative conflict outcomes, including the number of conflict events or deaths per

cell-year, as well as conflict onset, defined as transitions from peace to war. These estimates remain consistent with the paper's main findings.

Table D.8: Wildlife Trade Restrictions and the Number of Conflict Events

	Dep. Var.: log (# Conflict Events+1)					
	Wild Animals			Wild Precious Trees		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
	(1)	(2)	(3)	(4)	(5)	(6)
Habitat × *Policy*	0.0486***	0.0046***	0.0177***	0.0691***	0.0162***	0.0198***
	(0.0149)	(0.0105)	(0.0060)	(0.0084)	(0.0056)	(0.0043)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	1,430,970	3,338,930	4,960,696	1,435,230	3,348,870	4,975,464
Dep. Var. Mean	0.0707	0.0406	0.0212	0.0707	0.0406	0.0212
Dep. Var. SD	0.385	0.273	0.1887	0.385	0.273	0.1887

Notes: The table reports LPM estimates using the Borusyak et al. (2024) imputation difference-in-differences estimator. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife w at time t. The dependent variable is log number of conflict events in a given cell-year, based on the conflict datasets referenced in the column title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table D.9: Wildlife Trade Restrictions and the Onset of Conflict Events

	Dep. Var.: Conflict Onset (0/1)					
	Wild Animals			Wild Precious Trees		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
	(1)	(2)	(3)	(4)	(5)	(6)
Habitat × *Policy*	0.0112***	0.0065***	0.0056***	0.0206***	0.0025**	0.0070***
	(0.0041)	(0.0026)	(0.0016)	(0.0026)	(0.0013)	(0.0010)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	1,430,970	3,338,930	4,960,696	1,435,230	3,348,870	4,975,464
Dep. Var. Mean	0.0453	0.0143	0.0088	0.0453	0.0143	0.0088
Dep. Var. SD	0.2081	0.1188	0.0935	0.2081	0.1188	0.0935

Notes: The table reports LPM estimates using the Borusyak et al. (2024) imputation difference-in-differences estimator. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife w at time t. The dependent variable is the onset of conflict events in a given cell and year, based on the conflict datasets referenced in the column title. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Alternative Event-Study Estimators

Recent innovations in the literature on panel data econometrics highlight the potential for bias in estimating heterogeneous treatment effects. While the main estimates rely on the Borusyak et al. (2024) estimator, which accounts for such bias, Table D.10 reports estimates based on alternative heterogeneous treatment effect estimators (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). The estimates are consistent with the main estimates presented in Table 1 and Figure 8.

Table D.10: Wildlife Trade Restrictions and Conflict Likelihood: Alternative Estimators

	Dep. Var.: Conflict (0/1)					
	Wild Animals			Wild Trees		
	ACLED	UCDP	GTD	ACLED	UCDP	GTD
Panel A: Callaway and Sant'Anna (2021)						
Habitat × *Policy*	0.0315***	0.0067	0.0226***	0.0612***	0.0153***	0.0126***
	(0.0077)	(0.0048)	(0.002)	(0.0064)	(0.0022)	(0.0019)
Panel B: Sun and Abraham (2021)						
Habitat × *Policy*	0.0294***	0.008**	0.0203***	0.0733***	0.013***	0.0126***
	(0.0097)	(0.0038)	(0.0052)	(0.0091)	(0.0041)	(0.004)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	575,892	1,126,720	1,673,984	575,892	1,126,720	1,673,984
Dep. Var. Mean	0.0757	0.0302	0.0173	0.0757	0.0302	0.0173
Dep. Var. SD	0.2645	0.1712	0.1306	0.2645	0.1712	0.1306

Notes: The table reports LPM estimates using the Callaway and Sant'Anna (2021) and Sun and Abraham (2021) difference-in-differences estimators. Each observation corresponds to a cell-year. The variable *Habitat* is an indicator measuring the suitability of cell k for wildlife species w, and *Policy* indicates the timing of CITES trade restrictions imposed on wildlife w at time t. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell and year, based on the conflict datasets referenced in the column title. Coefficients are reported with bootstrapped standard errors (in parentheses). * significant at 10%; ** significant at 5%; *** significant at 1%.

Sensitivity Checks Related to the 2SLS Ivory Market Analysis

This sub-section provides three different sensitivity analyses addressing concerns regarding the exogeneity of policies in the ivory market and other potential confounders. Table D.11 shows regression estimates of the policy shocks on the log detrended price series of ivory and other minerals. As can be seen, the shocks have predictive power only for the ivory price series. Table D.12 reports placebo estimates for the 2SLS ivory market analysis shown in Table 2, where I intentionally code the policy shocks two years earlier. Reassuringly, all conflict coefficients are statistically insignificant. Finally, Table D.13 replicates the ACLED estimates from Table 2, excluding different continental sub-regions sequentially. This shows that the effect is not driven by a particular location, alleviating concerns that CITES targeted the policy based on specific regional conditions.

In estimating the effect of the ivory shock on conflict, I use the price of mammoth ivory. This is considered a close substitute for elephant ivory (Farah et al., 2015; Hauenstein et al., 2019), and because mammoth ivory is traded legally, its price series is both the longest (1992-2024) available and likely the most reliable. However, Table D.14 reports estimates based on alternative ivory price sequences. Columns 1–2 and 4–5 use the price series constructed by Sosnowski et al. (2019) for 1990–2016 and Do et al. (2021) for 1985–2013, both derived from confiscation data, whereas Columns 3 and 6 use prices obtained from art and antique auction websites for 2012–2021. All coefficients are positive and statistically significant, consistent with the main estimates in Table 2.

Table D.11: Placebo Estimates for Elephant Ivory Policy Shocks and Mineral Prices

	Dep. Var.: Detrended Log Price										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Ivory	Gold	Silver	Copper	Platinum	Iron	Lead	Nickel	Tin	Zinc	Aluminum
Ivory Policy Shocks	0.7702**	0.1398	0.0900	0.1299	−0.1358	−0.2189	0.1113	−0.2588	0.2805	0.0275	−0.2041
	(0.3500)	(0.3652)	(0.3926)	(0.4582)	(0.4189)	(0.4443)	(0.4579)	(0.4064)	(0.4018)	(0.3819)	(0.3268)
Observations	26	54	54	54	54	54	54	54	54	54	54

Note: The table reports placebo OLS estimates for the effect of supply-side policies in the ivory market on ivory prices and on the prices of other minerals. Each observation corresponds to a year. *Ivory Policy Shocks* is an indicator variable for the two supply-increasing policies (1998, 1999, 2007, 2008) and the supply-decreasing shocks (2017 and 2018), with signs applied accordingly. The outcome variable is the detrended log price of the resource mentioned in the title. Coefficients are reported with standard errors (in parentheses), which allow for infinite temporal correlation. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table D.12: Placebo Estimates for Elephant Ivory Policy Shocks and Conflict Likelihood

	Dep. Var.: Conflict (0/1)		
	ACLED	UCDP	GTD
	(1)	(2)	(3)
Panel A: IV Estimates			
$\widehat{Habitat \times Price}$	−0.0012	0.0031	0.0041
	(0.0078)	(0.0055)	(0.0042)
Panel B: First Stage			
Habitat × Expansionary Policy	−0.4974***	−0.6478***	−0.6478***
	(0.0914)	(0.0882)	(0.0882)
Habitat × Contractionary Policy	0.7964***	0.7964***	0.7964***
	(0.0639)	(0.0639)	(0.0639)
F-stat	12,054	17,945	17,945
Cell FE	Y	Y	Y
Country-Year FE	Y	Y	Y
Industrial Mineral	Y	Y	Y
Dep. Var. Mean	0.0811	0.0370	0.0137
Dep. Var. SD	0.2730	0.1887	0.1163
Observations	272,600	283,504	283,504

Note: The table reports placebo 2SLS estimates for African elephants, where policy shocks are intentionally coded two years before the actual policy dates (1996, 1997, 2005, 2006, 2015, 2016). Each observation corresponds to a cell-year, and the sample is restricted to Africa. Panel A reports the main 2SLS estimates, where the variable *Habitat* is an indicator measuring the suitability of cell k for African elephants, and *Price* denotes the log price of ivory at time t. The estimates are based on first-stage predicted values based on equation 4. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell-year, based on the conflict datasets referenced in the column titles. Panel B reports the first-stage estimates, in which policies explain the price shocks. *Expansionary Shock* is an indicator for policy-driven increases in ivory supply, while *Contractionary Shock* reflects policy-induced supply reductions. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table D.13: Policies, Price Shocks, and Conflict Likelihood in the Elephant Ivory Market: 2SLS with Sequential Exclusion of Subregions

	Dep. Var.: ACLED Conflict (0/1)				
	Excluded African Region				
	South	East	Centre	West	North
	(1)	(2)	(3)	(4)	(5)
Panel A: IV Estimates					
$\widehat{Habitat \times Price}$	0.0196***	0.0203**	0.0219***	0.0192***	0.0188***
	(0.0063)	(0.0083)	(0.0083)	(0.0067)	(0.0063)
Panel B: First Stage					
Habitat × Expansionary Policy	−0.8291***	−0.8291***	−0.8291***	−0.8291***	−0.8291***
	(0.0947)	(0.1251)	(0.1078)	(0.1084)	(0.0953)
Habitat × Contractionary Policy	0.7663***	0.7663***	0.7663***	0.7663***	0.7663***
	(0.1644)	(0.2172)	(0.1872)	(0.1883)	(0.1655)
F-stat	24,786	18,889	18,971	19,024	17,520
Cell FE	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y
Dep. Var. Mean	0.0811	0.0667	0.0841	0.0759	0.0990
Dep. Var. SD	0.2729	0.2495	0.2775	0.2649	0.2987
Observations	272,475	207,650	208,550	209,125	192,600

Note: The table reports 2SLS estimates for African elephants, where I iteratively exclude the region mentioned in the title. Each observation corresponds to a cell-year, and the sample is restricted to Africa. Panel A reports the main 2SLS estimates, where the variable *Habitat* is an indicator measuring the suitability of cell k for African elephants, and *Price* denotes the log price of ivory at time t. The estimates are based on first-stage predicted values based on equation 4. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell-year, based on the ACLED conflict dataset. Panel B reports the first-stage estimates, in which policies explain the price shocks. *Expansionary Shock* is an indicator for policy-driven increases in ivory supply, while *Contractionary Shock* reflects policy-induced supply reductions. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table D.14: Conflict and Ivory Price Shocks: Alternative Price Sequences

	Dep. Var.: Conflict (0/1)					
	ACLED			UCDP		
	Sosnowski et al. (2019)	Do et al. (2021)	Art and Antique Markets	Sosnowski et al. (2019)	Do et al. (2021)	Art and Antique Markets
	(1)	(2)	(3)	(4)	(5)	(6)
Elephant Habita × *Ivory Price*	0.0065***	0.0063***	0.0093***	0.0057***	0.0085***	0.005*
	(0.0017)	(0.0025)	(0.004)	(0.0022)	(0.003)	(0.003)
Cell FE	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Observations	294,816	182,250	110,556	393,088	182,250	110,556
Dep. Var. Mean	0.06	0.049	0.112	0.028	0.026	0.0472
Dep. Var. SD	0.237	0.217	0.316	0.166	0.026	0.212

Notes: The table reports OLS estimates for African elephants, using alternative price sequences. Each observation corresponds to a cell-year, and the sample is restricted to Africa. The variable *Elephant Habitat* is an indicator for the suitability of cell k for African elephants, and *Ivory Price* denotes the log price of ivory at time t, based on the source indicated in the table title. The dependent variable is a binary indicator for conflict incidence, equal to one if at least one conflict event occurs in a given cell-year, as defined by the conflict datasets referenced in the column titles. Coefficients are reported with spatially clustered standard errors (in parentheses), which allow for spatial and temporal correlation within a 500 km radius of each cell's centroid. * significant at 10%; ** significant at 5%; *** significant at 1%.