LANDMINES: THE LOCAL EFFECTS OF DEMINING

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Abstract. Anti-personnel landmines are one of the main causes of civilian victimization in conflict-affected areas and a significant obstacle for post-war reconstruction. Demining campaigns are therefore a promising policy instrument to promote long-term development. We argue that the economic and social effects of demining are not unambiguously positive. Demining may have unintended negative consequences if it takes place while conflicts are ongoing, or if they do not lead to full clearance. Using highly disaggregated data on demining operations in Colombia from 2004 to 2019, and exploiting the staggered fashion of demining activity, we find that post-conflict humanitarian demining generates economic growth (measured with nighttime light density) and increases students' performance in test scores. In contrast, economic activity does not react to post-conflict demining events carried out during military operations, and it *decreases* if demining takes place while the conflict is ongoing. Rather, demining events that result from military operations are more likely to exacerbate extractive activities.

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1 Introduction

Landmines –explosives buried under the surface that are triggered upon contact and have the purpose of killing or injuring people–are one of the most pressing challenges to post-war recovery and long-term development. Together with unexploded ordnance (UXO) from aerial bombing campaigns, landmines threaten people's life and mobility, affecting agricultural investment, access to markets and basic services, and schooling (CNMH, 2017). They are also an obstacle for humanitarian aid and post-conflict reconstruction (Parker, 2018). Landmines are cheap to fabricate and their use is widespread in internal armed conflicts, making them especially dangerous to the poor. Estimates suggest that the stock of buried anti-personnel mines today amounts 110 million globally, affecting over 60 states.[1] The estimated stockpile of landmines that have yet to be planted is more than double that figure. Up to 26,000 people are directly victimized every year (Hall, 2017), and about 42% of the victims are children. But the damage inflicted by landmines extends well after the end of war. Indeed, landmines are hard to detect and costly to remove.[2] Estimates suggest that if the world stops planting landmines and the current demining rate persists, it would take over a thousand years to strip the entire planet of landmines.[3]

This implies that demining campaigns are one of the most pressing and likely profitable post-conflict endeavours. However, and perhaps surprisingly, research on the economic effects of demining is rather scarce and largely based on statistical association. A recent exception, which we discuss below, is Chiovelli et al. (2019). Our paper contributes to this thin but important area of inquiry by studying the socio-economic and political effects of demining in Colombia, the country with the second-highest number of landmine victims since 1999, behind Afghanistan (Landmine Monitor, 2019b) and the country with the highest number of victims of improvised handmade mines. To that end, we exploit the exact coordinates of a demining event as well as yearly variation over the period 2004-2019 to study the local effects of different types of demining treatments, some of which had not been previously studied. First, we examine the comprehensive humanitarian mine clearance campaign that started at the beginning of the peace negotiations with the *Revolutionary Armed Forces of Colombia* (FARC from its Spanish acronym), and which is still ongoing.[4] Second, we look at demining events resulting from military operations that took place over the course of the conflict. Finally, we examine demining events in military operations carried out after the

[1]See http://www.landminefree.org/2017/index.php/support/facts-about-landmines (last accessed 8/22/2021).

[2]While building a landmine can cost between \$3 and \$75, removing it requires an investment of up to \$1,000 (Doswald-Beck et al., 1995).

[3]However, mines only remain active for about 50 years.

[4]Humanitarian demining refers to the thorough efforts of local and international NGOs to locate mine fields, alert the local communities of their existence, and remove all the existing landmines until the area can confidently be called mine-free.

end of conflict with FARC.[5]

Our identification strategy relies on the timing of demining campaigns that took place both over the course of the conflict and after the peace negotiations with FARC started, allowing for a thorough humanitarian mine-clearance. Specifically, we compare the evolution of various outcomes of interest –including nighttime lights and population density, schooling outcomes, and proxies of extractive economic activities–in areas subject to demining and areas known to host anti-personnel mines but that had yet-to-be or were never subject to intervention during our sample period. Because our data on demining is geo-referenced, we focus on highly disaggregated local effects within a 5 Km radius in the baseline results.

Our estimation of the causal effect of demining on the treated areas takes into account the recently documented problems of using two-way fixed effects to estimate causal effects in difference-in-differences settings with staggered adoption and heterogeneous treatment effects. First, we assess how relevant this is for our context by computing the decomposition suggested by Goodman-Bacon (2021), and we find evidence against using standard linear techniques. Second, our baseline specification uses the estimator proposed by Callaway and Sant'Anna (2020) that is based on a parallel trends assumption and computes group-time ATTs that are later aggregated to compute an overall ATT. Third, we explore the robustness of our results to using alternative estimators, such as those proposed by Borusyak et al. (2021), De Chaisemartin and d'Haultfoeuille (2020), and Wooldridge (2021). Fourth, to assess the validity of our main identifying assumption (namely, that the post-treatment potential outcomes of treated cohorts has the same trend as those of the never treated and the soon-to-be-treated cohorts) we report the dynamics of the estimator, as well as corrections for potential bias coming from pre-treatment differential trends (Roth, 2021) and the robustness of our results to moderate linear and non-linear violations of the parallel trends assumption (Rambachan and Roth, 2021). Fifth, we show the robustness of our results to: i) adding municipality-specific time trends, as well as pre-treatment municipality and event-level covariates in a doubly-robust fashion as suggested by Sant'Anna and Zhao (2020); ii) using different radiuses around the demining event; iii) accounting for potential spillover effects; iv) using different comparison units and periods; v) excluding treated cohorts from the analysis; and vi) winsorizing outliers in our dependent variables.

We find that humanitarian demining campaigns that took place during the post-conflict period led to improvements in socio-economic conditions. In particular, we find a 12.7% increase in nighttime luminosity –a validated proxy of local economic activity (Henderson et al., 2011)–and a 2.7% increase in population density. A back-of-the-envelope calculation

[5]In the latter two cases, demining is a byproduct of a military anti-insurgency operation, advancement, or maneuver. Such cases seldom result in the official clearance of entire areas.

yields that each humanitarian demining event increases the municipal per capita by 0.8%, and that each dollar invested in humanitarian demining yields $7 in benefits after only one year.

We also find a 6.7 (8.1) percentage points improvement in students' performance in math (reading) standardized national test scores.[6] We show that the positive effect that demining has on nighttime lights is larger in areas that are better connected to labor, inputs, and output markets through the available road network. Indeed, connectivity is key to reap the economic potential that follows mine clearance campaigns. Moreover, we also find that a denser road network makes the effect of demining on students' performance larger, which is consistent with demining facilitating school attendance.

However, in sharp contrast with the case of humanitarian demining, demining in military operations during the same period, which did not have the objective of achieving the complete clearance of targeted areas, had no statistically significant effects on nighttime luminosity and students' performance. Instead, they decreased population density. Something similar occurred during the conflict period, when no humanitarian demining took place and the only demining was that resulting from military operations. In these instances, demining also reduced population density. Importantly, it also caused a differential *reduction* in nighttime luminosity. We posit that one potential mechanism why demining during conflict decreased population density and nighttime light is that it exacerbated violent territorial disputes. Indeed, because armed groups use landmines to prevent the territorial advancement of enemies (Fundación Seguridad y Democracia, 2006), demining can trigger violent confrontation between groups as well as the victimization of civilians thought to collaborate with the enemy (CNMH, 2017 and Procuraduría, 2011). We thus explore the municipal-level correlation between demining and variables related to the incidence of violence and forced internal displacement and find that these variables are positively correlated with military demining only, and that this correlation is much stronger during the conflict period.

To complement the results obtained for nighttime lights, and because demining lowers the entry barriers of both productive and extractive economic activities and landmines are disproportionally a rural phenomenon, we also study the effect of demining on forest cover. We find that while post-conflict humanitarian demining had no significant effects on deforestation, demining events resulting from military operations both over the course of the conflict and after its ending caused large increases in deforestation. To shed light on the potential

[6]This is in line with Prem et al. (2021c), who document an improvement in students' performance after the start of a permanent ceasefire in municipalities previously affected by FARC violence, with the effect being especially large in areas that had landmine explosions.

mechanisms underlying this finding, we look at spatially disaggregated data on soil suitability. We find that the deforestation surge after military demining is more pronounced in areas that are suitable to extractive agricultural activities such as oil palm, cattle ranching, banana growing, rubber plantating, and forestry.[7] We interpret these findings as consistent with the idea that demining in military operations serves the interest of elites with stakes in extractive economies. Moreover, such investments are unlikely to result in the type of economic growth that is captured by nighttime luminosity. On the contrary, and as mentioned, demining during conflict seems to have reduced growth.

One of the main strategic uses of landmines during the Colombian conflict was the protection of coca fields (Fundación Seguridad y Democracia, 2006; CNMH, 2017). Coca leaves are the main precursor of cocaine, of which Colombia is the main exporter worldwide, including about 90% of the U.S. market. We thus also explore the effects of demining on coca cultivation –as estimated by the United Nations Office on Drugs and Crime (UNODC) using satellite images and verification flights–and find that demining events that took place during the post-conflict period decreased coca cultivation locally. This contrasts with demining during conflict, which did not affect coca-growing and hence the potential production of cocaine. We also exploit the implementation of an illegal crops-substitution program that was implemented after the signature of the peace agreement with FARC to estimate heterogeneous effects parametrized by the program's presence. We find that all of the demining-led decrease in coca cultivation is driven by municipalities where the crop-substitution program was implemented. This implies that the coexistence and mutual reinforcement of different policies (illegal crops substitution and demining) can be an effective way to reduce illegal drugs production. This is particularly relevant given the failure of the War on Drugs in producing countries (see Prem et al., 2021b for a thorough review and an recent example for the Colombian case).

In short, we find that the local effects of demining largely depend on the type of mine removal strategy as well as on its timing. When demining is carried out by domestic and international NGOs with the objective of protecting local communities and clear entire areas from landmines, this increases productive economic activities, population density and the quality of education as measured by students' test performance. Instead, if demining takes place in the context of military activity which does not results in mine free zones, and especially if this occurs while the conflict is still active, then it hurts economic growth and reduces population density, while at the same time it increases the intensity of the conflict and exacerbates extractive economic activities.

[7]This result is consistent with Prem et al. (2020), who document a differential increase in deforestation –most likely related to extractive activities–after the start of the ceasefire in municipalities previously exposed to FARC violence.

Our paper contributes to the recent evidence on the economic effects of demining. Chiovelli et al. (2019) exploit the timing of mine clearance campaigns across localities in Mozambique to estimate the causal effect of demining on nighttime luminosity. They find that, between 1992 and 2015, output per capita grew by additional 16% thanks to the demining campaign. While we corroborate the findings of Chiovelli et al. (2019) using much more spatially disaggregated variation and for the case of Colombia, our paper advances our knowledge of the effects of demining in two key dimensions.[8] First, we offer a comprehensive analysis of the effects of demining on various socio-economic and political outcomes, including –but not limited to–nighttime lights. Second, we study demining activity under different institutional environments and with different scopes, as well distinguishing between demining during an ongoing conflict during the post-conflict period. This approach allows us to add much more nuance to the idea that demining is unambiguously good.

Our paper also contributes to the literature that studies the long term economic effects of the massive U.S.-led aerial bombing campaigns that took place during the Vietnam War (1955-1975), the Cambodian Civil War (1967-1975), and the Laotian Civil War (1959-1975). While some authors find large negative long-term effects in terms of economic activity and agricultural productivity (see, e.g. Lin, 2020 for the case of Cambodia and Riaño and Valencia Caicedo, 2020 for the case of Laos), other conclude that the Vietnam aerial bombing campaign had no long-term effects in terms of poverty (Miguel and Roland, 2011) and political attitudes Dell and Querubin (2018). Whether the short-term devastation caused by bombings persisted over time or dampened down seems to depend on post-war policy responses related to public investment and public goods provision, as well as on plausibly exogenous factors such as soil quality (since bombs were more likely to explode in barren and less fertile soil). We posit that the long-term negative effects of buried aerial UXO are likely only a fraction of those that come from mines that are cheaper to fabricate and intentionally hidden underground instead of accidentally unexploded. In fact, landmine contamination is still a problem in around 60 countries, while unexploded aerial bombs are currently prevalent only in Cambodia and Laos. Finally, we also contribute to the literature studying the effects of landmine contamination on health (Arcand et al., 2015), education (Merrouche, 2011), and poverty (Merrouche, 2008).

The rest of the paper is organized as follows. Section 2 provides context for the Colombian conflict in general and on its use of landmines in particular. Section 3 describes the

[8]The similarity of the nighttime light results is interesting, since Mozambique and Colombia are quite different countries. According to the World Bank's Open Data (see `https://data.worldbank.org` –last accessed 09/14/21), Colombia's GDP per capita is over 11 times that of Mozambique; Mozambique's economy is much more dependent on agriculture (the share of agriculture value added over GDP is 26% versus 6% in Colombia); and Mozambique receives 3.5 times more official development assistance per capita than Colombia.

data sources for the different types of demining, the various outcomes we explore, and the variables used to explore potential mechanisms. Section 4 discusses the empirical strategy, particularly how we address all the recent criticism of estimating difference-in-differences models with staggered adoption using two-way fixed affects. Section 5 reports and interprets the main results and includes a number of robustness tests that enhance their credibility. Section 6 explores the role of road connectivity and armed conflict, the potential mechanisms related to the suitability of land for different uses and extractive activities, and the interaction of demining with other government policies. Finally, section 7 concludes.

2 Context

2.1 Colombia's civil war and the peace process The start of the most recent internal armed conflict in Colombia dates back to the 1960s, when FARC and another large left-wing guerrilla (the *National Liberation Army*, ELN from its Spanish acronym) were launched. Other smaller insurgencies appeared later, and a common cause to all of them was the political exclusion of non-traditional parties in Colombia. Indeed, the political landscape was dominated by two parties that represented the urban elite and had similar policy stances: the Liberal and the Conservative parties (Fergusson et al., 2021). As a result, left-wing guerrillas claim to represent the rural poor and have the ultimate objective of overthrowing a government that they judge illegitimate.

This effort has been financed through different sources through the course of the conflict, from extortion, ransom, and kidnappings to illegal activities such as illicit crops and drug trafficking, and unlawful mining. Thus, sub-national territorial control is an important intermediate objective of the guerrillas, as well as of other illegal groups active in the conflict. The main such actor are right-wing paramilitary groups, originally armed by the state in the early 1970s and trained as self-defense organizations. In the mid-1990s, splintered paramilitary groups colluded under the umbrella organization of the *United Self-Defense Groups of Colombia* (AUC by its Spanish acronym). This escalated the conflict substantially, since competing actors in civil wars commonly victimize civilian targets as a means of achieving territorial control (Kalyvas, 2006; Prem et al., 2021a). Indeed, today over 9 million people are registered as victims of the Colombian conflict.[9]

In October 2012, the Colombian government and FARC started peace negotiations in Cuba. This marked the start of the new and more peaceful equilibrium in the long history of the Colombian conflict. FARC's offensive activity started to curtail and quickly dropped by 98% (CERAC, 2016). Humanitarian demining efforts also started to pick up soon after the start of peace negotiations. On December 20 2014, FARC declared a permanent ceasefire

[9]Source: Victims' Registry, from the Unit for the Victims Assistance and Reparation, June 2021 figure. Available form: https://www.unidadvictimas.gov.co/ (last accessed 8/22/2021).

to signal its commitment to the peace process and its capacity of holding accountable all of its fronts, which were scattered throughout Colombia. The organization then started to withdraw troops to more remote areas, where military contact with government security forces and other armed groups was unlikely to take place. As a result, the victims from anti-personnel landmines plummeted by 69% (Prem et al., 2021c). Based on these dynamics, we distinguish between a pure "conflict period" (from the first year of our sample, 2002, until 2012) and what we call a post-conflict period, from 2013 onward.

2.2 Landmines in Colombia Colombia is second only to Afghanistan in terms of countries with the most landmine victims since 1999. It is also the country with the highest number victims of improvised anti-personnel mines. Over 10,000 Colombians have been directly affected by such artifacts since 1999. Improvised landmines are homemade explosives that detonate by contact *or even in proximity* of a person or object. They are harder to detect and remove without risking an explosion (Landmine Monitor, 2019b). While landmines have been used by all the actors of the conflict, improvised mines were commonly manufactured and planted by guerrilla groups with the objective of protecting their strongholds as well as areas with illicit crops.

In fact, 2008 constitutes a turning point in the fabrication and planting of improvised mines in Colombia. Then, FARC's secretariat launched a strategy that they called *Plan Renacer Revolucionario de las Masas* (Revolutionary Rebirth of the Masses), by which all fronts were encouraged to strengthen their guerrilla warfare tactics in order to regain territory as well as protect their strongholds. Among other orders, commander 'Alfonso Cano' from the secretariat instigated the troops to take courses on making and plating mines. Cano justified the strategy as the only way to counteract the advance of a larger and better equipped enemy (the Colombian army).[10]

But the history of landmines in the Colombian conflict did not start with *Renacer*. In the 1970s, the Colombian government imported large numbers of anti-personnel mines with the objective of protecting key military bases from the guerrillas. Most of these mines were deployed during the 1980s.[11] In any case, while the extent of the contamination with mines is highly uncertain, by the end of 2018, at least 88% of Colombian departments (equivalent to U.S. states) were suspected to host landmines. The contaminated area was officially estimated in 2017 to be around 11,400 acres (Landmine Monitor, 2019a).

The 1997 Ottawa Convention forbids the employment, storage, production, and transfer of

[10]The internal document that Cano sent to all front commanders was later leaked and made public. A copy of it in the original Spanish can be found in Figure A1 of the Appendix.

[11]See http://www.accioncontraminas.gov.co/AICMA/desminado/historia-del-minado-y-desminado-en-bases-militares-de-colombia (last accessed 8/22/2021).

anti-personnel mines. Colombia is one of the 164 nations that subscribed the convention, which was ratified in 2000 and came into force in 2001. As part of the commitments adopted from the Convention, Colombia started an official periodic registry of landmine explosions, suspicion of presence, and demining events. To this end, in 2002 the country adopted and implemented the Information Management System for Mine Action (IMSMA) of the Geneva International Centre for Humanitarian Demining (GICHD). The first humanitarian demining operations took place in 2004, and they targeted the military bases where mines were planted two decades prior. 40 acres of land were cleared and over 3,500 mines were deactivated.[12] Colombia's current commitment is to clear landmines from the entire territory by 2025.

But other than that specific demining event and other localized actions, and largely due to the intensity and territorial reach of the ongoing conflict, large scale humanitarian demining and full clearance operations did not pick up until after the start of peace negotiations with FARC. Indeed, the Decree 3570 of 2011 established that any national or foreign non-governmental organization (NGO) could undertake humanitarian demining, and the first NGO that engaged in demining activity was Halo Trust. It did so in 2013, the first year of the period that we label "post-conflict" in our statistical analyses.[13] In fact, since the start of peace negotiations, the parties agreed to allow the establishment of humanitarian demining campaigns, and in the final peace agreement, the involvement in demining activities was highlighted as a key activity for the reincorporation of former FARC combatants.[14]

In sharp contrast, military demining operations have long existed as part of the dynamics of the internal conflict. The military constantly engages in mine removal and controlled explosions as part of their anti-insurgency operations and maneuvers, and as a way to clear paths for the advancement of troops and warfare equipment. By March 2021, almost 25,000 demining events in military operations had been registered. Clearly, this implies that humanitarian and military demining are fundamentally different "treatments." While in the former, the clearance of an entire mined area is the main objective and the demining enterprise involves several experts and government officials, in the second, demining is an intermediate objective to achieve a strategic goal other than demining *per se*, and thus it is seldom comprehensive within demined areas and is disassociated from wider state building efforts.

[12] See `http://www.accioncontraminas.gov.co/Estadisticas/operaciones-dh` (last accessed 8/22/2021).
[13] As of today Colombia hosts 7 demining organizations, 5 international and 2 local.
[14] See excerpts 3.2.2.6-part b, 4.1.3.1 and 6.2.3-part of the text of the agreement.

3 Data

3.1 Demining We obtained detailed geo-referenced data on all landmine demining events, as well as on the presence or the suspected presence of antipersonnel mines, improvised explosive devices and UXO. Its source is the IMSMA database, managed by the Integrated Action Against Antipersonnel Mines, a division of Colombia's Office of the High Commissioner for Peace. The data covers in a systematic way the period from 2003 until the present.[15] As of March 31 of 2021, the database includes 24,746 demining events in military operations, all geo-located with GPS devices carried by the military.[16] Most of these events took place before 2013, when demining in military operations started dropping due to the de-escalation of the conflict that followed the start of the peace negotiations with FARC (see section 2).

In contrast, humanitarian demining was very rare before 2013 due to the dangers of engaging in landmine clearance campaigns amidst an active internal armed conflict.[17] In 2013, with the arrival of the British NGO HALO Trust, the international community started official humanitarian demining campaigns in Colombia. HALO Trust was followed by other organizations and, as of today, there are seven accredited organizations that engage in humanitarian demining, five of which are international. We had access to the data bank that records all the operations of these demining NGOs, and the recorded information accurately coincides with IMSMA. As of June 31 of 2021, the NGOs had established 2,272 hazardous areas. Of these, 1,141 had been confirmed to host landmines and 645 had been cleared.

From these data, we code three treatments: i) humanitarian demining during the post-conflict period (2013-2019); ii) demining in military operations during the post-conflict period; and iii) demining in military operations during the period of active conflict (2004-2012). The coded information includes the exact location of all demining events and the year in which it was carried out. Moreover, and key for identification, we code the location of areas known to be contaminated but not yet demined (as of 2021).

3.2 Outcomes Our set of outcomes is limited by the choice of focusing on the local effects of demining in areas located within a 5 Km radius of the demining event. This subsection describes such outcomes and discusses their measurement and sources.

[15]IMSMA was adopted in 2001 after Colombia signed the Ottawa Convention but the information available for the first couple of years is not comprehensive.

[16]Despite of the fact that the majority of military operations take place in rural areas, the quality of the GPS-generated coordinates is quite accurate. Camp et al. (2016) show that in Ecuadorean Andes (a topography very similar to Colombia's) the location error of the GPS information is 9.6 meters (with a standard deviation of 4.7 meters). Given the baseline radius that we use to estimate the local effect of demining (5 Km), a location error of such magnitude should not be a major concern.

[17]One exception was the demining of military bases in 2004, as mandated by the Ottawa Convention.

3.2.1 Nighttime lights Nighttime light has been shown to be a reliable proxy for economic activity both nationally and in geographically small areas (Henderson et al., 2011; Bleakley and Lin, 2012; Michalopoulos and Papaioannou, 2013; Storeygard, 2016; Goldblatt et al., 2018). We use the global harmonized nighttime light (NTL) dataset constructed by Li et al. (2020), which addresses all the known problems of nighttime lights, such as intercalibration, geometric correction, and blurring. Nightlight images are available for grids of 1Km $\times$ 1Km, so for our outcome of interest we take all the pixels that intersect the buffer of a demining event and compute a weighted average of their luminosity value. The weights are given by the product of the luminosity value of each intersecting lit pixel and the fraction of the buffer area that overlays with that pixel.[18]

Figure A6 corroborates that this measure is highly correlated with various socio-economic outcomes at the municipality level. These include value added, mortality rate under five years old, an index for fiscal performance, literacy rate, and a poverty index. This correlation is high both for the entire country and for the relatively more rural municipalities, which host the vast majority of landmines and thus where most demining takes places.

3.2.2 Population density Population density is an alternative proxy of economic activity that has been widely used by economic historians. For instance, Acemoglu et al. (2002) argue that only prosperous areas can support dense populations, and that population density contributes to economic growth by encouraging the exchange of ideas. We therefore compute a buffer-specific population density measure. To that end, we use the 1Km $\times$ 1Km population rasters provided by WorldPop and the Center for International Earth Science Information Network (CIESIN).[19] We then compute the average of the estimated population density within each buffer of our sample.

3.2.3 Schools and the performance of students in test scores To assess the impact of demining on students' performance in standardized test scores, we start by constructing a novel geo-referenced database of all schools in Colombia.[20] We then merge to this dataset the average academic achievement of all the school students in the reading and math standardized

[18] To deal with outliers and with observations with zero average light, we use as our dependent variable the hyperbolic sine transformation of the average luminosity within the buffer.

[19] The data can be downloaded from `https://www.worldpop.org/geodata/listing?id=76`. The population raster is estimated by the source following the methodology proposed by Stevens et al. (2015), which uses disaggregated census data and a *Random Forest* machine learning model that includes remotely-sensed data and geographic administrative data to predict grid-level population values. The variables used for the prediction include various types of land use, nighttime lights, climate and geographic characteristics, and the presence of local facilities.

[20] We did so by web-scraping the school information from the Education System of Educational Sites (SISE): `https://geoportal.dane.gov.co/SISE/sise/`. This is a cross-section database, but the change of school locations is very rare, especially in the more rural areas where demining takes place Gómez Montoya et al. (2018).

national tests (called "Saber"), that are implemented yearly in selected grades (3rd, 5th, and 9th). This information comes from administrative datasets of the Colombian Institute for the Evaluation of Education (ICFES from its Spanish acronym) and is available for the period 2012-2018 in the form of school-level averages.[21] We construct our measure of buffer level students' performance by computing the weighted average of the fraction of students enrolled in schools within the buffer that passed the test. The weight is the number of students that took the test in each school/year. Interestingly, we find that 96% (77%) of the buffers around a humanitarian (military) demining event have at least one school. Moreover, on average nine schools fall within each (5 Km radius) buffer in our estimation sample.

3.2.4 Extractive activity We also measure buffer-specific yearly forest loss using the satellite-based estimates of the Global Forest Change (GFC) project, which includes information of forest cover changes with a resolution of approximately 30m $\times$ 30m, estimated from Landsat images (Hansen et al., 2013). Deforestation is identified by GFC when a specific pixel changes its forest cover status from one year to the other. For each buffer of our sample, we compute the area occupied by pixels that became deforested in a specific year and use the hyperbolic sine transformation of this variable.

With the increasing use of fire as a deforestation tool, most of which is illegal, we explore the robustness of our deforestation results to using the imagery data from NASA's Fire Information for Resource Management System (FIRMS). With this input we compute the total number of fires that take place each year withing each buffer.

We also have geo-referenced data on the existence and the geographic extension of illegal alluvial gold mining (EVOA from its Spanish acronym). This information is available in 1Km $\times$ 1Km grids for the years 2014, 2016, 2018, and 2019, and is estimated by UNODC using remote sensing methods. The illegality of the mines can be inferred after overlaying the EVOA raster with official geo-referenced data on mine titles.[22] Moreover, UNODC cross-checks the estimates with local environmental NGOs that often corroborate the existence of an alluvial gold mine.

3.2.5 Coca cultivation To measure the size of illicit coca crops, the leaves of which are mixed with chemicals to produce cocaine and crack, we rely on the satellite-based annual estimation performed by the Integrated Monitoring System of Illicit Crops (SIMCI from its Spanish acronym) of the United Nations Office on Drugs and Crime (UNODC). SIMCI uses satellite imagery to estimate coca production by the end of each calendar year with

[21]We do not include test scores from the end-of-high-school national test ("Saber 11"), as these are not comparable across years during our sample period, due to several methodological changes documented in ICFES (2019).

[22]In 2019, 66% of the detected EVOA area corresponds to illegal exploitation, 27% corresponds to legal (titled) exploitation and the remaining 7% are mines in the process of being legalized UNODC (2020).

remote sensing tools, which are the validated with high definition photographs taken from a helicopter.[23] The data is produced in grids of 1Km × 1Km, from 1999 to 2019. This allows us to compute the buffer-specific area covered with coca crops. Our dependent variable is the hyperbolic sine transformation of this measure.

3.3 Other variables

3.3.1 Soil suitability To study heterogeneous effects based on soil suitability, we build a novel cross-section database by rasterizing –at a resolution of approximately 30m × 30m the suitability zoning shapefiles provided by the Agricultural Rural Planning Unit (UPRA) of the Colombian Ministry of Agriculture. Each pixel contains estimated information on different degrees of suitability for a wide range of activities, based on physical, socio-ecosystemic, and technical factors; socioeconomic and legal criteria; and regulatory guidelines that affect the delimitation of areas according to national level planning and regulation.[24] We construct information for key activities largely related to deforestation, such as palm oil growing, cattle herding, growing grass used for cattle, rubber crops, banana crops, and forestry. Based on this information, we can create soil suitability at the buffer level using the proportion of the buffer area with suitability for each type of land use.

3.3.2 Road network We also use detailed information of the location of the entire roads network of Colombia, including all road types from primary (highways) to tertiary (intra municipal non-paved) roads. These data were obtained from the *Instituto Geográfico Agustin Codazzi (IGAC)* for the 2012 cross section.

3.3.3 Geographic and municipality characteristics We complement the variables described above, used as either as the main outcomes or to test potential mechanisms, with weather and geographic characteristics that are geo-referenced at the buffer level. These include temperature and rainfall measures, altitude, distance to rivers and national parks, and the terrain ruggedness Nunn and Puga (2012).[25] Finally, we also add municipality characteristics from the CEDE municipal panel, compiled by the Acevedo et al. (2014).

[23]SIMCI uses satellite images for a wide window around December 31st. In particular, about 70 percent of the images are obtained between mid-November of the year of the estimate and late February of the following year. Of the remaining 30 percent, roughly half is obtained from August to November of the year of the estimate, and the residual is obtained between March and April of the following year.

[24]The physical component considers temperature, precipitation, climatic index, adequate depth, soil moisture, nutrient availability, textural class, degree of erosion, slope, landslide susceptibility, flood susceptibility, and volcanic hazards. The socio-ecosystem component includes ecological integrity, land cover, fire hazards, strategic ecosystems, and deforestation. Finally, the socioeconomic component considers institutional framework, security, labor market, living conditions, land size distribution, infrastructure and logistics, cost of rural land, and municipal economic indicators. For a detailed discussion about the weights of each criteria and the construction process, see https://www.upra.gov.co/uso-y-adecuacion-de-tierras/evaluacion-de-tierras/zonificacion.

[25]The temperature, rainfall, and altitude data was constructed from Fick and Hijmans (2017), and the distance to rivers and parks was computed based on IDEAM national shapefiles of rivers and national parks.

3.4 Summary statistics We start by plotting the intensity of demining across the country, aggregated for the whole period. Figure 1 plots the spatial distribution of demining events between 2004 and 2019. During this period, there was at least one demining event in 438 (38%) of the municipalities in Colombia. In Table 1, we present summary statistics for each outcome variable as measured within the sample buffers used to identify the effect of each of the three demining types. Overall, we find that areas in which humanitarian demining took place tend to have more intense nighttime luminosity, better students' test performance, and lower levels of coca crops. Population density is larger for areas demined during the post-conflict period (regardless of whether demining took place in military operations or carried out by humanitarian agencies) and forest loss is similar across the three treatments.

In Figure A3, we show that there are no substantial differences in grid characteristics across demined and not-demined areas within the same municipalities. Likewise, we find no substantial differences regarding the timing of demining events.

4 Empirical Strategy

4.1 Staggered Difference-in-Differences To study the local effects of demining before and after the end of the conflict with FARC, we exploit both the timing of demining events as well as their exact geo-referenced location. Our unit of analysis is therefore the geographic location of the event, and we create a 5 Km-radius circumference around it in order to estimate the local effects of demining.[26] Because demining activity takes place at different times along our sample period, we could estimate a staggered difference-in-differences specification of the form:

$$y_{it} = \alpha_i + \lambda_t + \beta \times Post_{it} + \varepsilon_{it}, \tag{4.1}$$

where y_{it} are different measures of local activity measured within buffer i and in time t. $Post_{it}$ is a dummy that takes the value one in buffer i after an event of demining and zero otherwise. α_i are event/buffer-level fixed effects and λ_t are year fixed effects.

A recent literature had documented that this type of *two-way fixed effects* (TWFE) statistical model can suffer from a severe bias, that makes the estimated coefficient of interest (β) different from the true average treatment effect on the treated (ATT). This is likely to occur when treatment effects are heterogeneous over time and across units. To asses the extent to which this is the case in our context, we start by performing the decomposition suggested by Goodman-Bacon (2021). We report the results in Table A1, and find that in the case of humanitarian demining (which happened during the post-conflict period), 5% of the TWFE

[26]In the Appendix, we show the robustness of our results to different radiuses, specifically 3, 4, 6, and 7 Km around the location of the demining event.

estimate comes from the "forbidden comparison" (that uses the early treated units as controls for units treated later). The proportion is much larger for the case of military demining during conflict (11%) and after its termination (27%). In turn, these figures are consistent with the fact that the share of never-treated units is relatively low, especially for the case of post-conflict military demining events.[27]

Given the results of these diagnostics, we follow the recent developments regarding the estimation of these type of models. In particular, we follow the Callaway and Sant'Anna (2020)'s procedure, which estimates group (g)/time (t)-level ATTs ($ATT(g, t)$) avoiding incorrect comparisons. These are then aggregated in ways that allow the presentation of both "event-study" figures and average estimates, using a range of potential weighting functions.[28]

Importantly, in the Appendix we corroborate that our results are robust to using alternative estimation methods, that also address the potential problems of TWFE, including those suggested by Borusyak et al. (2021), De Chaisemartin and d'Haultfoeuille (2020), and Wooldridge (2021).

One key feature of this type of models is the inclusion of a set of "never-treated" units, that however *could have been* treated. To this end, we need to identify landmines that where not demined during our sample period but that could have been so. For the case of post-conflict (2013-2019) military demining, we use as never treated the demining events that occurred in 2020 and 2021, after the end of our sample period. For the case of humanitarian demining (which happened primarily in the post-conflict period), we use as never treated both the 2020-2021 demining as well as the areas confirmed to have mines but not yet demined due to the limited capacity of humanitarian demining organizations. Finally, for the case of military demining during the course of the conflict with FARC (2004-2012), we use as never treated the military demining events carried out in 2013.

Figure A2 reports, for each demining type, the number of treated units by year together with the never treated. It can be concluded that while the number of never-treated units used for the analysis of humanitarian demining and military demining during conflict is fairly

[27] Since the estimated β is a weighted average of event-specific ATTs, we follow De Chaisemartin and d'Haultfoeuille (2020) to compute the share of ATTs that enter the computation with a negative weight. Consistent with Goodman-Bacon (2021)'s decomposition, we find that the share of negative weights is zero for humanitarian demining and 12% (27%) for demining in military operations carry out during the conflict (in the post-conflict period).

[28] We use the "simple" aggregation, recommended by the authors and that uses as weight the size of the group-year cell. However, we also present the "group"-level aggregation in the Appendix, which first computes the ATT for each cohort g and then takes the average across them.

large, that available for post-conflict military demining is relatively small.[29] This speaks to the salience of using the "not-yet-treated" units as complementary comparison group is important, particularly to identify the local effects of post-conflict military demining. The methodology of Callaway and Sant'Anna (2020) allows to using this alternative control groups.[30]

Finally, as suggested by Callaway and Sant'Anna (2020), we balance our estimation period around the event data, so to avoid the estimates being confounded by changes in the weights driven by sample composition. Specifically, we use three years before and three years after the demining event.

4.1.1 Identifying assumption The main identifying assumption for the "not-yet-treated" version of the Callaway and Sant'Anna (2020) estimator is that the evolution in potential outcomes after the treatment is the same for treated cohorts g and never-treated (and/or soon-to-be-treated) units. We present the dynamic treatment effect version of the authors' estimator in order to partially assess the validity of this assumption (Marcus and Sant'Anna, 2021). We also present the corrections for pre-testing bias and bias from a pre-demining linear trend following Roth (2021), as well as for the robustness of our results to moderate linear and non-linear deviations from the parallel trend assumption following Rambachan and Roth (2021).

5 Main results

This section discusses our estimated results. We start by summarizing our findings regarding the impact of post-conflict humanitarian demining efforts and then turn to that of demining in military operations –first during the post-conflict period and then during the period of active conflict with FARC. We then assess the validity of the main identifying assumption of our empirical strategy and report a battery of robustness tests.

5.1 Post-conflict humanitarian demining Table 2 reports the main results concerning the effects of the humanitarian demining efforts that started after the end of conflict. We do so in terms of six substantive outcomes: nightime lights (Column 1) and population density (Column 2), which are proxies of economic activity; math (Column 3) and reading (Column 4) test scores; forest loss (Column 5) and the size of coca crops (Column 6).

Recall that we estimate the causal effect of all demining treatments using Callaway and Sant'Anna (2020)'s procedure, and report group-time aggregate ATTs together with their

[29]While it is impossible to know with the data at hand, it may also be the case that the never treated units were not mined at the start of the sample period.

[30]In the appendix, we show that results are similar if we estimate the baseline model using *only* either the "never-treated" or the "not-yet-treated" units as controls.

respective standard errors. The latter are clustered at the event (buffer) level. Table 2 reports the baseline results, estimated for buffers of 5 Km radius around the geo-located event and for a three-year windows around the event date.

The table includes four panels with the objective of exploring the robustness of the estimated impact of humanitarian demining. Panel A is the baseline specification with no controls. Panel B adds buffer-level geographic covariates in a doubly robust way, following Sant'Anna and Zhao (2020). This procedure allows the specification to be robust to either a misspecification of the kernel-based difference-in-differences estimator that includes covariates in a flexible way (Heckman et al., 1997), or misspecification of the inverse probability weighted estimator (Abadie, 2005).[31] Also following the doubly-robust procedure, Panel C includes municipal-level covariates, notably the variables that are often mentioned to drive the prioritization of humanitarian demining.[32] Finally, Panel D residualizes the outcomes from municipality-specific linear trends. We estimate the municipality-level trends using the untreated observations, similar to Borusyak et al. (2021). Our baseline estimates are robust to these alternative specifications in terms of both magnitude and statistical significance.

Regarding the effect of humanitarian demining on nighttime luminosity, Column 1 suggests that night lights increase by 12.7% on average, in the three years after a demining event.[33] This effect is about a third of the one found by Chiovelli et al. (2019) for the case of demining in Mozambique, namely a 37.3% increase in luminosity after a locality is cleared from landmines. Consistent with the finding reported in Column 1, Column 2 shows that population density also increases after demining. It does so by 2.7% when compared to the sample average.

How does the increase in nighttime light density triggered by humanitarian efforts to clear landmines translates into more traditional metrics of economic performance? We answer this question by computing the share of the municipal area affected by 5 Km-radius buffers around demining events in the median municipality and multiplying it by the estimated average surge in nighttime lights as reported in Column 1. We then take the product of the resulting number and the median elasticity of GDP to nighttime luminosity, as estimated by Henderson et al. (2011) (0.3). This back-of-the-envelope-calculation suggests that a humanitarian demining event increases the municipal GDP by 0.8%.

[31]The set of characteristics includes buffer-level temperature, precipitation, altitude, distance to the closest river and distance to the closest National Park.

[32]The set of municipal characteristics includes population, a coca suitability index, distance to the country's capital, a rurality index, exposure to FARC violence, and a poverty index, all of them measured at the beginning of our sample period.

[33]As suggested by Bellemare and Wichman (2020), we compute the percentage change in the outcomes subject to a hyperbolic sine transformation as $e^{\hat{\beta}} - 1$.

In turn, this figure can inform a cost-benefit analysis in which we compare the median municipal value-added to the cost of humanitarian demining per square meter and the size of the average demined area.[34] Following this procedure, we find that the benefit/cost ratio is 7.1. That is, humanitarian demining increased income in over seven dollars per invested dollar. This is likely a lower bound as it considers only the benefits realized the year after the humanitarian demining takes place.

But the positive effects of demining are not limited to economic activity. For instance, we also find that students' performance in national standardized tests improve after demining events that take place in the vicinity of the school. In particular, we find an increase in the share of students with a satisfactory performance in the math (reading) test of 6.7 (8.1) percentage points (Columns 3 and 4, respectively). This increase is statistically significant and its magnitude is large: it translates to a 32% (36%) increase in math (reading) relative to the sample mean. In Table A2 of the Appendix, we present the results of the effects of demining on grade-specific test scores. Interestingly, the magnitude of the effect is larger for younger students, especially for the math test.

Humanitarian demining also reduced forest loss, albeit by a small and non significant magnitude (Column 5). In contrast, the reduction that it caused in the size of illegal coca crops, the first activity in the chain of cocaine traffic to the US and other consumption destinations, is large and significant. As shown in Column 6, after a demining event in the vicinity, the area cultivated with coca decreased by 10.4%.

5.2 Demining in post-conflict military operations Table 3 follows the same structure as Table 2 to study the effect of demining events that result from military operations carried out during the post-conflict period on the same set of outcomes. This demining treatment has no robust effect on nighttime light density (Column 1). It is positive and significant only when covariates are added in a doubly-robust way in Panels B and C (Sant'Anna and Zhao, 2020). When no covariates are added or when the outcome is residualized from municipal-specific trends the point estimates are nearly zero. We conclude that demining in military operations after the end of conflict does not affect nighttime luminosity. In contrast, it does significantly decrease population density by 2.9% when compared with the sample average (Column 2).

Demining activity in military operations during the post conflict period has no robust effect

[34] We use the municipal value-added since Colombia has no official GDP statistics at the municipality level. However, the correlation between these two variables at the department level (the smallest administrative unit for which GDP figures are available) is 0.81 and its strongly significant. We obtained the median cost of demining per square meter –COP 66,700 ($ 18)–from Mutual-Co (2021). The actual cost, however, varies substantially depending on how isolated are the areas.

on math test scores (Column 3) and seems to reduce reading test scores by a small magnitude (Column 4). However, this is not robust to the inclusion of buffer-specific geographic covariates in a doubly-robust fashion (Panel B). Nonetheless, this demining treatment does increase deforestation in treated buffers in a magnitude equivalent to 29.4% (Column 5), and it also reduces coca crops by 9.2% (Column 6).

5.3 Demining in military operations during conflict Finally, Table 4 repeats the same analysis to study the effect of demining events that result from military operations carried out over the course of the conflict. For this period (2004-2012), we have no data on the performance of students in standardized test score, so we focus on the other four outcomes. The first finding, which is robust in terms of magnitude and significance to the addition of controls and municipality-specific trends, is that demining events during conflict decrease economic activity, as measured both in terms of nighttime light density and population density (Columns 1 and 2, respectively). In terms of magnitudes, demining events that take place during the conflict decrease average nighttime luminosity by 1.3% and population density by 1.8% relative to the sample mean. The second finding is that demining in military operations during conflict increases deforestation by 10.2%, but has no impact on coca growing.

In short, we find that post-conflict humanitarian demining increases –in the small buffers around the events–both economic activity and the performance of students in standardized test scores. It also reduces coca growing but has no effect on forest loss. In contrast, demining in military operations that took place during the post-conflict period did increase deforestation with no effect on either nighttime lights or students' performance. It also decreased coca growing. Finally, demining in military operations during the conflict period decreased economic activity and increased forest loss. Importantly, the credibility of these estimates depends to a large extent of the validity of the methodology's identifying assumption. We discuss this in the next subsection.

5.4 Main identifying assumption The main assumption of the validity of Callaway and Sant'Anna (2020)'s approach to identify causal effects is that, in the absence of the treatment, the evolution of the potential outcomes would be the same for the treated cohort (g) and the never-treated or soon-to-be-treated units. To partially assess the validity of this assumption, we present the event-study version of the estimated ATTs aggregated according to the relative time to the demining event.

Figure 2 reports the Callaway and Sant'Anna (2020)'s event study of the effect of humanitarian demining on the outcomes of interest. We find that, before the treatment the coefficients tend to move around zero and show no discernible differential pre-treatment trend. This is particularly so for nighttime lights (Panel A) and student's test scores (Panels C and D).

There seems to be a drop in (relative) year -1 in the differential level of coca growing (Panel F). Likewise, Figure 3 suggests that, for the case of demining in military operations after the end of the conflict, most of the outcomes lack differential pre-trends. The exception is forest loss, for which the differential trend is slightly decreasing prior to the demining event. Finally, Figure 4 shows no differential pre-treatment patterns for any of the outcomes.

We complement the event study figures with a formal test of whether the pre-treatment trends are parallel. Following Roth (2021), we use the precision of our estimates in the pre-treatment period to compute the pre-trend that has a 50% power of being detected, as well as the adjusted pre-trend that takes into account the pre-testing bias that arises from the fact that the reported analysis is conditional on passing a pre-test. We report the average biases in Table A4 of the Appendix.[35] We find that, for the case of the humanitarian demining treatment, the bias is around 50% for both nighttime lights and student's performance, while in the case of population density and coca cultivation the size of bias is similar to the size of the estimate (see Panel A). This suggest that the finding that humanitarian demining increases population density and decreases coca cultivation should be interpreted with caution. Panels B and C respectively report the results of the test for the cases of demining in military operations after and before the end of the conflict. In the first case, we find that the bias is around 30% of the estimate for both population density and coca cultivation, and around 10% for forest loss. In the second, all the reported significant effects tend to have a bias that is smaller than 50%.

Finally, we follow Rambachan and Roth (2021) and estimate the 90% confidence set for our parameters of interest after allowing for linear and non-linear deviations from the parallel trends assumption. We estimate such confidence set for the reported coefficient of the year after the demining event. In the case of non-linear deviations, we allow the change in the trend from consecutive periods to be as large as the size of the pre-trend that has a 50% power of being detected given the precision of the estimates in the pre-treatment period (as in Roth, 2021).

Figures A5 to A7 report the confidence sets resulting for the three treatments. In most of the cases, we find significant results even after allowing for a linear deviation of the parallel trends assumption ($M = 0$). When we allow for non-linear deviations –i.e., the trend can change size and sign for consecutive periods ($M > 0$)-we find that the increase in students' test performance after humanitarian demining are robust. However, the increase in nighttime luminosity following the same type of demining is robust to moderate non-linear violations in the parallel trends assumption only. In the case of demining resulting from post-conflict

[35] This is the average of the hypothesized trend that goes from (relative) year 0 to year 3, as well as the average of the pre-testing bias adjusted trend.

military operations, we find that significant baseline estimates are robust to both linear and non-linear violations, with the except of coca cultivation which is only robust to the former. Finally, for demining resulting from military operations during the conflict, the reported increase in forest loss and population density are robust to both linear and moderate non-linear violations.

Overall, we are confident that the baseline effects are robust to, at least, linear and moderate non-linear deviations of the parallel trends assumption, and that the size of the main point estimates are larger than 50% of the estimated coefficient if we account for biases based on pre-treatment linear trends as well as for pre-testing bias.

5.5 Robustness exercises

5.5.1 Other estimation methods In addition to Callaway and Sant'Anna (2020), other econometric procedures have been recently proposed to estimate causal effects in difference-in-differences settings with staggered adoption. This section shows that our results are robust to using three of them.

We start by estimating the effects of demining using Borusyak et al. (2021)'s approach in which the ATT is a weighted average of individual treatment effects. The individual treatment effects are in turn estimated with an imputation technique that recovers the missing (non-treated) potential outcome of the treated units. This counterfactual is constructed using a linear model for untreated observations.[36] Figures A8 to A10 report the dynamic specification resulting from this estimation procedure and Panel A of Tables A5 to A7 report the overall treatment effects. Reassuringly, most outcomes follow the same pre-treatment dynamics (with perhaps a more pronounced decreasing pre-trend for the case of population density in military demining). Moreover, in terms of the ATTs, the effects that are similar to the baseline estimates reported in Tables 2 to 4 for the three treatments.[37]

The second alternative approach that we explore is the one suggested by De Chaisemartin and d'Haultfoeuille (2020). In this case, the authors compute an ATT that measures the instantaneous treatment effect of moving from being untreated to becoming treated. Again, this model yields no substantial differences in terms of pre-treatment dynamics –with the exception of an increasing trend in nighttime luminosity prior to a humanitarian demining event– (see Figures A11 to A13 in the Appendix). The Panel B of Appendix Tables A5 to A7 report the overall ATTs derived from this model. In general, the estimates are of similar magnitude and significance for humanitarian demining, except for the increase in population

[36] We use the balanced version of their estimate to avoid results arising from changes in sample composition.

[37] The magnitude of the estimates are somewhat smaller for the effect of humanitarian demining on population density and for that of both military demining treatments on forest loss. In turn they are larger for the effect of humanitarian demining on forest loss.

density which has half the size found in the baseline estimate. In the case of both treatments pertaining to demining in military operations, the results are also similar to the baseline estimates with the exception of the changes in forest loss, the magnitude of which is half the reported for the Callaway and Sant'Anna (2020) model.

Finally, we estimate a model proposed by Wooldridge (2021), where the estimated ATT is a weighted average of the post-treatment group-year dummies that are estimated with a linear regression over the full sample of three years around the event date. We aggregate the group-year dummies in the same way we do it for the baseline specification and find treatment effects that are similar to those of Borusyak et al. (2021) (see Panel C of Appendix Tables A5 to A7).

5.5.2 Spillover effects We now explore the presence of spillover effects in our baseline results. Usually demining it is not an isolated event, specially for the case of demining events in military operations, which usually clear entire strategic corridors to allow the passing of foot soldiers from one are to the other. This implies that some of our not-yet-demined controls may soon become demined and thus contaminate our overall comparison group. We explore the extent of this potential threat to the internal validity of our results with two different but complementary strategies. First, we keep all our sample and add as a covariate (in a doubly-robust way Sant'Anna and Zhao, 2020) a dummy that identifies whether there was a (one year) prior demining event in the 3, 5, or 7 Km buffer around the current demining event.[38] Tables A8 to A10 of the Appendix report the results, which quite prove similar to those coming from the baseline specification that accounts for no potential geographic spillover.[39]

Second, we exclude from our estimating sample any demining event that experienced a (one year) prior demining within a 3, 5, or 7 Km buffer. Tables A11 to A13 of the Appendix also suggest that this alternative approach to account for potential spillovers yields similar results relative to our baseline specification.[40]

5.5.3 Alternative comparison groups Recall that our baseline specification uses as comparison group both the "never-treated" and the "not-yet-treated" mined areas. This section explore the robustness either of the two components of this group. First, Table A14 reports the average ATTs and Figures A14 to A16 the event-study counterpart of estimated the

[38]We also control for an indicator of whether there was a demining event that intersects with the buffer around never-treated controls during the year prior to the current demining event.

[39]Two exceptions are a smaller and more imprecise estimate of the increase in math test scores after humanitarian demining, and a smaller and more imprecise estimate of the decrease of population density after demining in post-conflict military operations.

[40]Two exceptions are a smaller and more imprecise estimate of the decrease in population density after a demining event in a post-conflict military operation, and a smaller increase in forest loss after a demining event in a military operation during the conflict.

effect of the three demining treatments on all the outcomes using only the "never-treated" as the comparison group. The event-study figures of both treatments related to demining in military operations become noisier, which is consistent with this treatment having fewer "never-treated" controls.

Second, Table A15 reports the average ATTs and Figures A17 to A19 the event studies of the effects of demining using only the "not-yet treated" as the comparison group. Again, the estimates are of similar magnitude and significance. However, consistent with the relevance of the "never-treated" group being larger and the number of treated units relatively small, the effect of humanitarian demining on nighttime lights and population density becomes more imprecise.

5.5.4 Accounting for anticipation effects We allow for a potential anticipation of the demining treatments by excluding from the comparison group the observations that occur one year prior to the demining events. [41] This is particularly important for humanitarian demining efforts as it may take several month for a targeted area to be fully cleared. Table A16 and Figures A20 to A22 show that the baseline results are robust to allowing a for a one-year anticipation, both in terms of magnitude and significance. The only exception is that now forest loss increases after humanitarian demining, but in that case there is an apparent positive pre-trend.

5.5.5 Alternative buffer sizes Our results are also robust to changing the size of the buffers that we draw around the geo-referenced demining events in order to delimit the area within which we study the local effects of demining. Appendix Tables A17 to A19 and Figures A23 to A25 report respectively the average estimates and event studies obtained when defining buffers of radii 3, 4, 6, and 7 Km. The results are remarkably similar both in terms of size and significance.

5.5.6 No influential observations: Excluding one cohort at the time and outliers Figures A26 to A28 in the Appendix show how the baseline average effects of each demining treatment on each outcome changes if we exclude one treated cohort at the time. With very few exceptions (such as forest loss after demining in post-conflict military operations which halves in magnitude when the 2015 or 2016 cohorts are excluded), our findings are unchanged.

In addition, Appendix Table A20 shows that all our results are robust to removing outliers. We do so by winsorizing the dependent variables at 1 and 3% level of the empirical distribution of the outcomes.

[41] By doing so, we change the comparison year of the ATT estimates from one to two years before the demining event.

5.5.7 Excluding events close to more populated areas Our results are not driven by the few demining events that are close to relatively more populated areas.[42] Appendix Figures A29 to A31 report the effect of each demining treatment on each outcome of interest excluding events that take place within a 250m, 500m, 750m or 1km from the centroid of a populated area.

6 Mechanisms

In this section, we explore the potential mechanisms behind the heterogeneous local effects of demining during peace and conflict. In particular, we study: i) the role of local road connectivity and that of the dynamics of conflict in explaining the nighttime lights results; ii) the differential effects of demining on deforestation in areas with different types of soil suitability; iii) and the complementarity of the demining efforts with other policies that seek to promote rural development, particularly with a recent illegal crops substitution program.

6.1 Road connectivity We start by exploring potential heterogeneous effects of the documented positive effect of humanitarian demining efforts on nighttime light density and on students' performance. As shown by Chiovelli et al. (2019), the potential economic benefits of demining are likely exacerbated if the clearance takes place in areas that are more connected to local markets through a network of roads. Once the mobility restrictions that landmines impose are lifted, a better access to inputs, markets for goods and services, and labor opportunities results in a faster and higher pick up of economic activity.

We explore this hypothesis by exploiting a rich network of geo-located paved and unpaved roads, available for the entire country and measured in 2012. Following the strategy proposed by Marcus and Sant'Anna (2021) to estimate heterogeneous effects in settings of difference-in-differences with staggered adoption, we re-estimate our baseline specification on two mutually exclusive samples of demining events: those that occurred in more connected areas and those that took place in less connected places. To that end, we use two different measures. The first one exploits the extensive margin of connectivity and looks at demining events in areas with at least one (paved or unpaved) road that crosses the demined area at maximum 1 Km away from its centroid.[43] The second one exploits the intensive margin, as parametrized by the length of all roads that cross the demined area at maximum 1 Km away from its centroid. To this end, we use the median of the empirical road length distribution to separate places with high and low connectivity.

[42]These areas called *centros poblados* by the Colombian Statistics Bureau and are the urban centers of the municipalities, where the city hall and other institutional supply is located.

[43]We have the coordinates of the centroid of the areas cleared in humanitarian demining operations.

Table 5 reports the results from this exercise. Based on the extensive margin of connectivity, we find that the increase in nighttime lights following a demining event is 17% in areas with at least one road close to the centroid (Panel A, Column 1). In contrast, the effect of demining of nighttime light density is less than half in areas with no road nearby (Panel A, Column 2). This difference is statistically significant at the 5% level. A similar pattern is found for students' performance, with the demining-triggered increase in test-scores being larger in more connected areas, even though the difference between the two samples is not statistically significant at conventional levels (Columns 1 and 2 of Panels B and C for math and reading test scores respectively).

The results are quite similar when we exploit the intensive margin of road connectivity. The effect of demining on both nighttime lights and student's performance is larger in areas better connected to markets (Columns 4 and 5 of Table 5). In this case, the effects of demining on the performance of students is significantly larger in relatively more connected areas, which is consistent with the interpretation that the risk of a landmines explosion prevents children to go to school. Indeed, the available anecdotal evidence suggests that, in several parts of Colombia, landmines are an important obstacle for accessing schools (CNMH, 2017).

6.2 Conflict and demining While the availability and the density of the road network can, at least partially, account for the positive effects of post-conflict humanitarian demining, the negative effect of demining in military operations during conflict in terms of declining nighttime lights and population density is perhaps more puzzling. We posit that, when the conflict was fully active, demining during military operations likely exacerbated violent dynamics of territorial contestation by illegal armed groups. Hence, and due to the absence of geo-referenced data on the incidence and intensity of violence, we explore this channel indirectly by studying the municipal-level correlation between demining events and variables related to the incidence conflict-related violence and forced internal displacement. To this end, we estimate a municipal panel specification of the effect of demining on the number of violent attacks and victims of forced displacement, y. That is, we estimate:

$$\begin{aligned} y_{mdt} = {} & \beta_1 \times \text{Conflict}_t \times \text{Military Demining}_{mt} + \beta_2 \times \text{Military Demining}_{mt} \\ & + \beta_3 \times \text{Humanitarian Demining}_{mt} + \alpha_m + \alpha_{dt} + \sum_{c \in \mathbf{X_m}} \gamma'(c \times \delta_t) + \epsilon_{mdt}, \end{aligned} \tag{6.1}$$

where m, d, and t stand for municipality, department, and time (year), respectively. We estimate this regression model over the entire sample period (2004-2019), and define $Conflict_t$ as a time dummy that takes the value one from the beginning of the sample period until the start of the peace negotiation with FARC, in 2012. Both our violence-related dependent variables and the right-hand-side military and humanitarian demining treatments are hyperbolic sine transformations of the variables in levels. We include municipality and department-year fixed effects as well as flexible trends parametrized by municipality characteristics measured before the beginning of our sample period.[44] The parameters β_2 and β_3 pick up the correlation between, respectively, military demining and humanitarian demining, on the incidence of violence during the post-conflict period (2013 onward). Instead, β_1 picks up the differential correlation between military demining and violence during the conflict period.[45]

Table 6 reports the results from estimating equation (6.1). We find a positive correlation between demining in military operations and violence during the post-conflict period. However, the magnitude of this relationship more than doubles during the conflict period. In contrast, the relationship between (post-conflict only) humanitarian demining and violence is *negative* (Columns 1 and 2). Moreover, we find that there is a negative association between demining in military operations and attacks by both FARC and paramilitary groups during the post-conflict period, but that this correlation turns positive and large during conflict period. The relationship between humanitarian demining and bellicose activity in the form of attacks is negative, though only statistically significant for the case of attacks perpetrated by FARC (Columns 3 and 4).

We interpret these results as aligned with the idea that (mostly illegal) armed groups use landmines to prevent the territorial advancement of enemies (Fundación Seguridad y Democracia, 2006), and therefore demining amidst the conflict triggers violent territorial contestation between armed groups, including the victimization of civilians thought to collaborate with the enemy (CNMH, 2017; Procuraduría, 2011). Importantly, by highlighting a potential demining-driven violence surge, these results are very much consistent with the documented decrease in nighttime luminosity and population density that partially demined areas experience along the conflict sample period.

6.3 Deforestation, soil suitability, and extractive activities As a final attempt to shed light on relevant underlying mechanisms behind our main results, and particularly on those regarding the effects of demining on deforestation, we exploit rich information about soil suitability at the level of 30m $\times$ 30m grids. Based on that input, we build average suitability measures within the 5 Km buffer around all the demining events of our sample. We then split the sample of demining events into those that took place in areas highly suitable for a specific land use, as well as those that took place in low-suitability areas. We do so based on the empirical distribution of buffer-specific average suitability.

With this input, we explore the potential heterogeneous effects that demining in military

[44] These include total population, a coca suitability index, distance to country's capital, a rurality index and a poverty index.

[45] Note that in equation (6.1) we do not interact *Humanitarian Demining* with the conflict period dummy since most of this type of demining took place during the post-conflict period.

operations have on deforestation according to the extent to which the soil is suitable to specific extractive activities such as oil palm crops, cattle herding, plantain crops, and rubber crops (Indepaz, 2008; Indepaz, 2020).

Table 7 reports the results from this analysis. The results are compelling in suggesting that the effect of demining on deforestation is driven by its occurrence in areas highly suitable to extractive activities. For instance, Panel A suggests that the documented post-military demining forest loss (both during conflict and during peace) is larger in areas more suitable for oil palm. This increase is of 21% (60%) in high suitable areas during conflict (peace) with no effects for low suitable areas. Similar figures are found when looking at the effect of military demining on forest loss in areas suitable to cattle herding (Panels B and C): military demining causes a large foreign loss in high cattle-suitable areas, with the effect being around 17% (56%) for military demining during conflict (peace). We find similar stories for banana, rubber, and forestry suitability. Importantly, the suitability of land to extractive activities does not exacerbate or attenuate the effects of humanitarian demining on deforestation (Columns 1 and 2).

To complement the idea that the change in forest loss can be related to an increase in extractive agricultural activities after military demining, we explore the effect of demining of the incidence of wild fires.[46] Anecdotal evidence has shown that, in the Colombian context, fires are used to clear forests for cattle ranching and other land-intensive agricultural activities.[47] Table A21 documents that demining in military operations during the conflict (post-conflict) period caused fired to increase by 5% (3.5%). This is consistent with the increase in forest loss that we documented in our baseline analysis (see Figure A32 for the event study estimates).

We also explore the effect of demining on illegal gold mining, a highly profitable extractive activity that has been widely used by illegal armed actors in Colombia to finance their operation (Idrobo et al., 2014). Due to data limitations, we can only do so for demining events during the post-conflict period, since UNODC estimates of illegal gold mining are available since 2014 only. Table A22 in Appendix shows that humanitarian demining events have no effect on illegal gold mining, neither in the extensive nor in the intensive margin (Columns 1 and 2). In contrast, demining activity in the context of military operations carried out during this period increased both the incidence of illegal gold mining and the extension of this activity (Columns 3 and 4). See Figure A33 for the event study estimates.

[46]This is similar to the approach followed by Harding et al. (2021) to study how deforestation is likely to be related to extractive illegal activities.

[47]See for example, https://news.mongabay.com/2019/09/as-the-amazon-burns-colombias-forests-decimated-for-cattle-and-coca/ and https://theecologist.org/2020/aug/17/deforestation-colombia (last accessed 10/9/2021).

6.4 Government programs and coca cultivation Finally, we exploit one of the main milestones of the 2016 peace agreement with FARC. The implementation of an ambitious illegal crops substitution program (PNIS from its Spanish acronym). This program was created in May 2017, 6 months after the peace agreement was ratified by the Colombian Congress. By 2018, it had reached almost 99,000 farmers in 56 municipalities, and two thirds of them had received payments (Garzón et al., 2019) as a reward for having successfully eradicated illegal coca crops and replaced then for a legal alternative. Given the relevance of this program for the rural development prospects of the main cocaine exporter of the world, we study whether the documented effect of demining during peace on the level of coca cultivation can be at least partially explained by the national roll out of the PNIS crop substitution program. To this end, we split our sample for those cohorts treated after 2017 (when PNIS was launched) into the areas where PNIS was present and those with no active crop-substitution policy. Table 8 summarizes the results. We find that peace-time demining decreases coca crops especially on PNIS-targeted areas. Moreover, the effect of the complementarity between demining and PNIS is over three times larger for humanitarian demining that for demining in military operations.

7 Conclusions

In spite of the tens of millions of planted anti-personnel landmines that persist today world wide, the enormous stock of manufactured but not yet planted landmines, and the thousands of landmine victims every year, the literature on the economic costs of conflict has surprisingly relegated the study of the long term economic and social consequences of landmines, as well as that of the potential benefits of demining campaigns. While recent efforts have highlighted that comprehensive landmine clearance operations result in increased economic activity, we know little about it's impact on other socio-economic and political outcomes and the effects of other types of demining, especially the kind that occurs as a result of military operations, both over the course of the conflict and during the post-conflict period. This paper contributes to filling this gap.

We study the case of Colombia, the country with the highest number of casualties from improvised handmade landmines, and that has engaged a range of demining activities since before the start of the peace process with FARC, Colombia's largest guerrilla group. Moreover, we focus on the local effects of demining by taking advantage of a unique dataset that includes the coordinates of both humanitarian demining campaigns and demining events resulting from military operations. Based on recent methodologies developed for difference-in-differences settings with staggered adoption, and exploiting the longitudinal variation of all demining events that took place from 2004 to 2019 in Colombia, we estimate the causal effect of demining on a range of outcomes including nighttime light density, students' performance in standardized tests, population density, deforestation, and coca growing.

Consistent with the previous literature, we find that comprehensive humanitarian demining events that take place after the end of the conflict increases economic activity. Moreover, we find that they also increase other variable associated with higher welfare, such as population density and students' test scores. Importantly, all these effects are significantly larger in areas that are more connected to inputs, goods and services, and labor markets through a denser road network.

However, unlike any previous literature, we document that demining events that occur in the context of military operations are likely to backfire, especially if they take place while the conflict is still ongoing. Indeed, we find that demining in military operations increases violent territorial contestation and, as a result, decreases economic activity and population density. It also increases deforestation rates, especially in areas that are suitable to extractive economic activities such as cattle ranching. This highlights the potential environmental costs of demining.

Finally, we find suggestive evidence that humanitarian demining campaigns are complementary to other policies that address the challenges to a productive rural land use. In particular, we find that the effect of a recent incentives program to substitute illegal crops for legal land uses is much larger in areas that have benefited from landmine clearance.

Altogether, our results highlight the fact that demining can, perhaps surprisingly, backfire. This suggests that, in order to trigger beneficial economic and social dynamics demining campaigns should be both comprehensive (in terms of mines' clearance) and complemented with other state building efforts and local investments.

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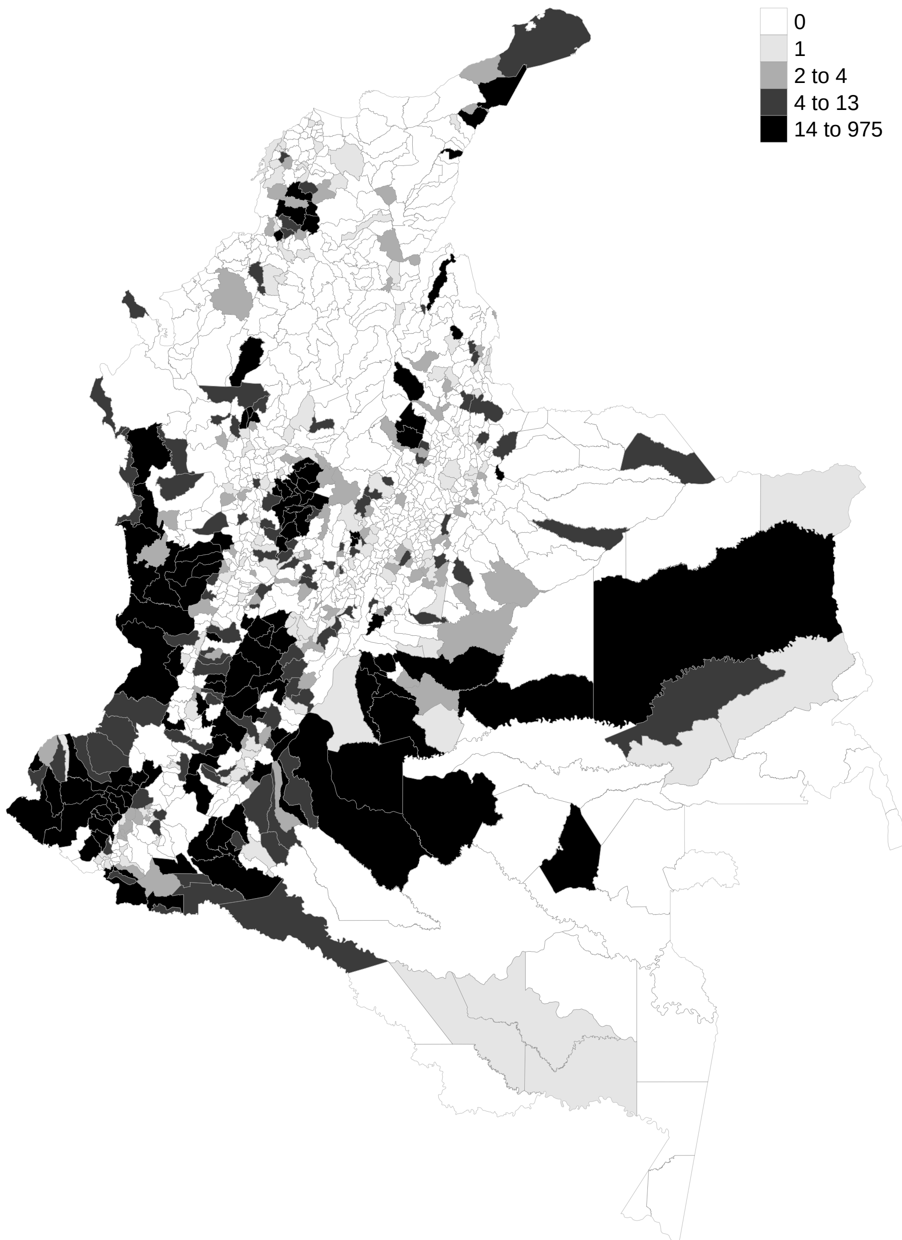
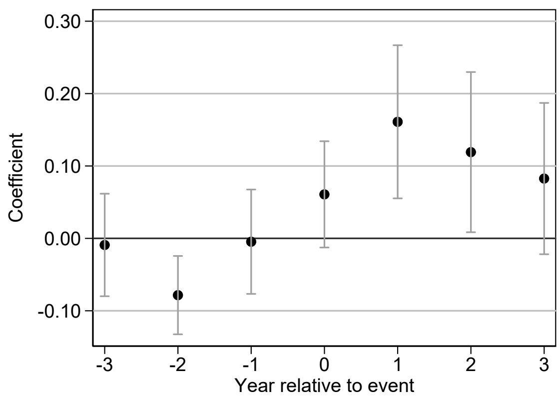
Figure 1. Number of demining events (2004-2019)

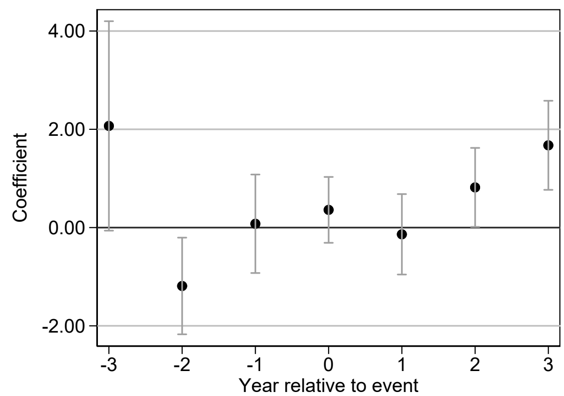


Notes: This map presents the spatial distribution of humanitarian and military demining events from 2004 to 2019.

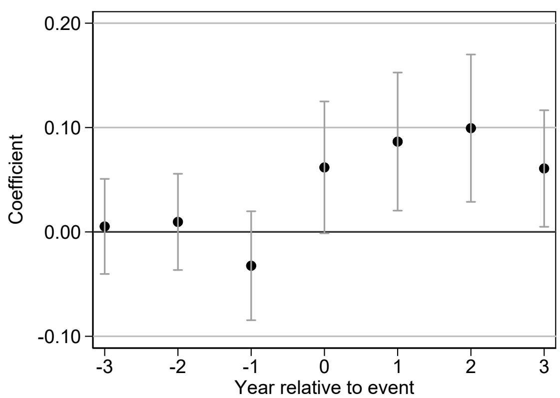
FIGURE 2. Humanitarian demining during peace and local activity



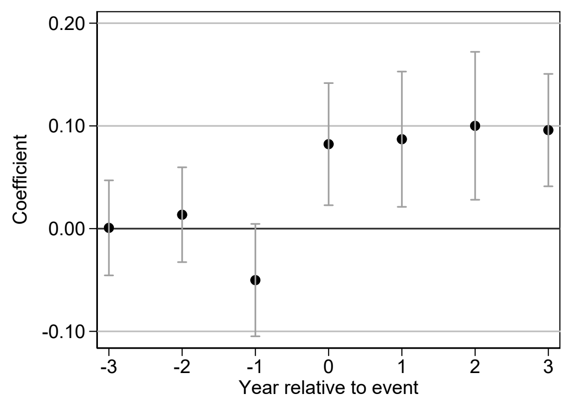
A. Nighttime lights



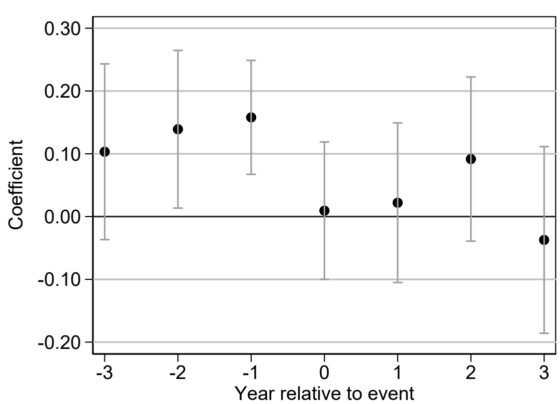
B. Population density



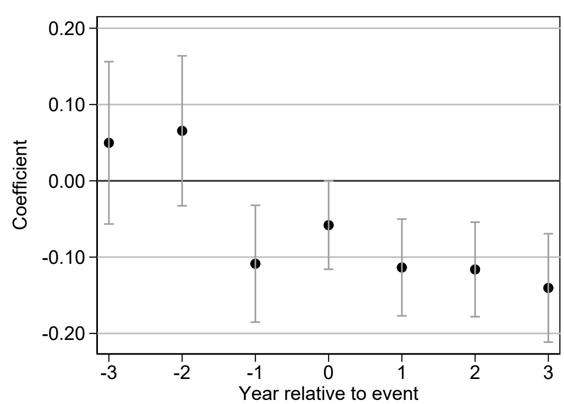
C. Test scores: Math



D. Test scores: Reading



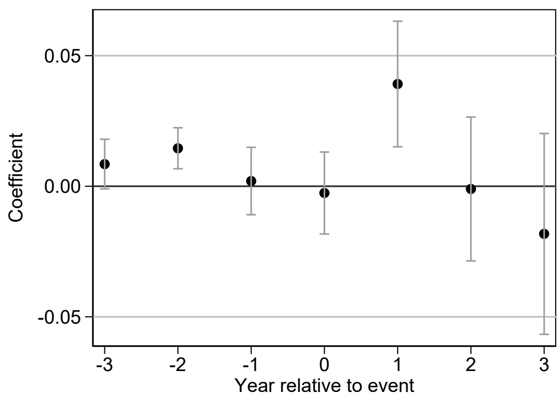
E. Forest loss



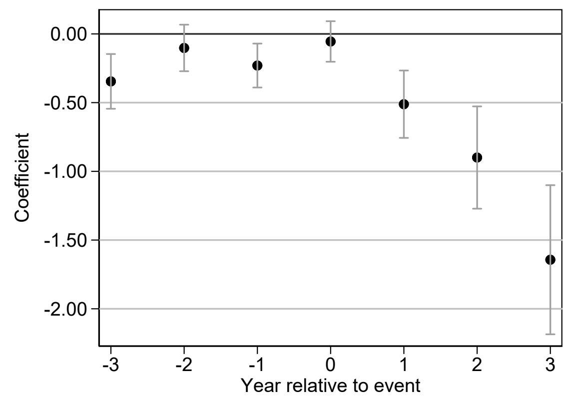
F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

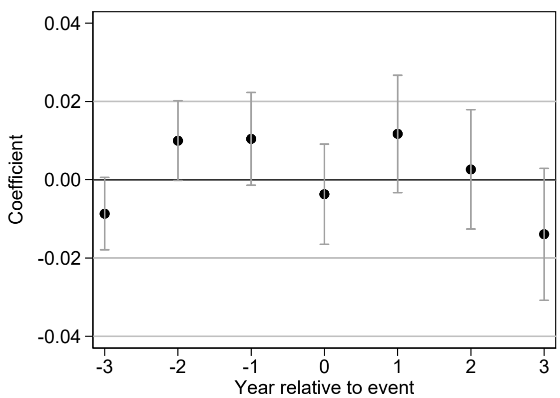
Figure 3. Military demining during peace and local activity



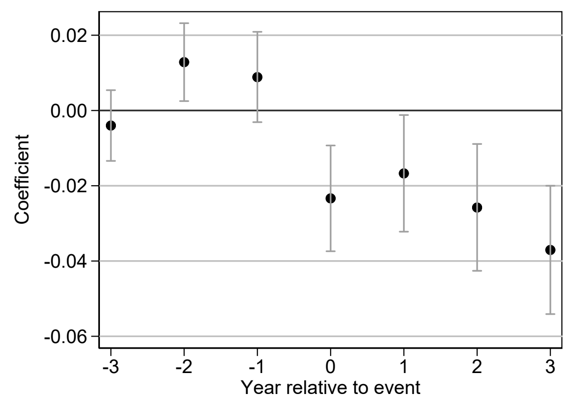
A. Nighttime lights



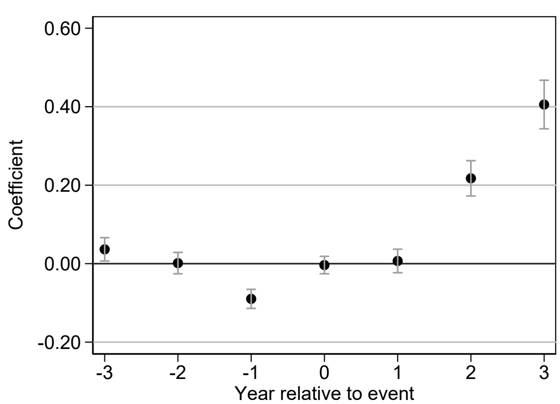
B. Population density



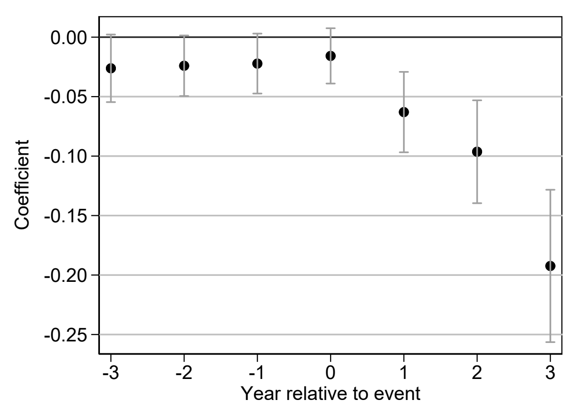
C. Test scores: Math



D. Test scores: Reading



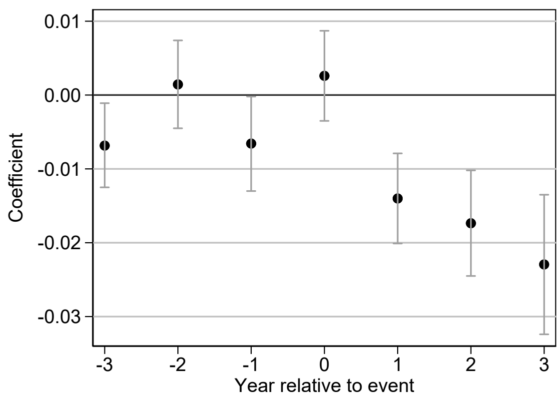
E. Forest loss



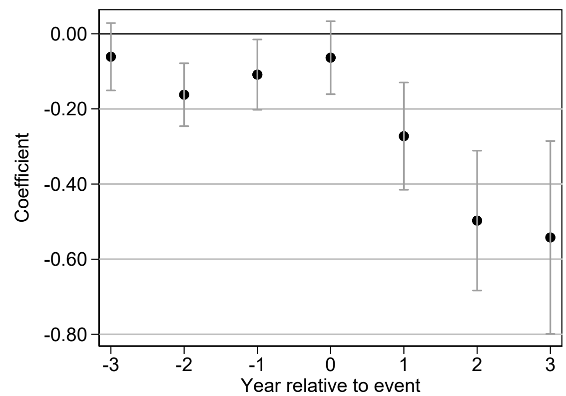
F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of demining during peace. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

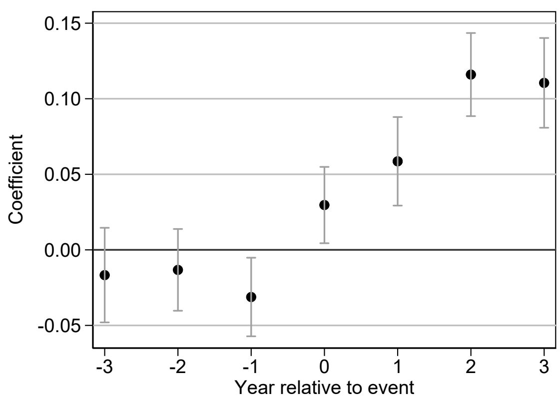
Figure 4. Military demining during conflict and local activity



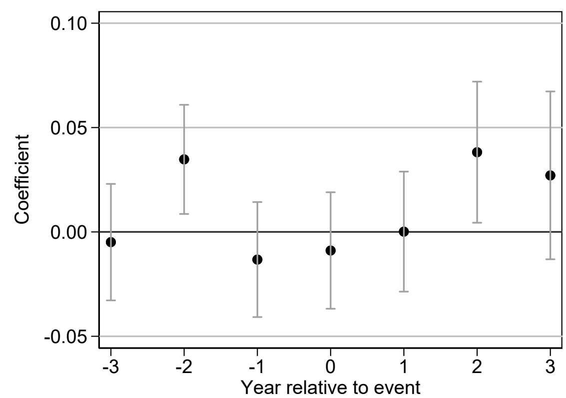
A. Nighttime lights



B. Population density



C. Forest loss



D. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of demining during peace. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

Table 1. Summary statistics

	(1) Average	(2) Standard deviation	(3) 90th percentile	(4) 50th percentile	(5) 10th percentile
Panel A: Humanitarian demining during peace					
Nighttime lights	1.343	1.058	2.585	1.436	0
Population density	34.407	30.752	66.871	26.092	7.839
Test scores: Math	0.191	0.35	0.861	0	0
Test scores: Reading	0.205	0.374	0.927	0	0
Forest loss	3.29	1.305	4.928	3.38	1.473
Coca hts	0.636	1.488	2.809	0	0
N Schools	10.138	7.809	19	9	1
Panel B: Military demining during peace					
Nighttime lights	0.973	1.156	2.611	0.196	0
Population density	33.381	56.452	76.459	14.362	2.332
Test scores: Math	0.103	0.266	0.618	0	0
Test scores: Reading	0.116	0.292	0.75	0	0
Forest loss	3.721	1.521	5.48	3.963	1.443
Coca hts	2.392	2.636	6.369	1.346	0
N Schools	8.084	12.688	18	5	1
Panel C: Military demining during conflict					
Nighttime lights	0.435	0.849	1.759	0	0
Population density	26.349	50.676	56.319	10.939	2.269
Forest loss	3.403	1.39	5.063	3.566	1.408
Coca hts	1.728	2.137	5.022	0	0

Notes: This table presents summary statistics for our main variables of interest. The outcomes in panels A, B, and C were computed using a radius of 5km around the demining event.

Table 2. The local effects of humanitarian demining during peace

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Baseline specification						
Post demining	0.120***	0.938***	0.067***	0.081***	-0.031	-0.110***
	(0.037)	(0.363)	(0.021)	(0.021)	(0.054)	(0.035)
Panel B: Adds geographic covariates						
Post demining	0.080**	0.868**	0.040*	0.042**	-0.078	-0.094**
	(0.034)	(0.352)	(0.021)	(0.020)	(0.049)	(0.037)
Panel C: Adds municipality covariates						
Post demining	0.111***	1.048***	0.060***	0.075***	-0.020	-0.106**
	(0.035)	(0.360)	(0.023)	(0.022)	(0.061)	(0.043)
Panel D: Adds municipality linear trends						
Post demining	0.143***	0.932***	0.067***	0.081***	-0.031	-0.109***
	(0.036)	(0.350)	(0.022)	(0.021)	(0.052)	(0.036)
Observations	7460	7460	6960	6960	7460	7460
Treated	294	294	283	283	294	294
Never treated	452	452	413	413	452	452
Average dep var	1.343	34.407	0.207	0.222	3.290	0.636

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. In Panels B and C, we use a doubly robust estimator following Sant'Anna and Zhao (2020). In Panel B, we use geographic covariates to predict the outcome. The set of covariates includes temperature, precipitation, altitude, distance to the closest river, and to the closest national park. In Panel C, we add a set of municipality characteristics as covariates that includes the logarithm of population, a coca suitability index, distance to the country's capital, a rurality index, a poverty index, and a dummy for FARC presence during 2007 - 2012. In Panel D, we residualized the outcome from municipality linear trends, that are computed using untreated observations. Bootstrap standard errors clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE 3. The local effects of military demining during peace

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Baseline specification						
Post demining	0.009	-0.983***	-0.001	-0.016**	0.258***	-0.097***
	(0.013)	(0.220)	(0.006)	(0.006)	(0.024)	(0.025)
Panel B: Adds geographic covariates						
Post demining	0.067***	-0.907**	0.010	-0.011	0.217***	-0.093***
	(0.016)	(0.375)	(0.009)	(0.009)	(0.026)	(0.030)
Panel C: Adds municipality covariates						
Post demining	0.070***	-1.063***	-0.013*	-0.037***	0.076***	-0.120***
	(0.018)	(0.368)	(0.008)	(0.007)	(0.027)	(0.028)
Panel D: Adds municipality linear trends						
Post demining	0.009	-0.979***	-0.001	-0.016***	0.258***	-0.094***
	(0.013)	(0.227)	(0.006)	(0.006)	(0.024)	(0.025)
Observations	90504	100560	69340	69370	100560	100560
Treated	9630	9630	6641	6641	9630	9630
Never treated	426	426	293	296	426	426
Average dep var	0.973	33.381	0.149	0.168	3.721	2.392

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. In Panels B and C, we use a doubly robust estimator following Sant'Anna and Zhao (2020). In Panel B, we use geographic covariates to predict the outcome. The set of covariates includes temperature, precipitation, altitude, distance to the closest river, and to the closest national park. In Panel C, we add a set of municipality characteristics as covariates that includes the logarithm of population, a coca suitability index, distance to the country's capital, a rurality index, a poverty index, and a dummy for FARC presence during 2007 - 2012. In Panel D, we residualized the outcome from municipality linear trends, that are computed using untreated observations. Bootstrap standard errors clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 4. The local effects of demining during conflict

	(1) Nighttime Lights	(2) Population density	(3) Forest Loss	(4) Coca
Panel A: Baseline specification				
Post demining	-0.013***	-0.478***	0.098***	-0.009
	(0.003)	(0.089)	(0.011)	(0.013)
Panel B: Add geographic covariates				
Post demining	-0.013***	-0.463***	0.090***	-0.027**
	(0.003)	(0.096)	(0.010)	(0.013)
Panel C: Adds municipality covariates				
Post demining	-0.012***	-0.325***	0.101***	-0.019
	(0.003)	(0.088)	(0.010)	(0.014)
Panel D: Adds municipality linear trends				
Post demining	-0.013***	-0.479***	0.099***	-0.009
	(0.003)	(0.084)	(0.011)	(0.014)
Observations	213000	213000	213000	213000
Treated	15150	15150	15150	15150
Never treated	2600	2600	2600	2600
Average dep var	0.435	26.349	3.403	1.728

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. In Panels B and C, we use a doubly robust estimator following Sant'Anna and Zhao (2020). In Panel B, we use geographic covariates to predict the outcome. The set of covariates includes temperature, precipitation, altitude, distance to the closest river, and to the closest national park. In Panel C, we add a set of municipality characteristics as covariates that includes the logarithm of population, a coca suitability index, distance to the country's capital, a rurality index, and a poverty index. In Panel D, we residualized the outcome from municipality linear trends, that are computed using untreated observations. Bootstrap standard errors clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 5. Heterogeneous effects for economic and social outcomes by road connectivity

	(1)	(2)	(3)	(4)	(5)	(6)
Demining:	Humanitarian demining					
Defs:	Any road			Road's density		
	Paved or Unpaved	No roads	p-value diff.	High	Low	p-value diff.
Panel A: Nighttime Lights						
Post demining	0.172***	0.071	0.045	0.179**	0.084**	0.173
	(0.051)	(0.046)		(0.070)	(0.042)	
Panel B: Test scores - Math						
Post demining	0.091***	0.046	0.163	0.152***	0.037	0.003
	(0.032)	(0.030)		(0.040)	(0.026)	
Panel C: Test scores - Reading						
Post demining	0.095***	0.070**	0.436	0.142***	0.058**	0.023
	(0.032)	(0.030)		(0.037)	(0.025)	
Observations (Panel A)	3360	4100		1860	5560	
Observations (Panel B)	3240	3720		1790	5170	
Observations (Panel C)	3240	3720		1790	5170	
Treated (Panel A)	139	155		88	206	
Treated (Panel B)	136	147		86	197	
Treated (Panel C)	136	147		86	197	
Never treated (Panel A)	197	255		98	354	
Never treated (Panel B)	188	225		93	320	
Never treated (Panel C)	188	225		93	320	

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for nighttime lights and students' performance after an humanitarian demining event. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. For each type of treatment, we divide the treated and never treated into events with any paved or unpaved road that crosses as close as 1km from the demined area and those with no close roads (columns 1 to 3). In columns 4 to 6, we follow a similar strategy but we divide the events into those that have a higher area of roads, measured by the length of the road that crosses as close as 1km from the demined area. We use the median of the empirical distribution to separate those with high and low connectivity. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 6. Demining and conflict

	(1)	(2)	(3)	(4)	(5)
	Victims		Attacks		
	Total	Forced displacement	Army	FARC	Paramilitaries
Conflict × Military demining	0.20***	0.10***	0.04***	0.15***	0.05***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Military demining	0.11***	0.08***	0.01	-0.03***	-0.02**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Humanitarian demining	-0.18***	-0.30***	-0.02	-0.09***	-0.01
	(0.05)	(0.05)	(0.02)	(0.03)	(0.01)
Observations	17,472	12,110	17,472	17,472	17,472
R-squared	0.912	0.883	0.309	0.458	0.473
Municipality fixed effect	Yes	Yes	Yes	Yes	Yes
Dept-year fixed effect	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Municipalities	1092	1073	1092	1092	1092
Average dep var	3.466	4.775	0.0473	0.0750	0.0850

Notes: This table presents the relationship between military and humanitarian demining and conflict related victims and attacks (see equation 6.1). All the dependent variables are measured using the hyperbolic sine transformation. Military (Humanitarian) demining is the total number of landmines demined by the army (humanitarian organizations) transformed using the hyperbolic sine transformation. $Conflict_t$ is a dummy that takes the value one before 2013. All the regressions include the set of covariates: the total population, log distance to the capital, a rurality index, and a poverty index all measured in 2003 and interacted with year fixed effects. Robust standard errors are clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 7. Heterogeneous effects for forest loss by soil suitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
During:	Peace						Conflict		
Demining:	Humanitarian			Military			Military		
Suitability:	Low	High	p-value diff.	Low	High	p-value diff.	Low	High	p-value diff.
Panel A: Oil palm									
Post demining	-0.072	0.037	0.294	-0.015	0.472***	0.000	0.021	0.189***	0.000
	(0.084)	(0.061)		(0.033)	(0.031)		(0.013)	(0.017)	
Panel B: Cattle									
Post demining	-0.020	-0.015	0.961	0.082***	0.450***	0.000	0.019	0.163***	0.000
	(0.078)	(0.067)		(0.030)	(0.035)		(0.014)	(0.015)	
Panel C: Grass									
Post demining	0.032	0.028	0.969	0.112***	0.364***	0.000	0.058***	0.156***	0.000
	(0.081)	(0.065)		(0.027)	(0.034)		(0.013)	(0.016)	
Panel D: Rubber									
Post demining	-0.016	0.014	0.780	0.084***	0.357***	0.000	0.046***	0.163***	0.000
	(0.087)	(0.063)		(0.032)	(0.030)		(0.014)	(0.017)	
Panel E: Banana									
Post demining	0.018	-0.001	0.865	0.231***	0.284***	0.278	0.051***	0.148***	0.000
	(0.093)	(0.062)		(0.033)	(0.036)		(0.014)	(0.016)	
Panel F: Forestry									
Post demining	0.001	0.052	0.641	0.157***	0.285***	0.005	0.108***	0.084***	0.244
	(0.083)	(0.071)		(0.032)	(0.032)		(0.013)	(0.016)	
Observations	3680	3780		44660	55900		119364	93636	
Treated	125	169		4309	5321		8640	6510	
Never treated	243	209		157	269		1307	1293	
Average dep var	2.811	3.757		3.147	4.179		2.904	4.039	

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for forest loss using the three demining treatments. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. For each type of treatment we divide the treated and never treated into high and low suitability. We do this by constructing the share of the area around the event with suitability for each activity and then define as high (low) the ones with suitability above (below) the median. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table 8. Heterogeneous effects for coca cultivation by substitution program

	(1)	(2)	(3)	(4)	(5)	(6)
	During peace:					
Demining:	Humanitarian			Military		
PNIS:	No	Yes	p-value diff.	No	Yes	p-value diff.
Post demining	0.131*	-0.511**	0.016	-0.047	-0.149***	0.084
	(0.068)	(0.257)		(0.046)	(0.037)	
Observations	4650	580		7860	11060	
Treated	60	14		639	828	
Never treated	405	44		147	278	
Average dep var	0.766	1.213		2.212	5.089	

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for coca cultivation using for both demining treatments during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. For each type of treatment, we divide the treated and never treated into events in municipalities without and within the PNIS program. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

APPENDIX (For Online Publication)

FIGURE A1. Plan "Renacer" by FARC

Camaradas del Secretariado. Mi saludo

1. Importante las relaciones del camarada TIMO. Con los amigos colaboradores del presidente CHAVEZ. Vale la pena darles a conocer el plan estratégico, asi como se le presento a su jefe, a su asesor y amigo CHACIN. Igual de importante reforzar en los encuentros con los ELENOS propiciados por el gobierno, la necesidad de crear la fusión en algunas regiones de domino primordial de las FARC EP y buscar el apoyo de los asistentes a estas reuniones. A la senadora PIEDAD, hablarle sobre la necesidad de crear un partido del pueblo y buscar su alianza al movimiento Bolivariano.

2. Ya todos conocemos los cambios en la situación política del país y al mismo tiempo la situación interna de nuestra organización guerrillera, por eso es tiempo de realizar algunos cambios temporales y pasar nuevamente a la táctica de GUERRA DE GUERRILLAS, plan propuesto como "RENACER REVOLUCIONARIO DE LAS MASAS" es allí donde se encuentra la estrategia y el éxito de la guerra de guerrillas con el desarrollo del PLAN PATRIOTA y la mal llamada POLITICA DE SEGURIDAD DEMOCRATICA, el enemigo ha ganado espacio geográfico y por mal utilización de nuestros recursos sociales también hemos visto afectado el espacio político social. Situación un poco distinta a la manejada por el camarada SANTRICH y MATIAS con las células del cauca, Valle y Nariño, estructuras que dejaron fortalecidas antes de trasladarse al área del Bloque Caribe. Por esto dentro del desarrollo de este plan propongo adelantar algunas actividades y otras ponerlas en consideración para su posterior ejecución.

3. Desarrollar por lo menos, antes de terminar el presente año, cursos de misiones especiales, programa desarrollado por el Comando Conjunto Central y que ha dado resultados positivos en corto tiempo luego de terminar el entrenamiento de las unidades.

4. Disponer de 5 á 6 millones de dólares del fondo del Secretariado, para adquirir intendencia, material de guerra y comunicaciones. Necesario para fortalecer la capacidad de lucha de los guerrilleros urbanos y milicias. Del manejo de este dinero se encargara el Bloque Oriental y cada bloque aportara entre 1 y 2 millones según condiciones para este fin.

5. Aumentar los visos defensivos y de movilidad con minados para detener el avance de las operaciones enemigas, ya conocemos que las minas son el único factor que los detiene y los intimida, por esto aumentar los cursos de explosivistas para lograr un nivel de conocimiento en explosivos, generalizados dentro de la guerrillerada e iniciar igualmente el entrenamiento del personal del MB y de milicias, haciendo énfasis en que no se debe de manipular los mismos con excesiva confianza los que lleva a accidentes.

6. El Comando Conjunto ya con capacidades en este ámbito, ejecutara algunas operaciones, para mantener el nombre de nuestra organización y evitar así crear un ambiente de derrota progresiva a las FARC EP.

7. En la medida que se vayan ejecutando los entrenamientos, como ejercicios finales se deben de colocar objetivos reales, que propicien golpes al enemigo.

8. Con el uso de minas y explosivos se equilibran las cargas frente a un enemigo numeroso, bastante equipado y con gran poder de fuego.

9. Los resultados logrados en el Guayabero, son una muestra de la necesidad de entrenar bien militarmente a las milicias y miembros del MB, aun cuando se trata de un poder invaluable y necesario, solo se encuentran proporcionando inteligencia y logística, situación que se dificulta cuando hay controles enemigos sobre las rutas o medios, ejemplo claro de esto es la situación presentada con Cesar. Hay que pensar en un mecanismo para reforzar ese mismo mecanismo sin exponer la seguridad y brindar más resultados al enemigo.

10. Es difícil para el enemigo mantener el despliegue de personal, material sobre un área permanente, por esto que al retomar la táctica de guerrillas móviles aunado con los golpes que pueden propinar las milicias y el MB. fortalecerá la presencia nuestra en áreas.

11. La táctica de francotiradores ya tratada desde la Octava Conferencia, se debe desarrollar con los recursos destinados dentro de la ejecución de este plan, adquirir el material necesario, fusiles y munición especializada por Bloque, el efecto de la ejecución de esta maniobra tendrá iguales resultados que los minados.

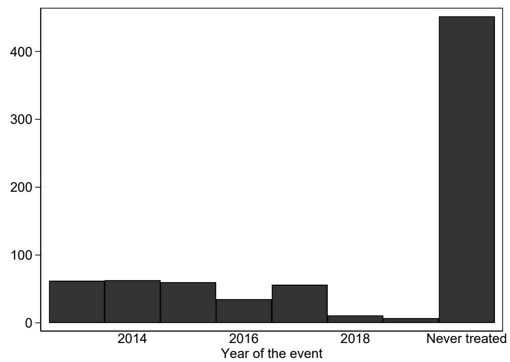
12. Los grupos encargados de la tarea telefónica se debe incrementar en todas las áreas de operaciones enemigas, está comprobado que estando lo bastando cerca de ellos arroja buenos resultados para IC.

13. Alistar por bloque unidades de confianza y que tengan el servicio militar para que se presenten como soldados profesionales y utilizarlos para IC. Como se esta trabajando en el Oriental y el Bloque Sur.

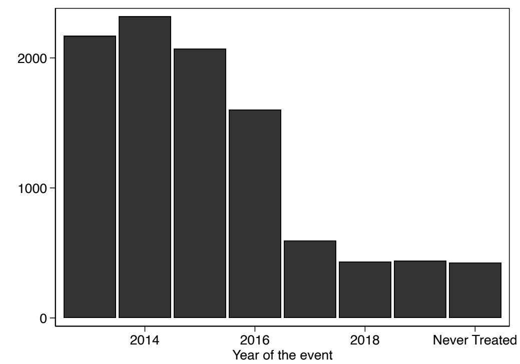
14. En la historia de las guerras de guerrillas, se ha demostrado que lo que ha creado un paralelo de negociación obligatorio entre la parte más fuerte y el apoyo aéreo, que termina por causar gran daño a la contraparte, pero también es claro que si se logra golpear este paral, los resultados en la balanza se inclinan a favor, es por esto que se hace de extrema necesidad lograr la negociación de misiles que nos permitan propinar golpes contundentes al poderío aéreo del enemigo. Las tareas de destrucción de aeronaves mediante la infiltración como lo ha hecho el Oriental nos ha demostrado que el precio es alto y se cometen errores.

Es todo y espero sus opiniones. Alfonso

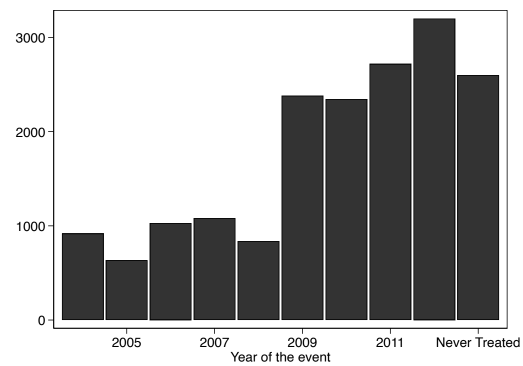
FIGURE A2. Events by year of occurrence



A. Humanitarian demining during peace



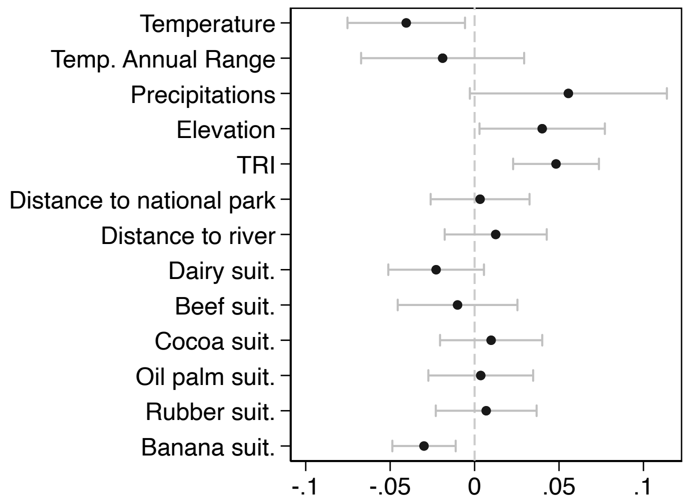
B. Military demining during peace



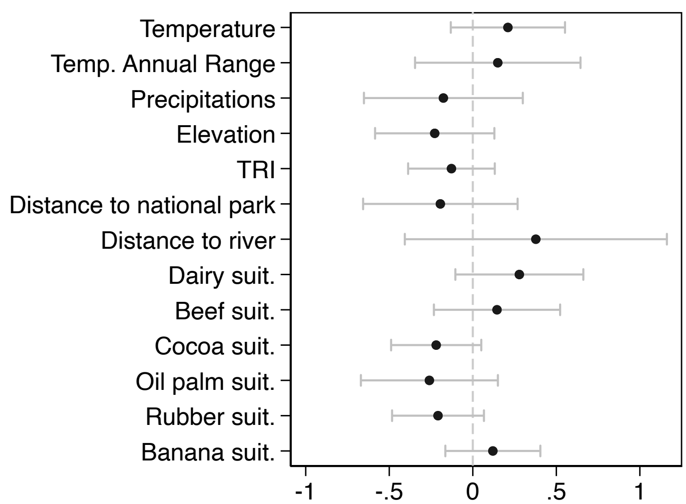
C. Military demining during conflict

Notes: This figure presents the number of treated units by cohort and the never treated units for the three treatments, humanitarian demining during peace (panel A), military demining during peace (panel B), and demining during conflict (panel C).

Figure A3. Differential characteristics by treatment status and timing of treatment



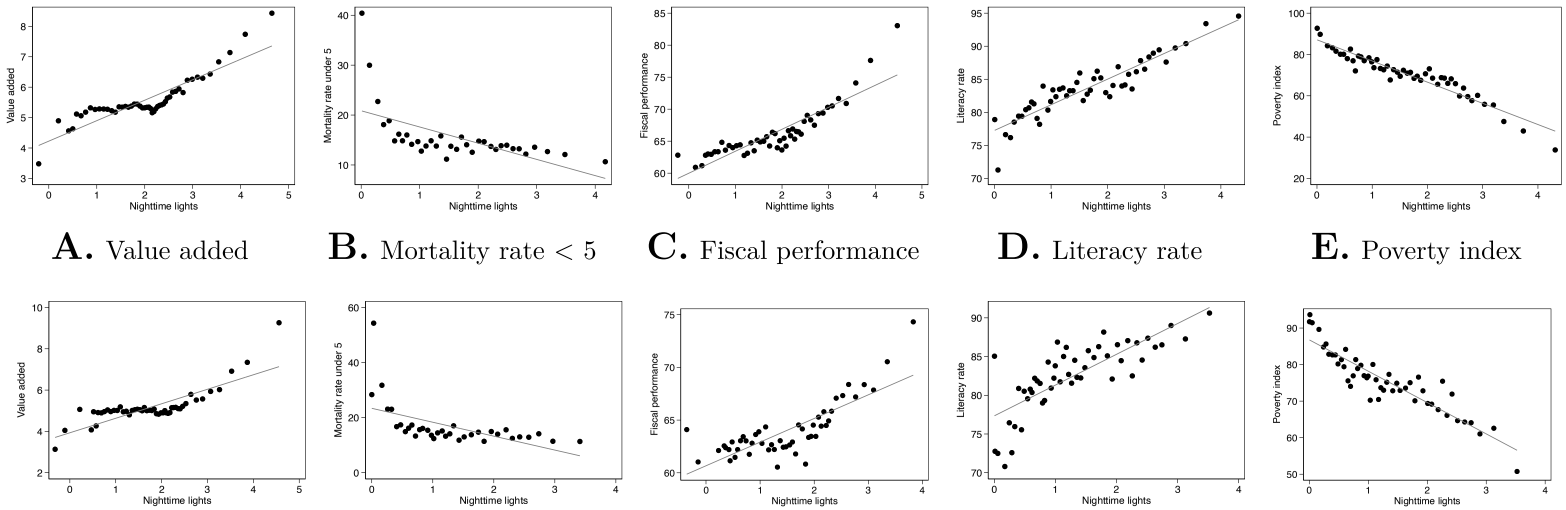
A. Treated versus non-treated



B. Timing of treatment

Notes: This figure presents the standardized differences by treatment status and treatment timing. In Panel A, we compare grids of 10x10km that were demined during 2004-2019 versus grids that were not demined within the same municipality. In Panel B, we compare within demined grids and look at the year of the first demining event. All characteristics are computed at the 10x10km grid.

FIGURE A4. Nighttime lights correlation with municipality characteristics

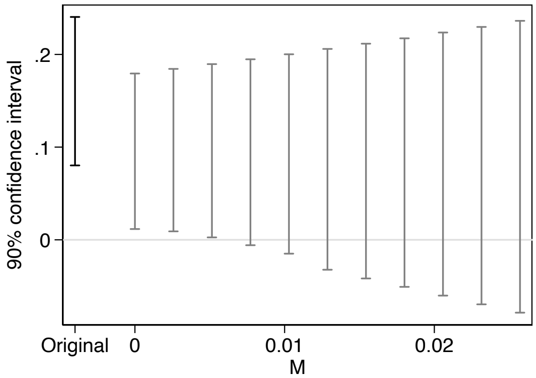


A. Value added **B.** Mortality rate < 5 **C.** Fiscal performance **D.** Literacy rate **E.** Poverty index

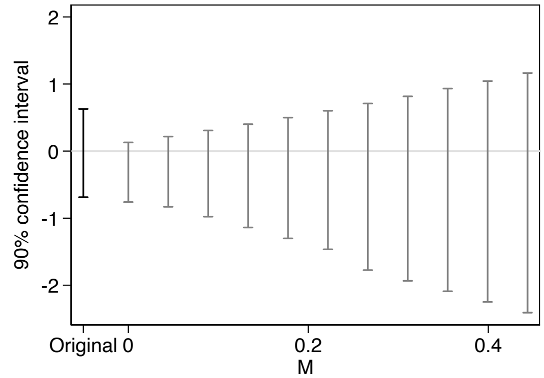
F. Value added (R) **G.** Mortality rate < 5 (R) **H.** Fiscal performance (R) **I.** Literacy rate (R) **J.** Poverty index (R)

Notes: This figure presents the correlation between nighttime lights and several municipality characteristics. Panels A to E present the result for the whole country, while panels panels F to J present the results for rural counties (those with a rurality index above the median). Panels A and F (B and G) present the correlation with value added (mortality rate under 5 years old) for to years 2011 to 2018, adding year fixed effects. Panels C and H present the correlation with fiscal performance for the years 2011 to 2016, adding year fixed effects. Panel C and H (E and J) present the correlation with literacy rate (poverty index) from the 2005 Population Census. Nighttime lights and value added are presented as the hyperbolic sine transformation of the values in levels.

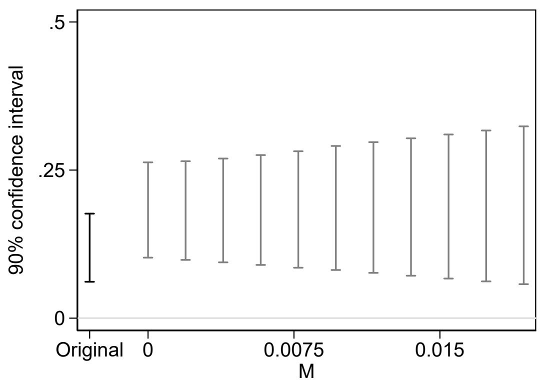
FIGURE A5. Violations to parallel trends assumption: Humanitarian demining during peace



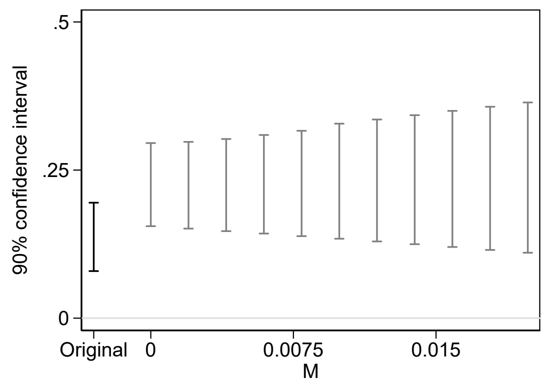
A. Nighttime lights



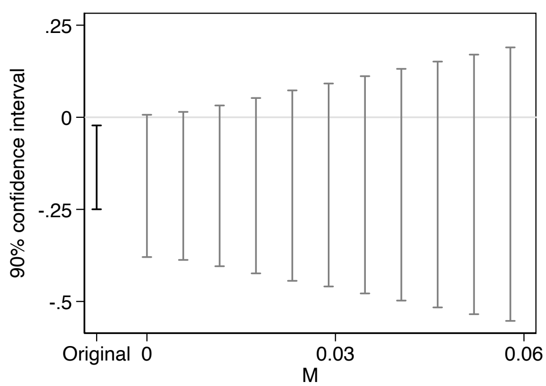
B. Population density



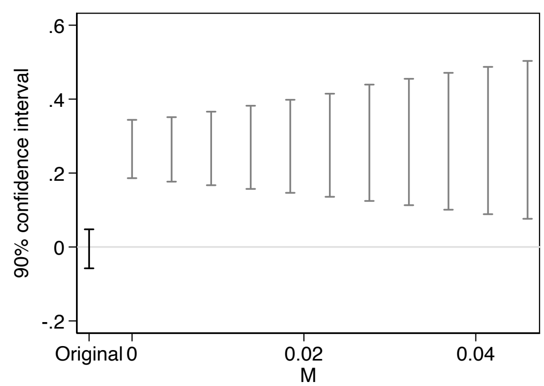
C. Test scores: Math



D. Test scores: Reading



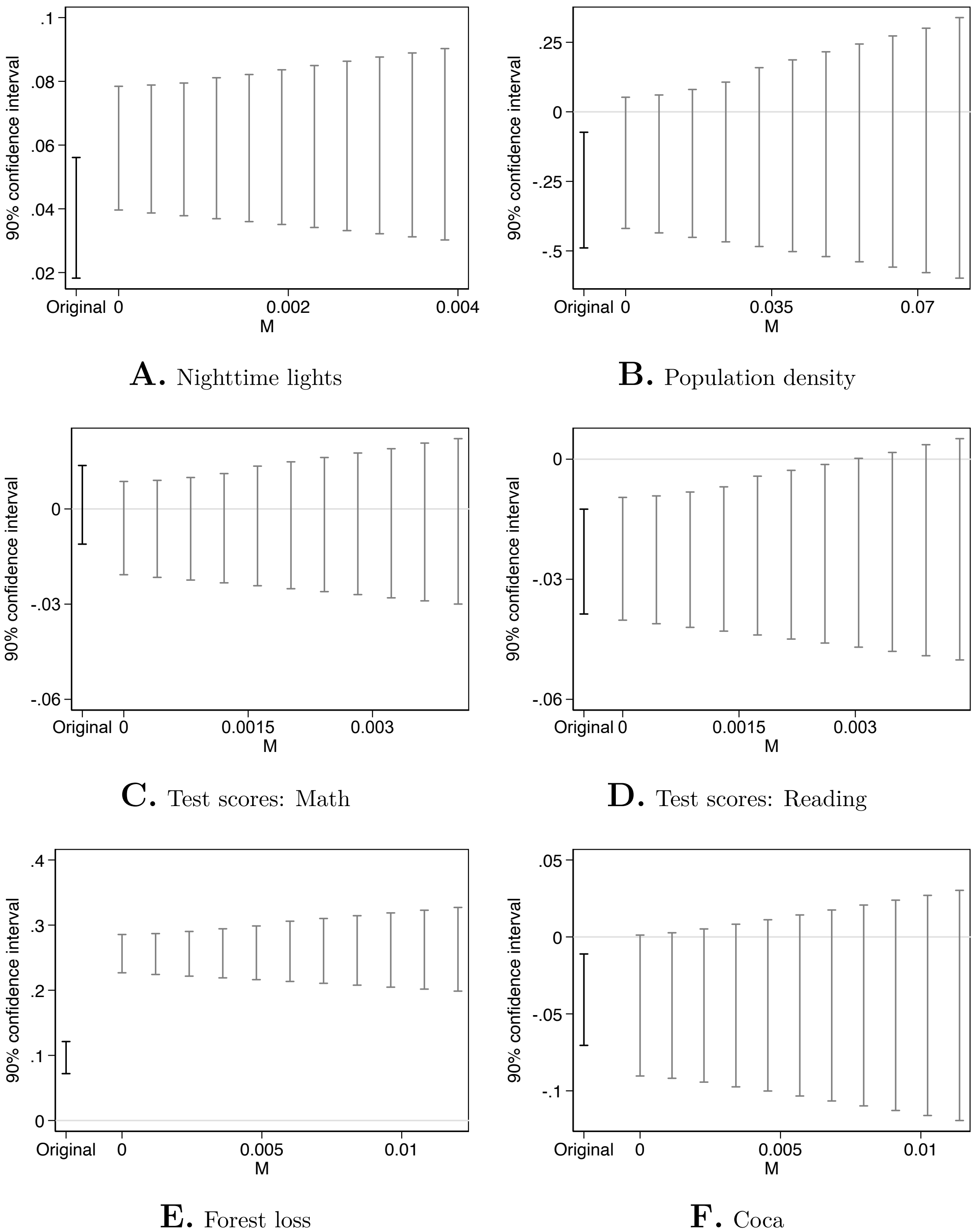
E. Forest loss



F. Coca

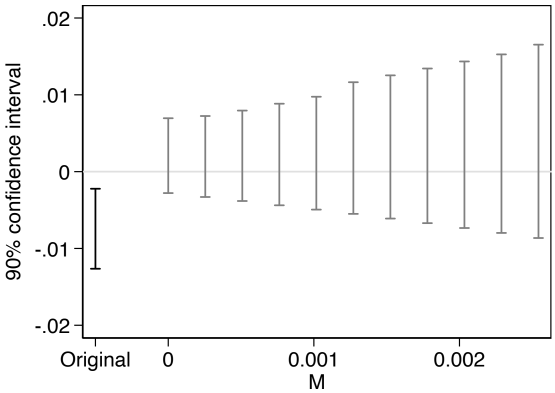
Notes: This figure presents the confidence set at 90% for linear and non-linear violation of the parallel trends assumption (Rambachan and Roth, 2021). The figure is shown for the coefficient the year after the demining event. The treatment is humanitarian demining during peace. M measures the size of the change in the trend between consecutive periods. Thus $M = 0$ is a linear violation of the parallel trend assumption. The maximum value of M is equal to the trend that has a 50% power of being detected given the precision of the estimates in the pre-period (Roth, 2021).

Figure A6. Violations to parallel trends assumption: Military demining during peace

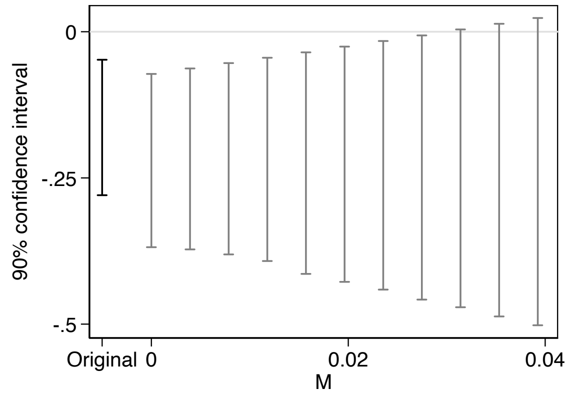


Notes: This figure presents the confidence set at 90% for linear and non-linear violation of the parallel trends assumption (Rambachan and Roth, 2021). The figure is shown for the coefficient the year after the demining event. The treatment is military demining during peace. M measures the size of the change in the trend between consecutive periods. Thus $M = 0$ is a linear violation of the parallel trend assumption. The maximum value of M is equal to the trend that has a 50% power of being detected given the precision of the estimates in the pre-period (Roth, 2021).

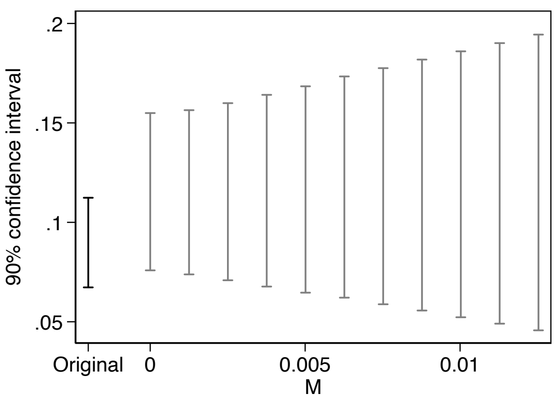
Figure A7. Violations to parallel trends assumption: Military demining during conflict



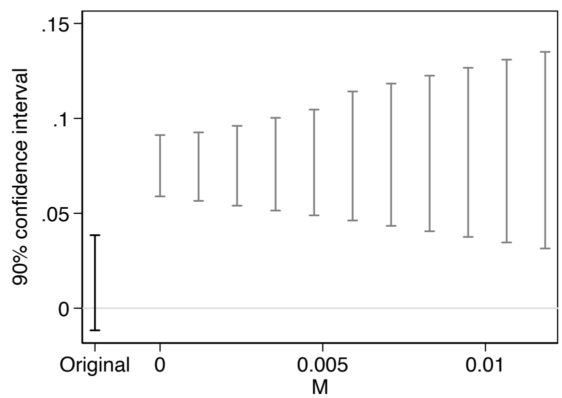
A. Nighttime lights



B. Population density



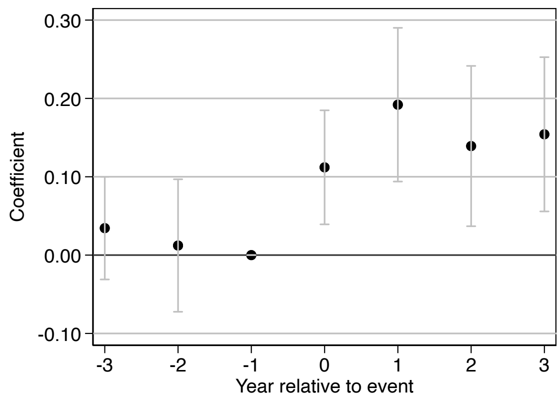
C. Forest loss



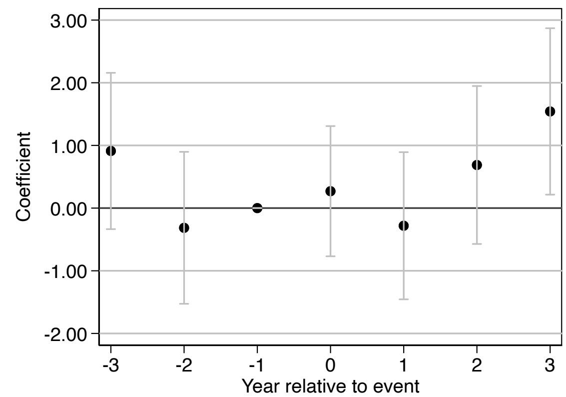
D. Coca

Notes: This figure presents the confidence set at 90% for linear and non-linear violation of the parallel trends assumption (Rambachan and Roth, 2021). The figure is shown for the coefficient the year after the demining event. The treatment is military demining during conflict. M measures the size of the change in the trend between consecutive periods. Thus $M = 0$ is a linear violation of the parallel trend assumption. The maximum value of M is equal to the trend that has a 50% power of being detected given the precision of the estimates in the pre-period (Roth, 2021).

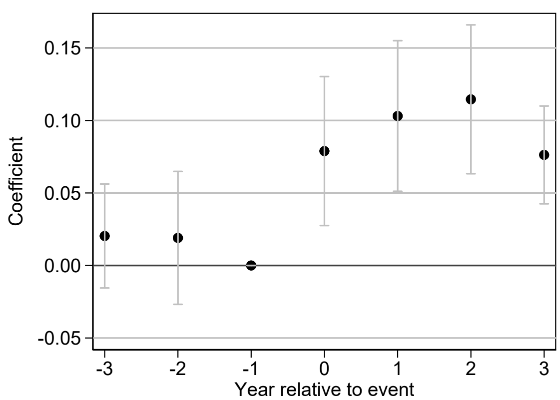
FIGURE A8. Humanitarian demining during peace and local activity: Borusyak et al. (2021)



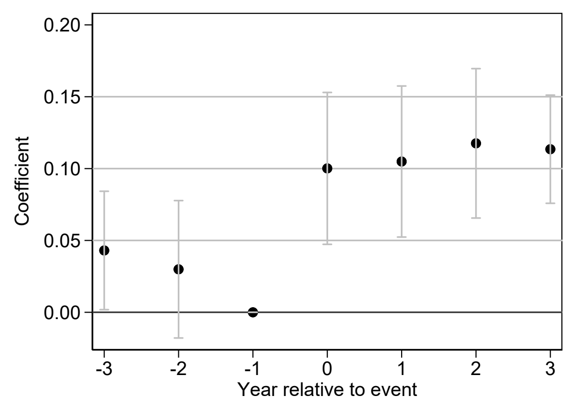
A. Nighttime lights



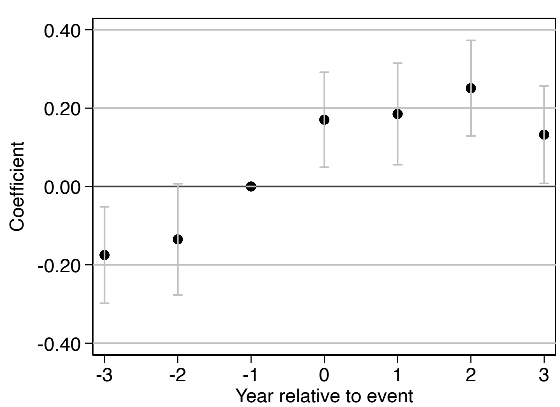
B. Population Density



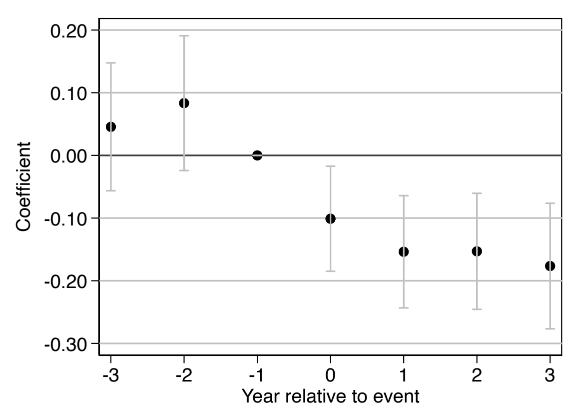
C. Test scores: Math



D. Test scores: Reading



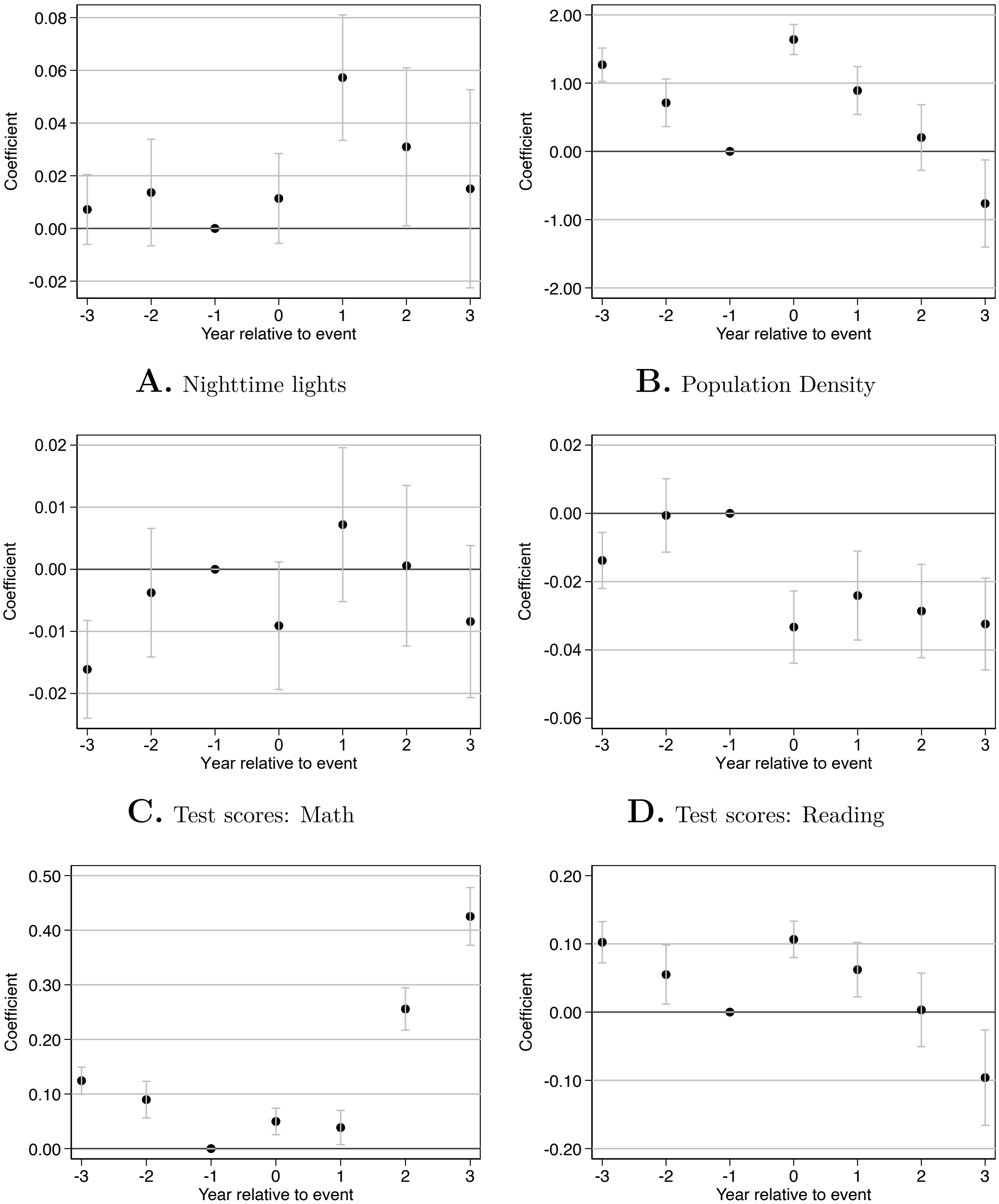
E. Forest loss



F. Coca

Notes: This figure presents the event study coefficients following Borusyak et al. (2021) for the treatment of humanitarian demining. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

FIGURE A9. Military demining during peace and local activity: Borusyak et al. (2021)



A. Nighttime lights

B. Population Density

C. Test scores: Math

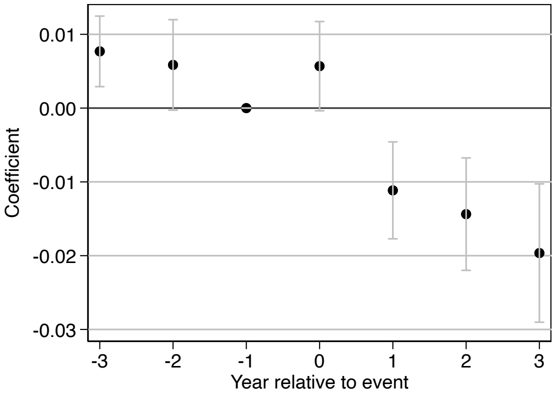
D. Test scores: Reading

E. Forest loss

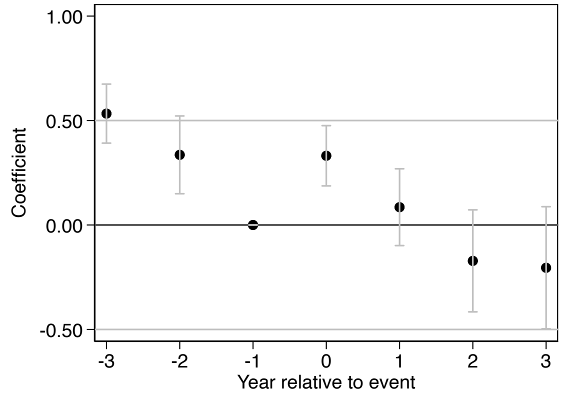
F. Coca

Notes: This figure presents the event study coefficients following Borusyak et al. (2021) for the treatment of demining during peace. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

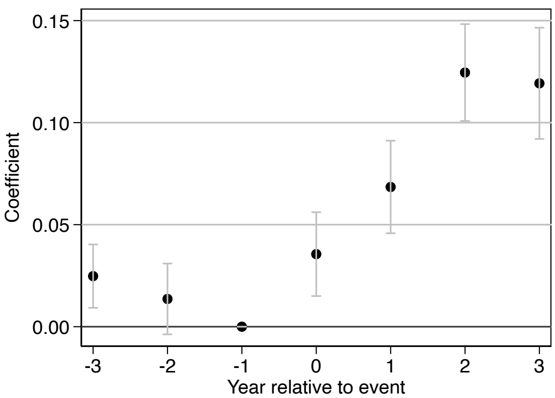
FIGURE A10. Military demining during conflict and local activity: Borusyak et al. (2021)



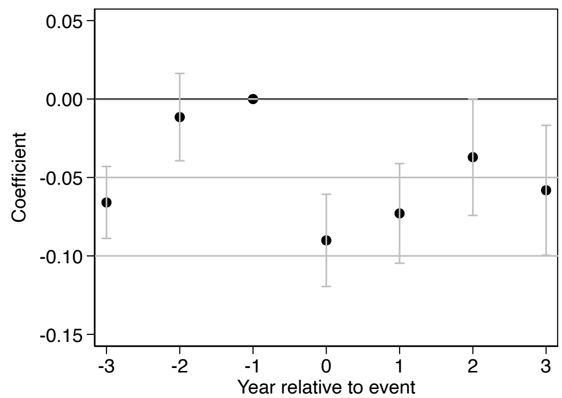
A. Nighttime lights



B. Population Density



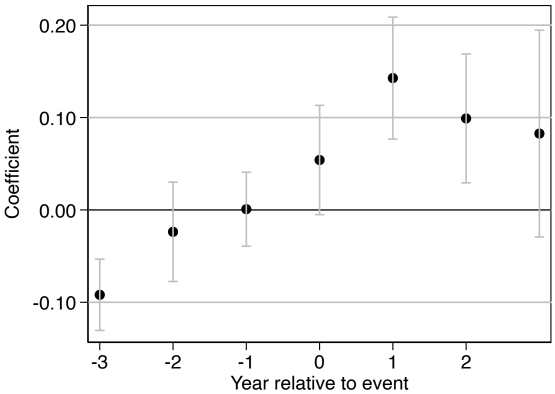
C. Forest loss



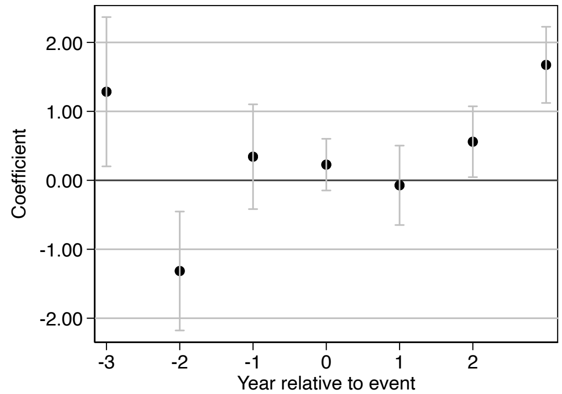
D. Coca

Notes: This figure presents the event study coefficients following Borusyak et al. (2021) for the treatment of demining during conflict. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

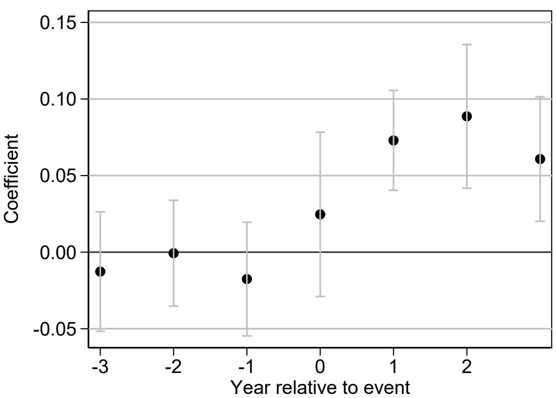
Figure A11. Humanitarian demining during peace and local activity: De Chaisemartin and d'Haultfoeuille (2020)



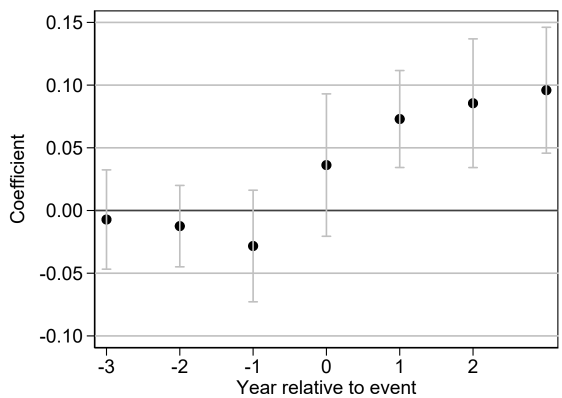
A. Nighttime lights



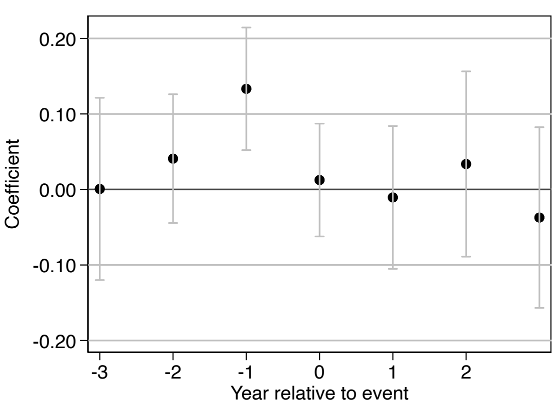
B. Population Density



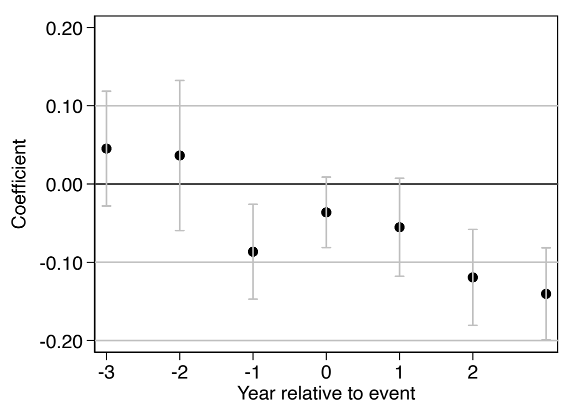
C. Test scores: Math



D. Test scores: Reading



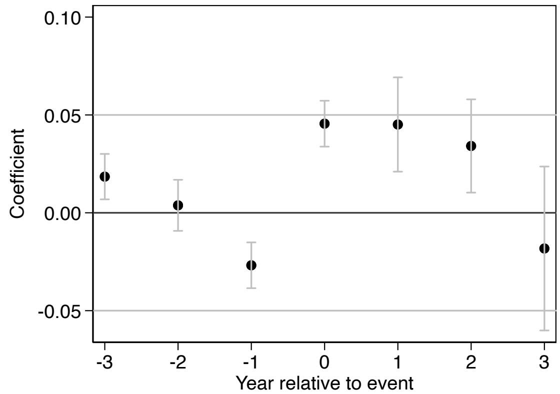
E. Forest loss



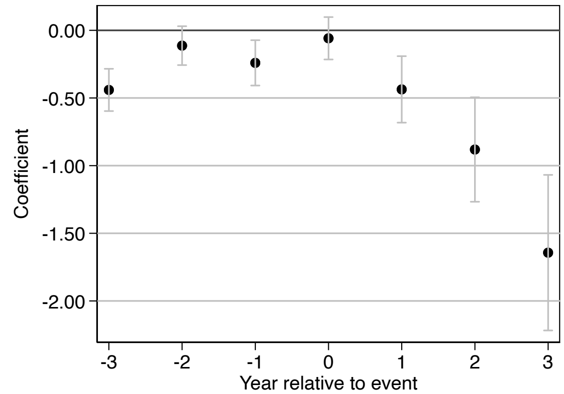
F. Coca

Notes: This figure presents the event study coefficients following De Chaisemartin and d'Haultfoeuille (2020) for humanitarian demining during peace. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

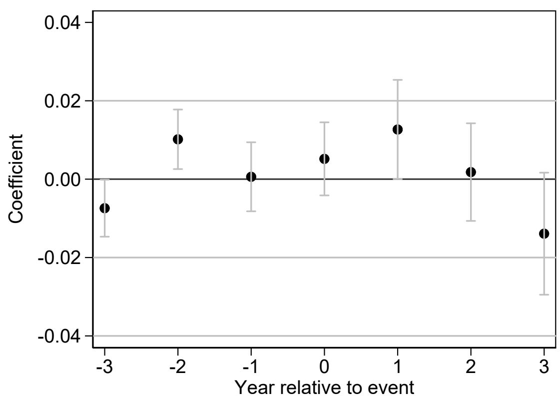
FIGURE A12. Military demining during peace and local activity: De Chaisemartin and d'Haultfoeuille (2020)



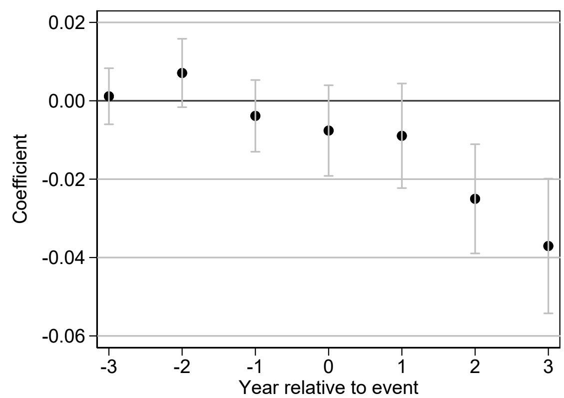
A. Nighttime lights



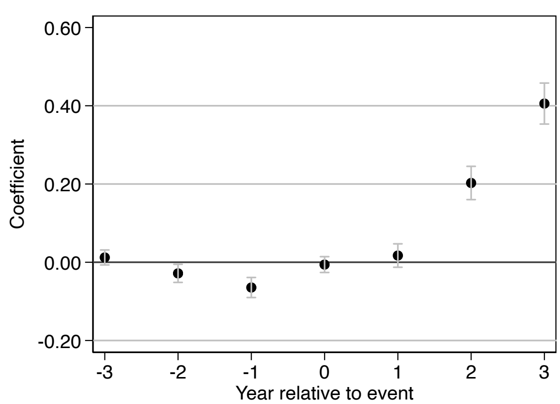
B. Population Density



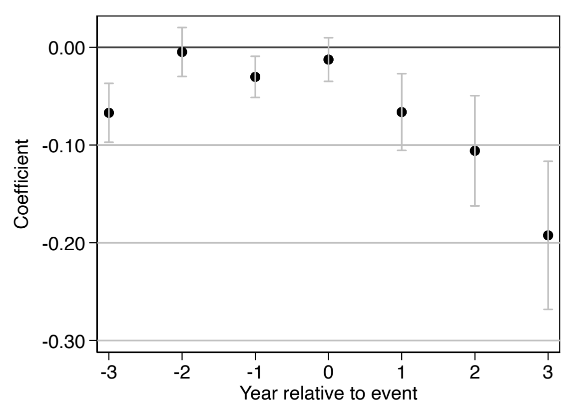
C. Test Scores: Math



D. Ratio Approved Reading



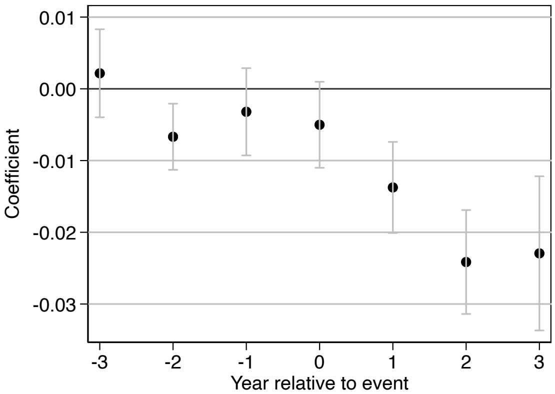
E. Forest loss



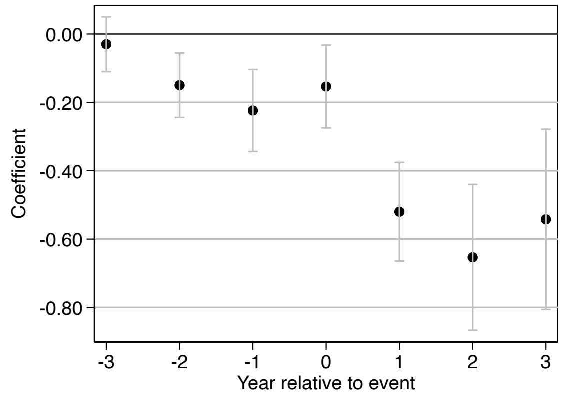
F. Coca

Notes: This figure presents the event study coefficients following De Chaisemartin and d'Haultfoeuille (2020) for military demining during peace. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

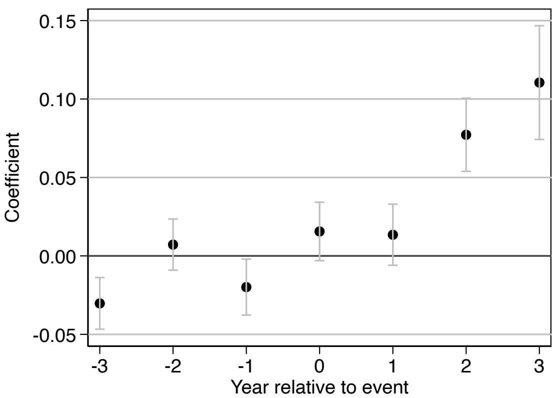
FIGURE A13. Military demining during conflict and local activity: De Chaisemartin and d'Haultfoeuille (2020)



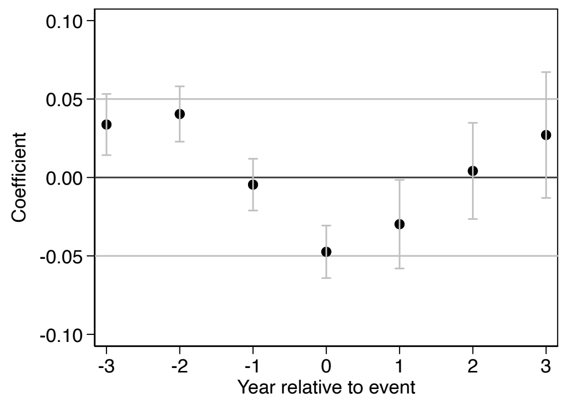
A. Nighttime lights



B. Population Density



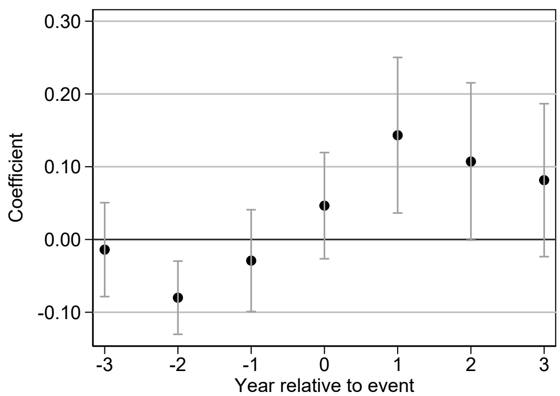
C. Forest loss



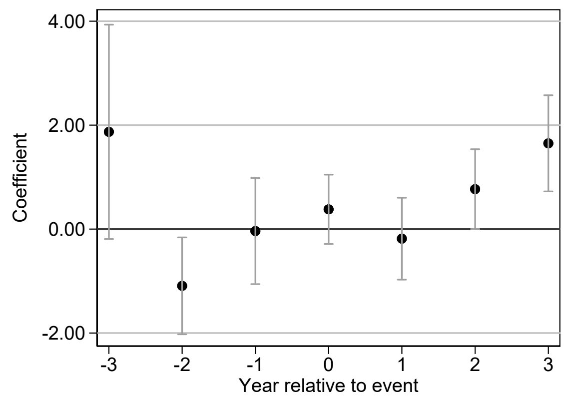
D. Coca

Notes: This figure presents the event study coefficients following De Chaisemartin and d'Haultfoeuille (2020) for military demining during conflict. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

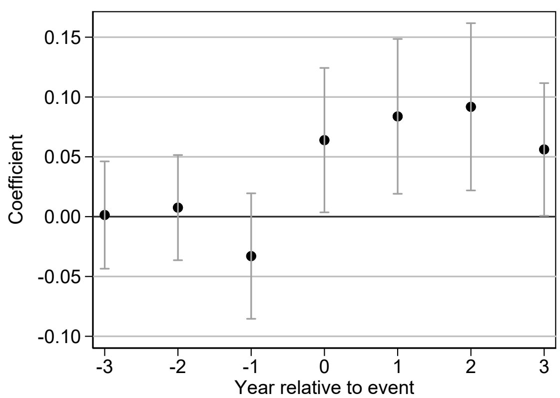
FIGURE A14. Humanitarian demining during peace: Using only never treated



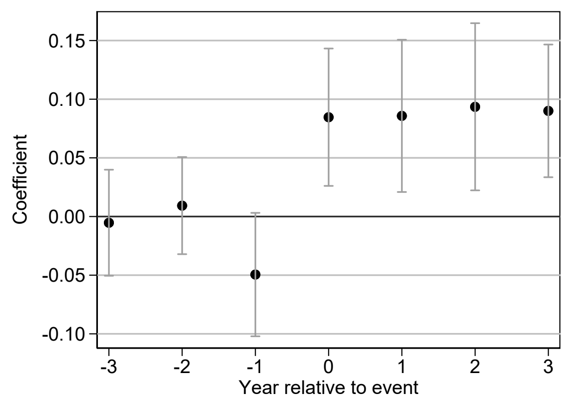
A. Nighttime lights



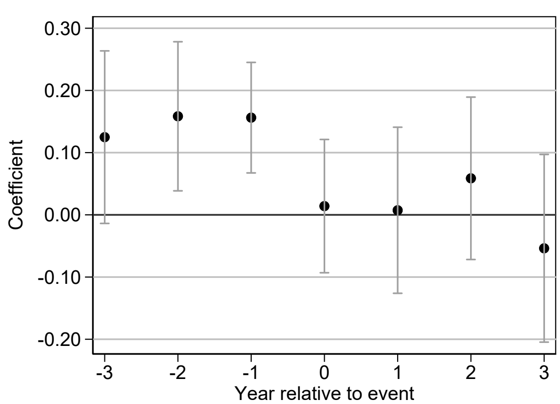
B. Population density



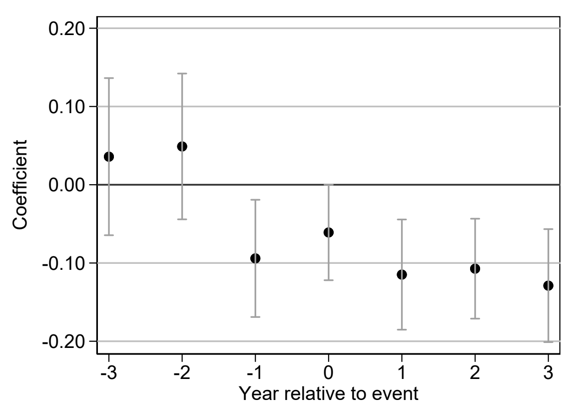
C. Test Scores: Math



D. Test Scores: Reading



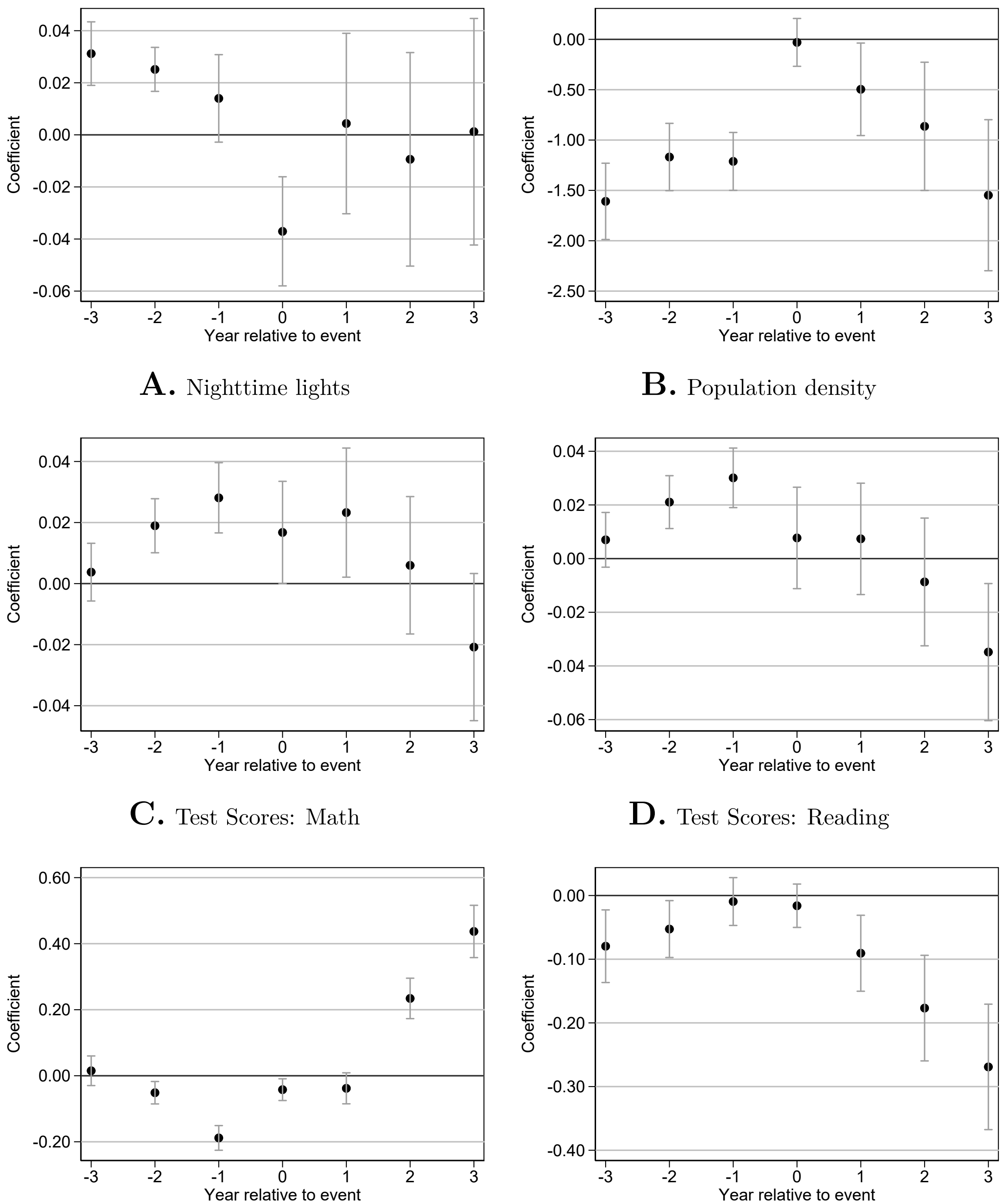
E. Forest loss



F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. The set of controls include only the never-treated. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

Figure A15. Military demining during peace: Using only never treated



A. Nighttime lights

B. Population density

C. Test Scores: Math

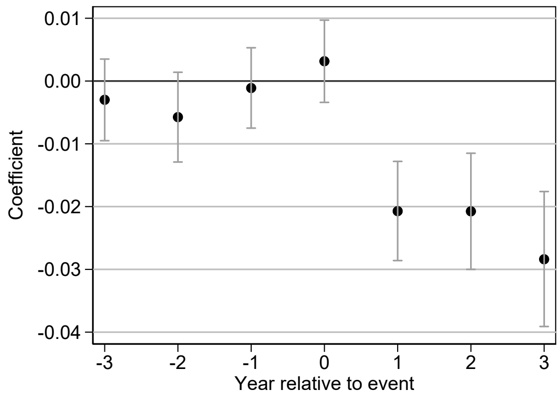
D. Test Scores: Reading

E. Forest loss

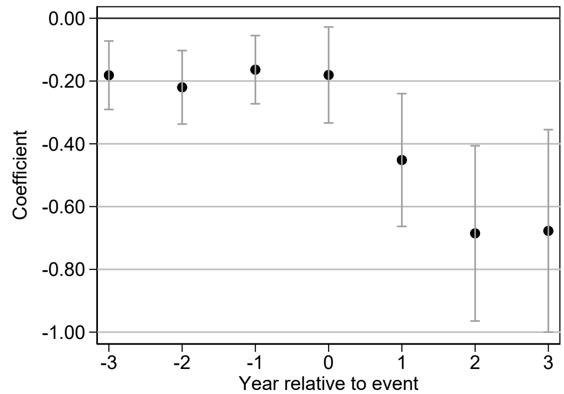
F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. The set of controls include only the never-treated. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

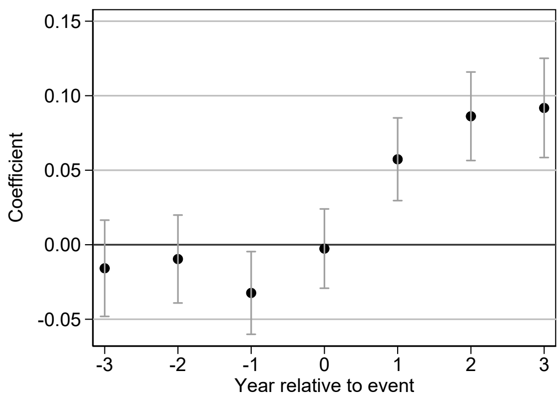
Figure A16. Military demining during conflict: Using only never treated



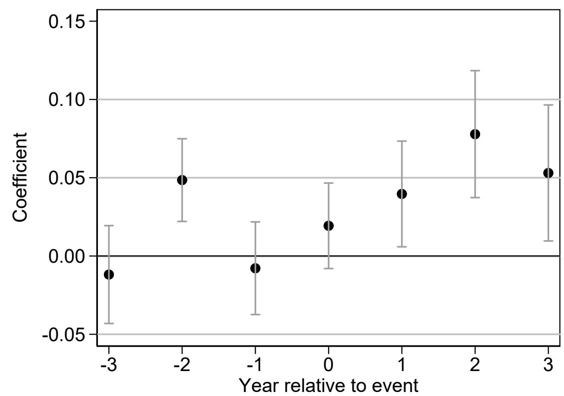
A. Nighttime lights



B. Population density



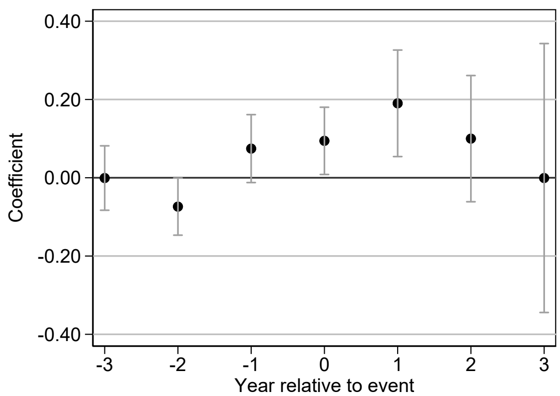
C. Forest loss



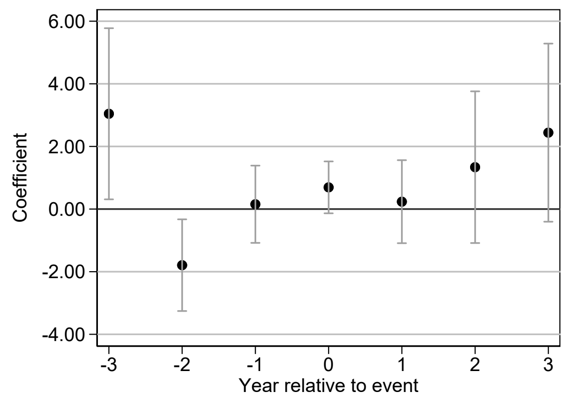
D. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. The set of controls include only the never-treated. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

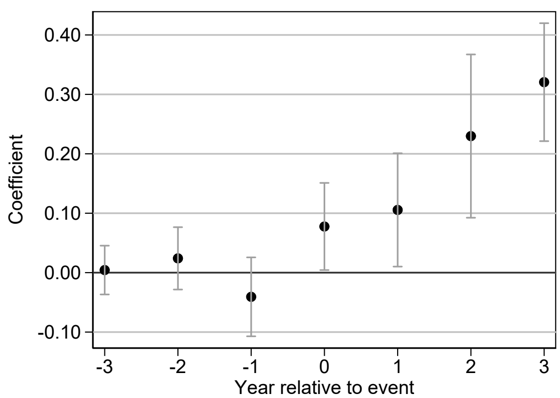
FIGURE A17. Humanitarian demining during peace: Excluding never treated



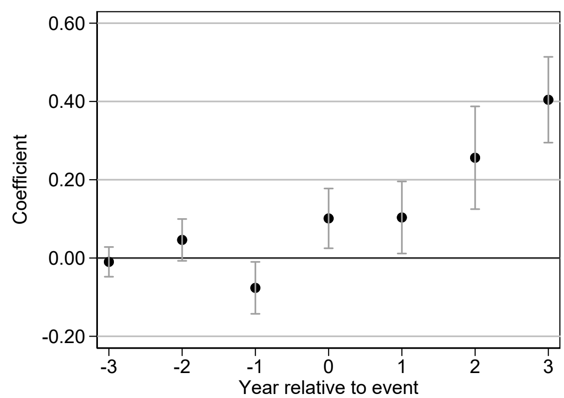
A. Nighttime lights



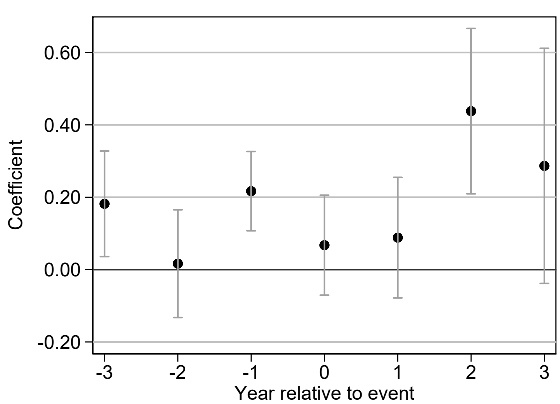
B. Population density



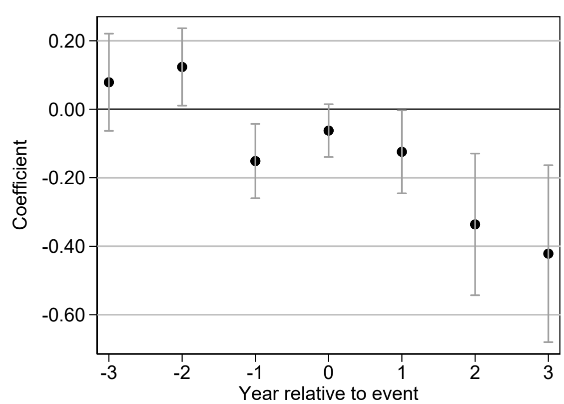
C. Test Scores: Math



D. Test Scores: Reading



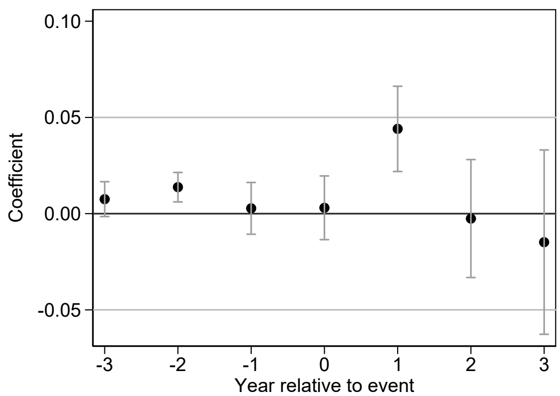
E. Forest loss



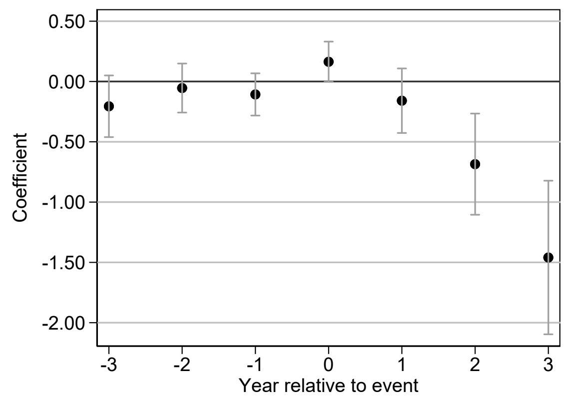
F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. The set of controls exclude the never-treated. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

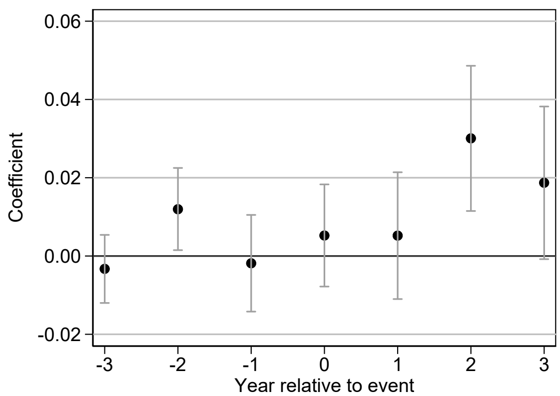
FIGURE A18. Military demining during peace: Excluding never treated



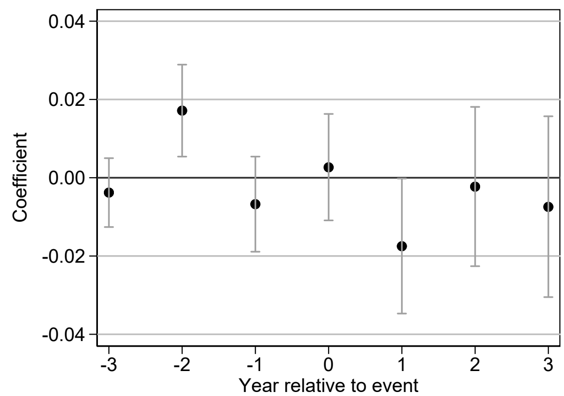
A. Nighttime lights



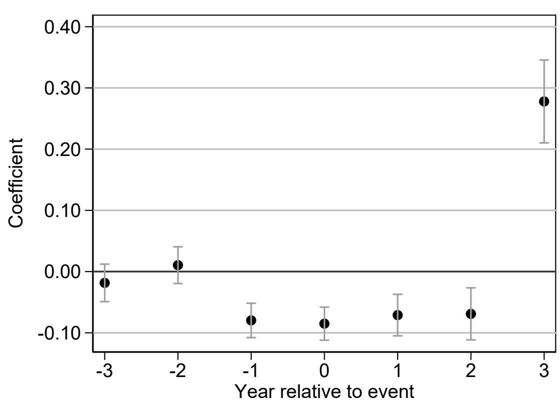
B. Population density



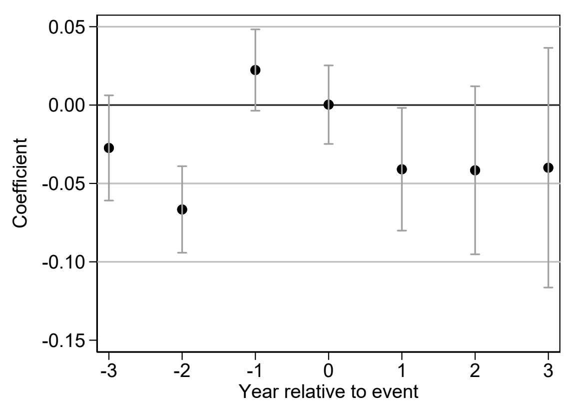
C. Test Scores: Math



D. Test Scores: Reading



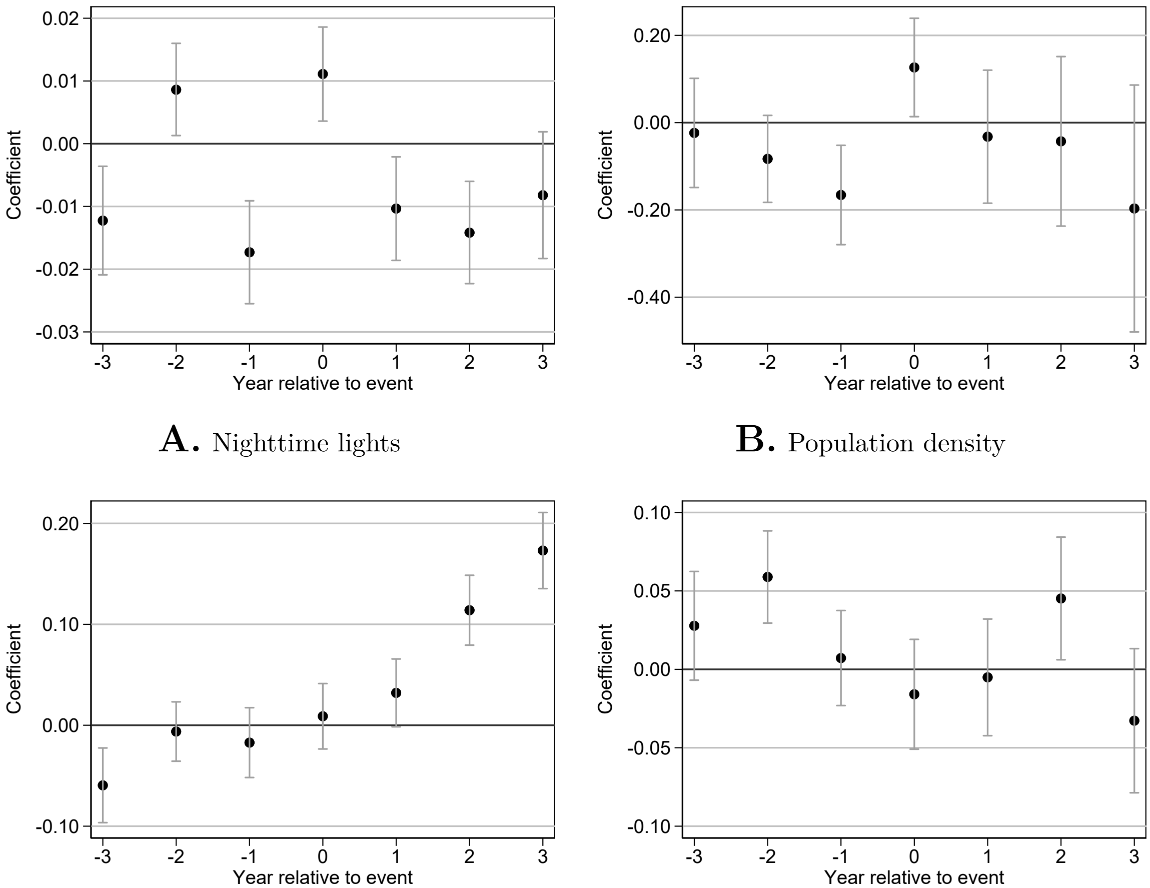
E. Forest loss



F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. The set of controls exclude the never-treated. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

Figure A19. Military demining during conflict: Excluding never treated



A. Nighttime lights

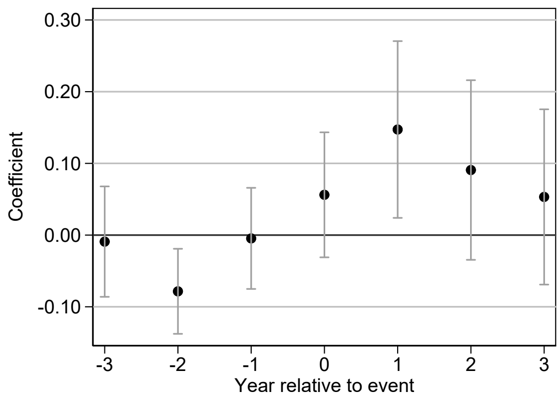
B. Population density

C. Forest loss

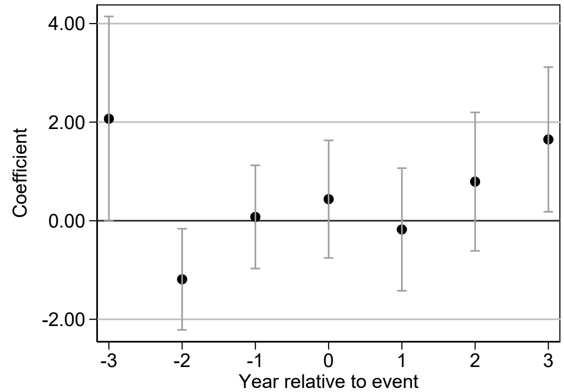
D. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. The set of controls exclude the never-treated. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

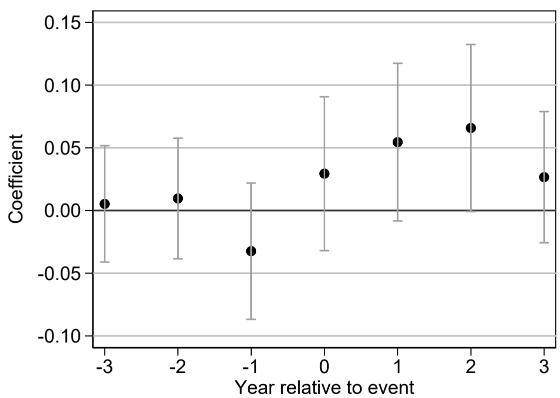
FIGURE A20. Humanitarian demining during peace: Allowing for one-year anticipation



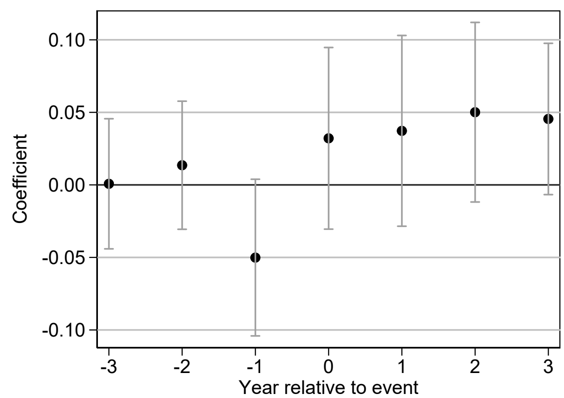
A. Nighttime lights



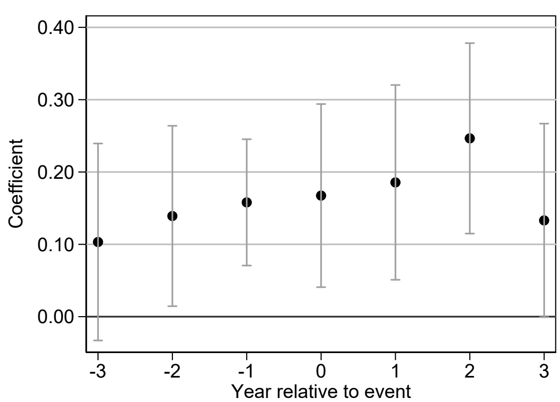
B. Population density



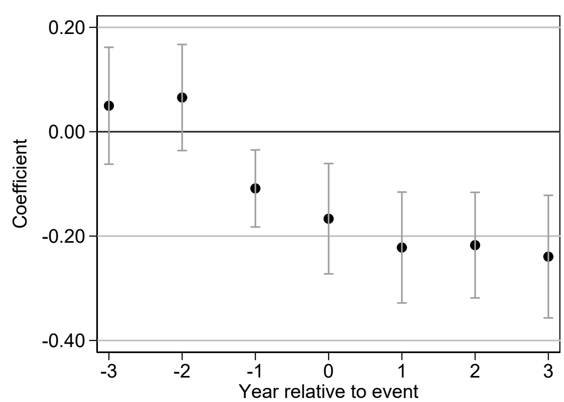
C. Test Scores: Math



D. Test Scores: Reading



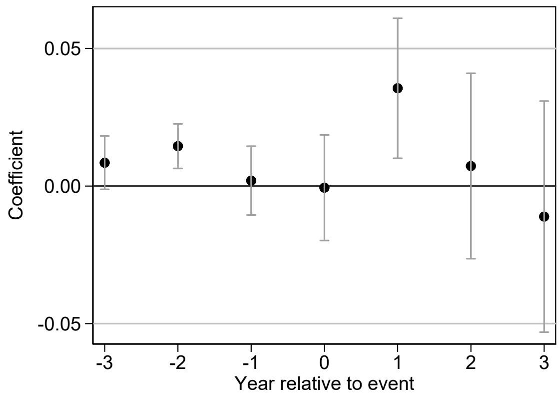
E. Forest loss



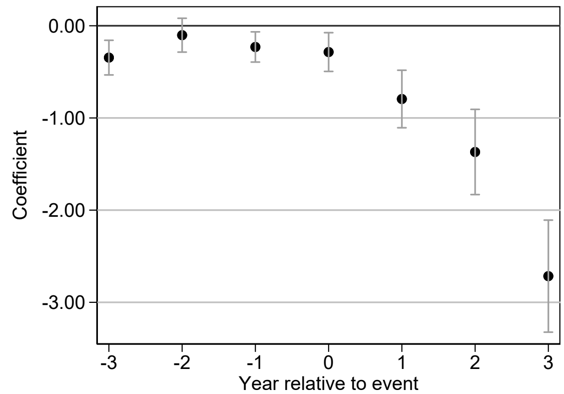
F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. The coefficients are estimated allowing for an anticipation of one year. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

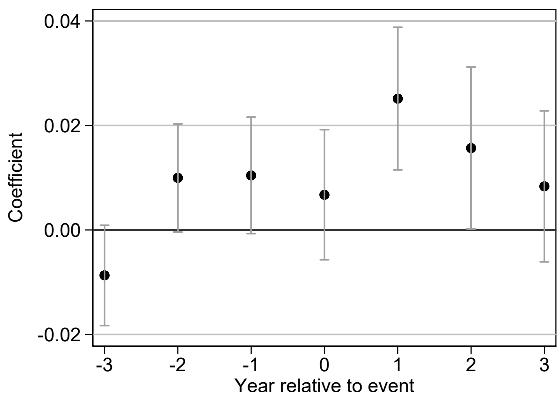
Figure A21. Military demining during peace: Allowing for one-year anticipation



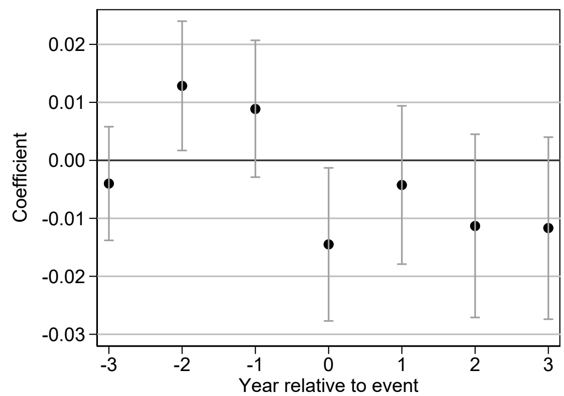
A. Nighttime lights



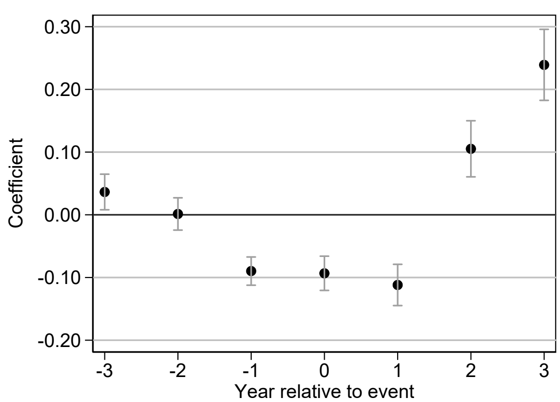
B. Population density



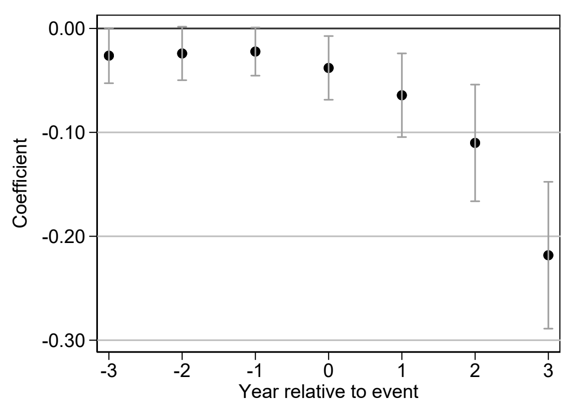
C. Test Scores: Math



D. Test Scores: Reading



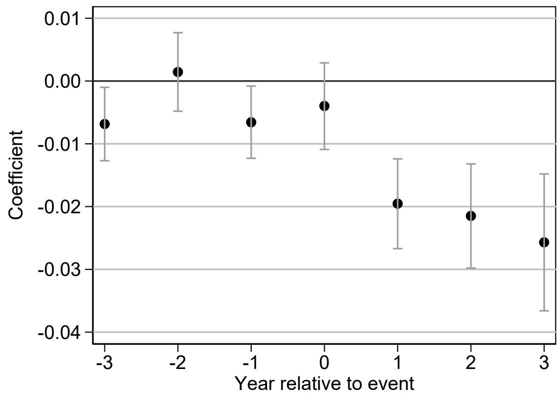
E. Forest loss



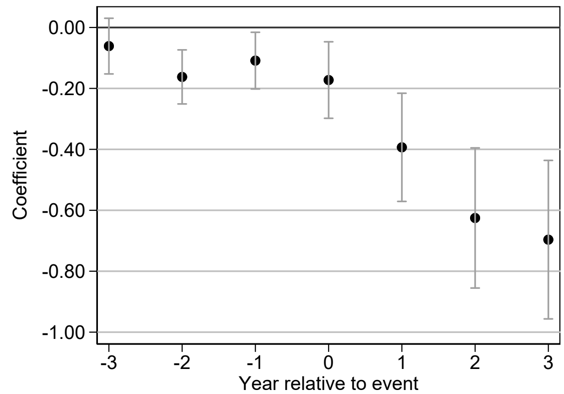
F. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. The coefficients are estimated allowing for an anticipation of one year. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

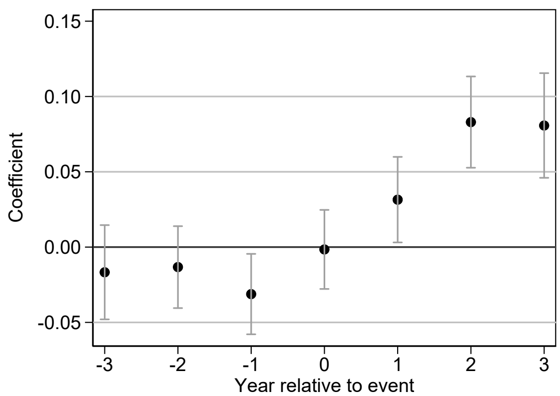
Figure A22. Military demining during conflict: Allowing for one-year anticipation



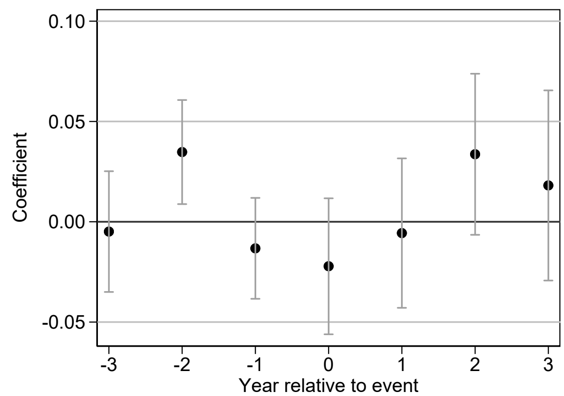
A. Nighttime lights



B. Population density



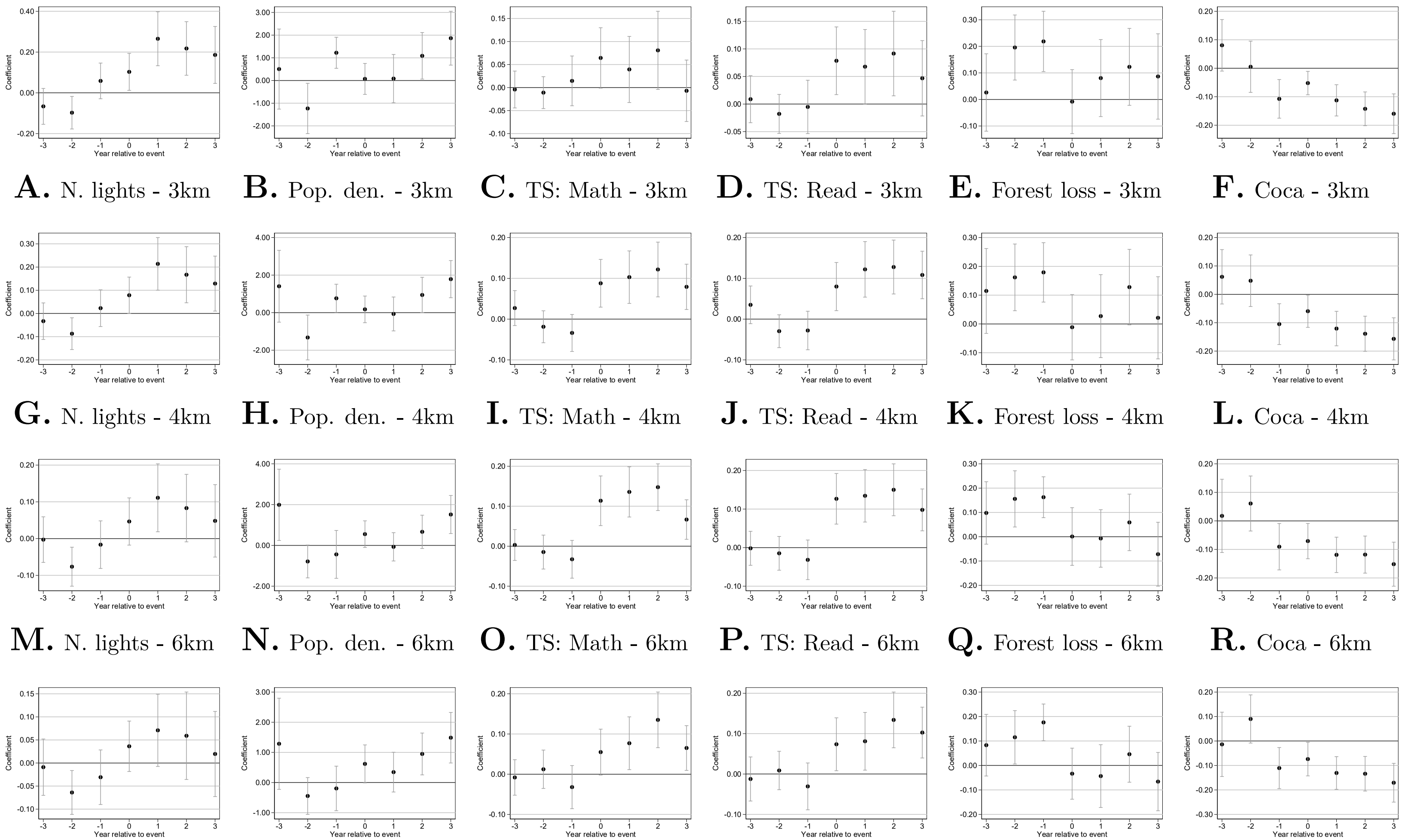
C. Forest loss



D. Coca

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. The coefficients are estimated allowing for an anticipation of one year. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining.

FIGURE A23. Humanitarian demining during peace over different radiuses



A. N. lights - 3km **B.** Pop. den. - 3km **C.** TS: Math - 3km **D.** TS: Read - 3km **E.** Forest loss - 3km **F.** Coca - 3km

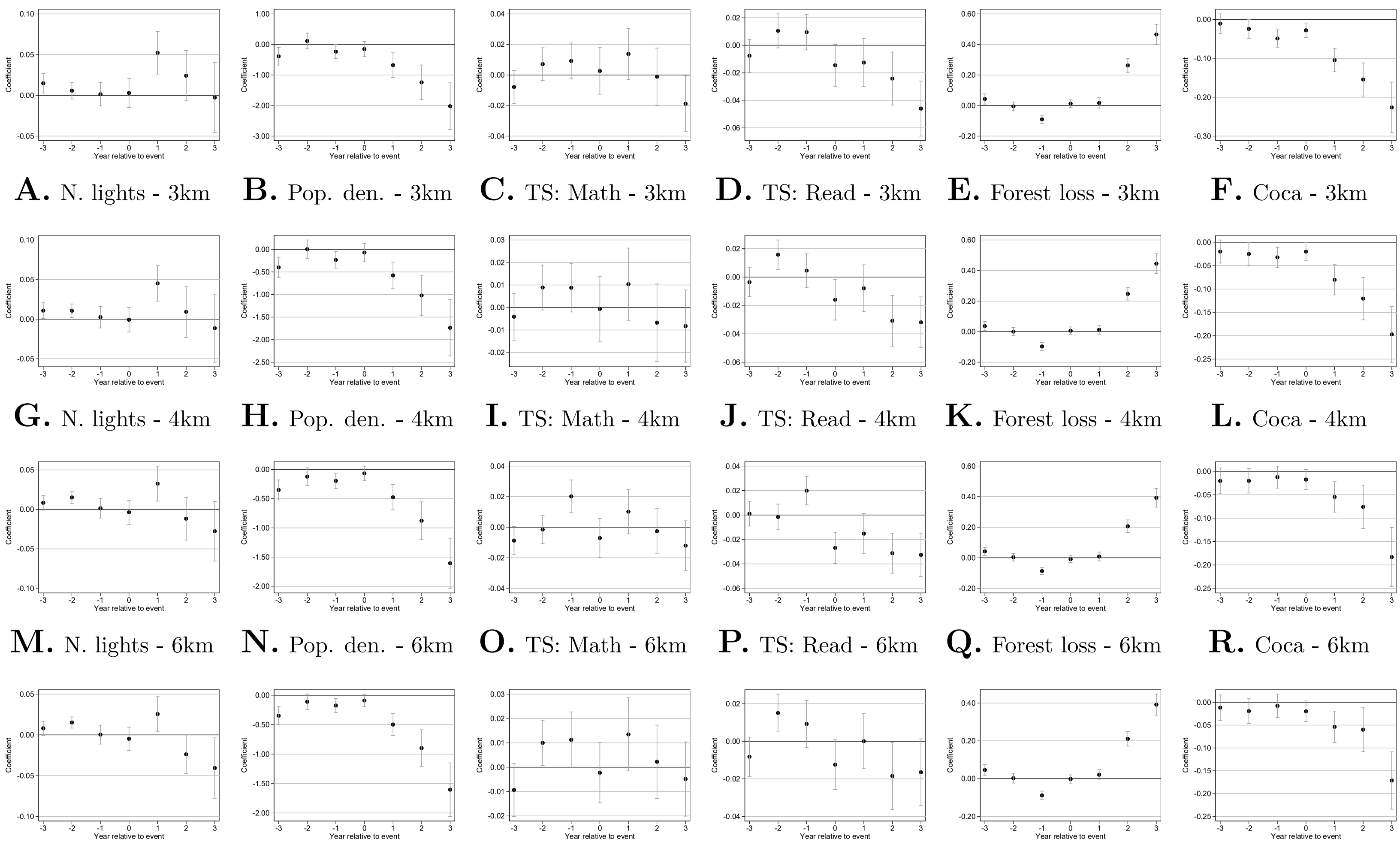
G. N. lights - 4km **H.** Pop. den. - 4km **I.** TS: Math - 4km **J.** TS: Read - 4km **K.** Forest loss - 4km **L.** Coca - 4km

M. N. lights - 6km **N.** Pop. den. - 6km **O.** TS: Math - 6km **P.** TS: Read - 6km **Q.** Forest loss - 6km **R.** Coca - 6km

S. N. lights - 7km **T.** Pop. den. - 7km **U.** TS: Math - 7km **V.** TS: Read - 7km **W.** Forest loss - 7km **X.** Coca - 7km

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using radiuses of 3, 4, 6, and 7km around the demining event.

FIGURE A24. Military demining during peace over different radiuses



A. N. lights - 3km **B.** Pop. den. - 3km **C.** TS: Math - 3km **D.** TS: Read - 3km **E.** Forest loss - 3km **F.** Coca - 3km

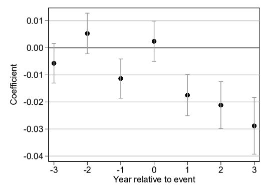
G. N. lights - 4km **H.** Pop. den. - 4km **I.** TS: Math - 4km **J.** TS: Read - 4km **K.** Forest loss - 4km **L.** Coca - 4km

M. N. lights - 6km **N.** Pop. den. - 6km **O.** TS: Math - 6km **P.** TS: Read - 6km **Q.** Forest loss - 6km **R.** Coca - 6km

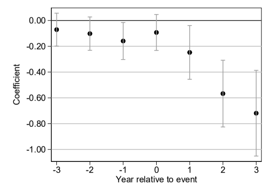
S. N. lights - 7km **T.** Pop. den. - 7km **U.** TS: Math - 7km **V.** TS: Read - 7km **W.** Forest loss - 7km **X.** Coca - 7km

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using radiuses of 3, 4, 6, and 7km around the demining event.

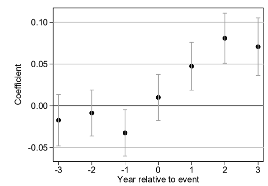
FIGURE A25. Military demining during conflict over different radiuses



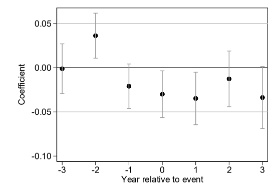
A. N. lights - 3km



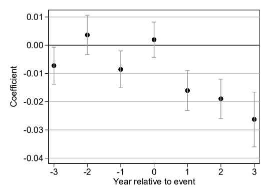
B. Pop. den. - 3km



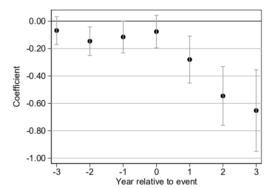
C. Forest loss - 3km



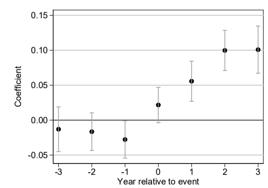
D. Coca - 3km



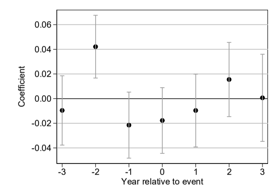
E. N. lights - 4km



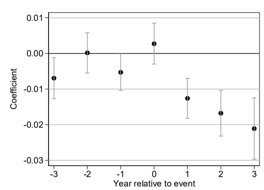
F. Pop. den. - 4km



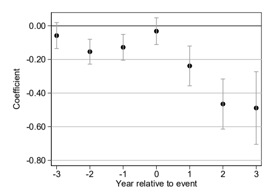
G. Forest loss - 4km



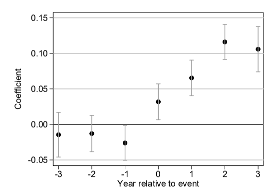
H. Coca - 4km



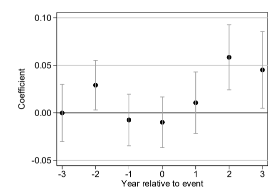
I. N. lights - 6km



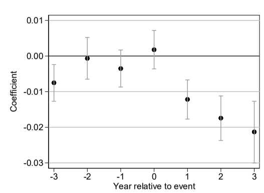
J. Pop. den. - 6km



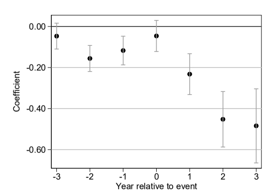
K. Forest loss - 6km



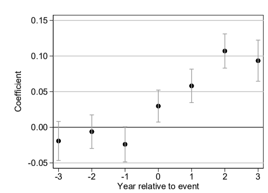
L. Coca - 6km



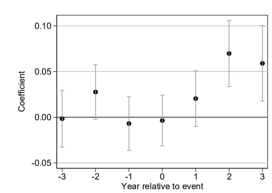
M. N. lights - 7km



N. Pop. den. - 7km



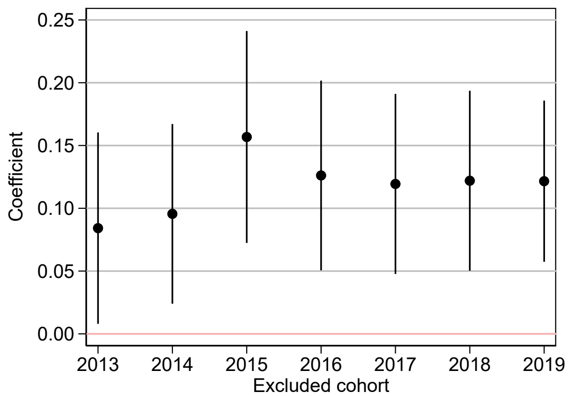
O. Forest loss - 7km



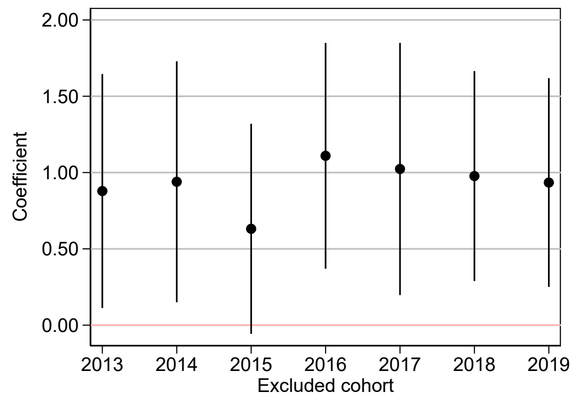
P. Coca - 7km

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using radiuses of 3, 4, 6, and 7km around the demining event.

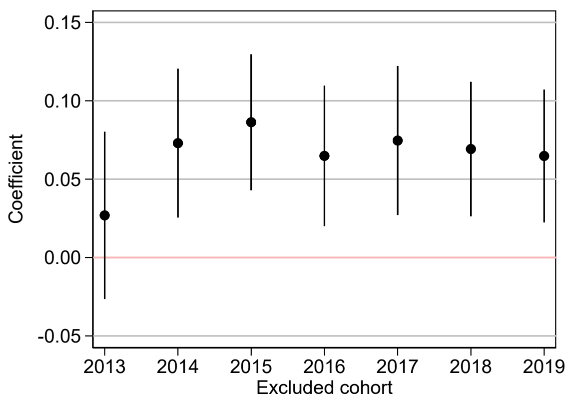
Figure A26. Humanitarian demining during peace: Exclude one cohort at the time



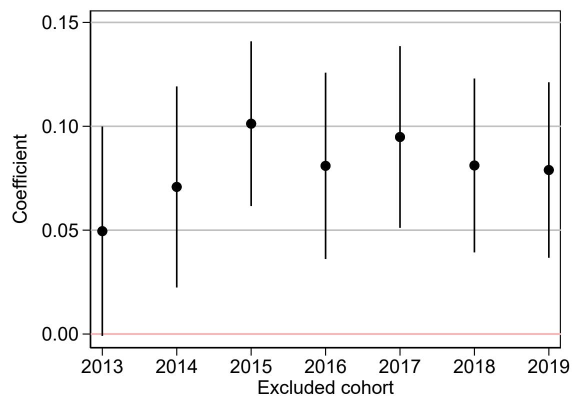
A. Nighttime lights



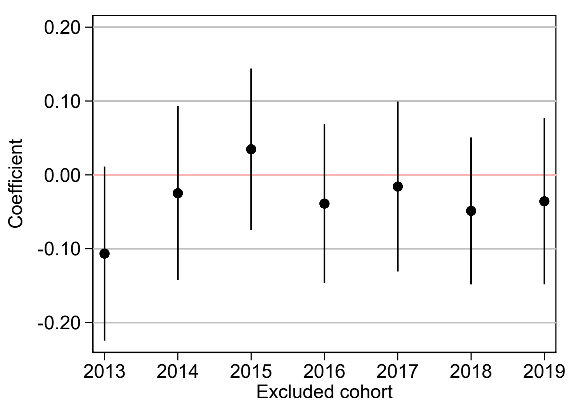
B. Population density



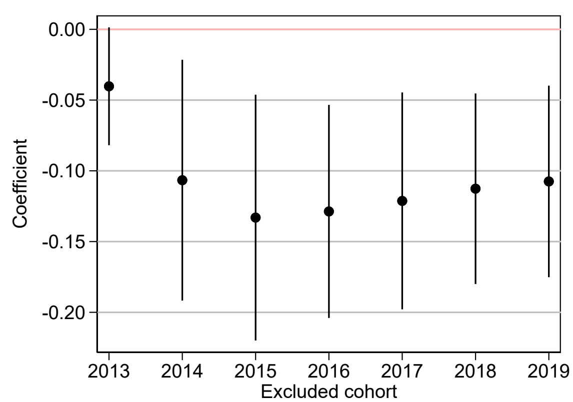
C. Test Scores: Math



D. Test Scores: Reading



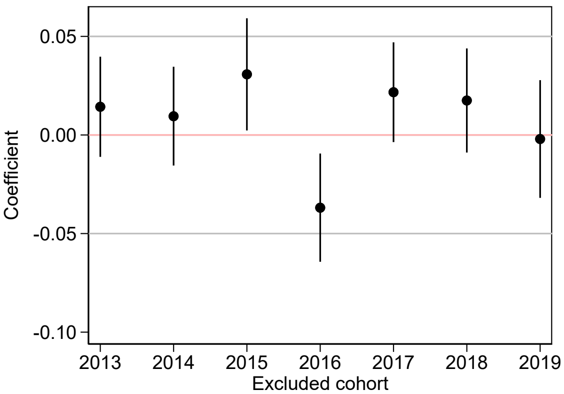
E. Forest loss



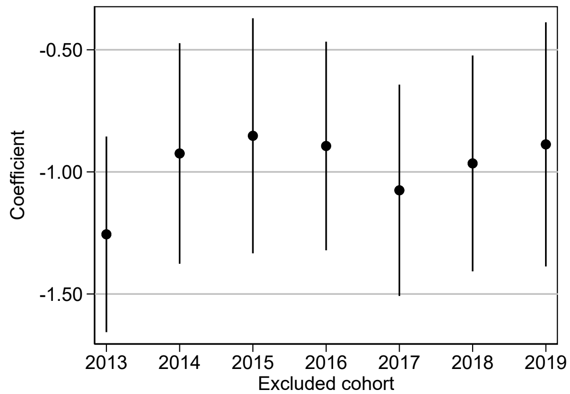
F. Coca

Notes: This figure presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. We present the overall ATT excluding one cohort of treated units at the time. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining

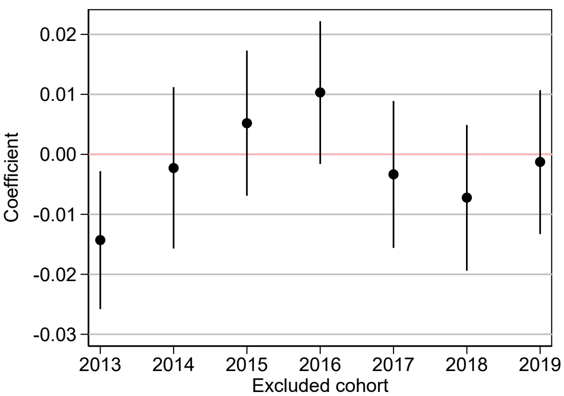
FIGURE A27. Military demining during peace: Exclude one cohort at the time



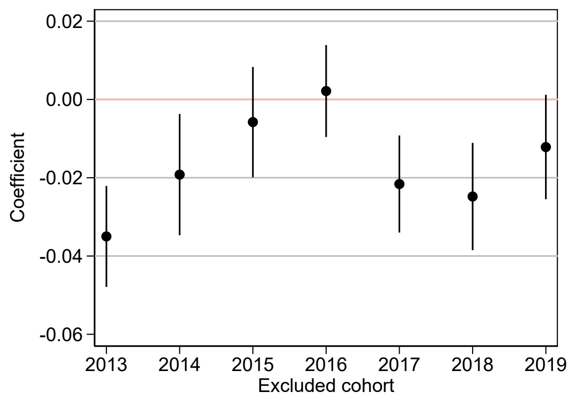
A. Nighttime lights



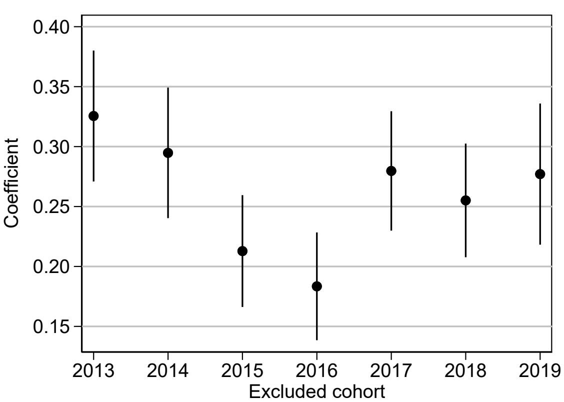
B. Population density



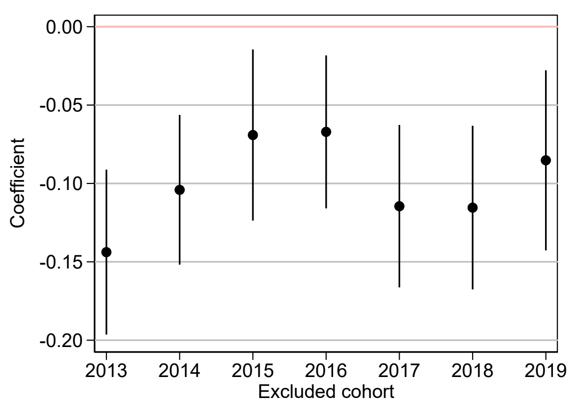
C. Test Scores: Math



D. Test Scores: Reading



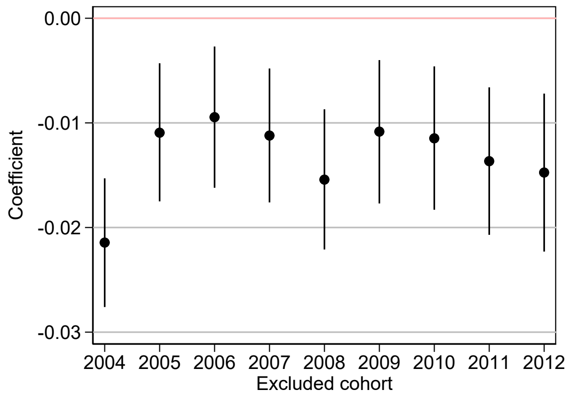
E. Forest loss



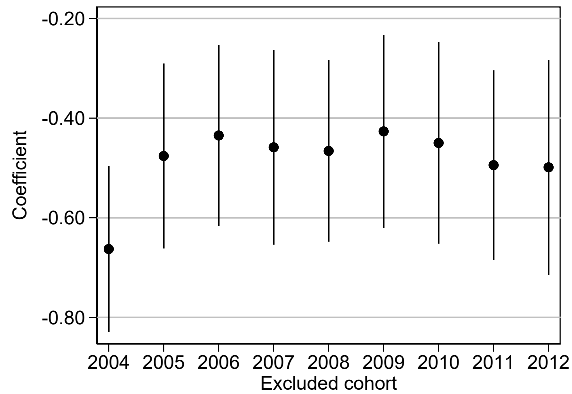
F. Coca

Notes: This figure presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. We present the overall ATT excluding one cohort of treated units at the time. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining

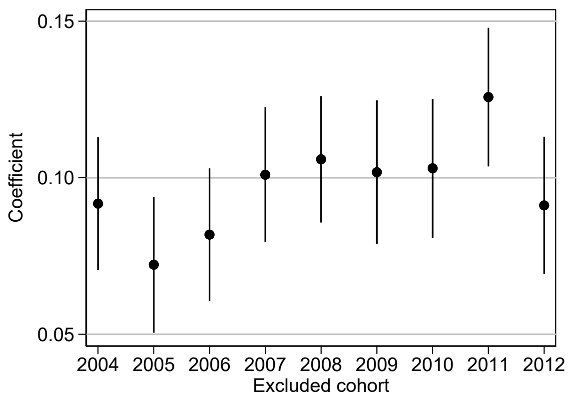
Figure A28. Military demining during conflict: Exclude one cohort at the time



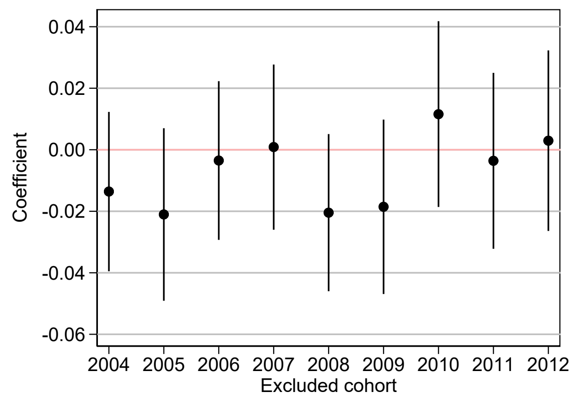
A. Nighttime lights



B. Population density



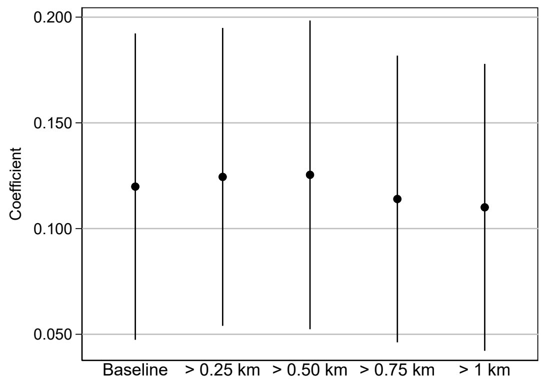
C. Forest loss



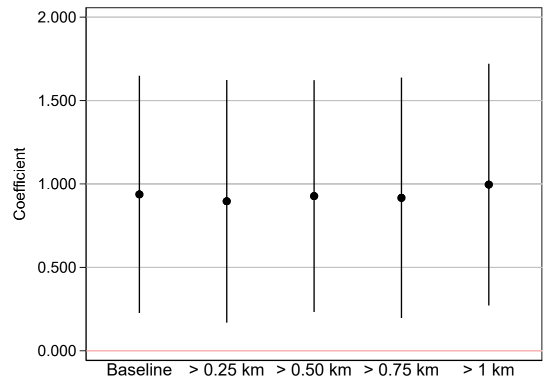
D. Coca

Notes: This figure presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. We present the overall ATT excluding one cohort of treated units at the time. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining

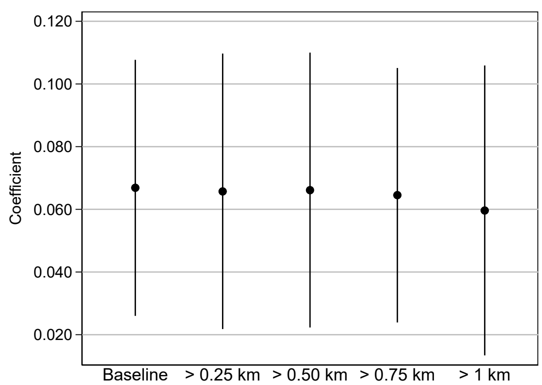
FIGURE A29. Humanitarian demining during peace: Excluding events to closest village



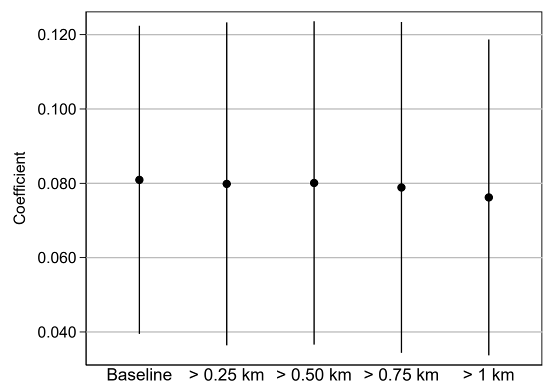
A. Nighttime lights



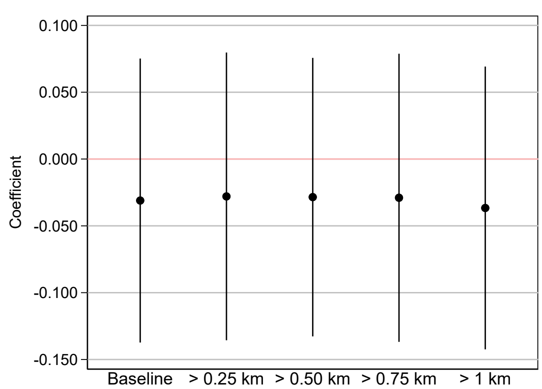
B. Population density



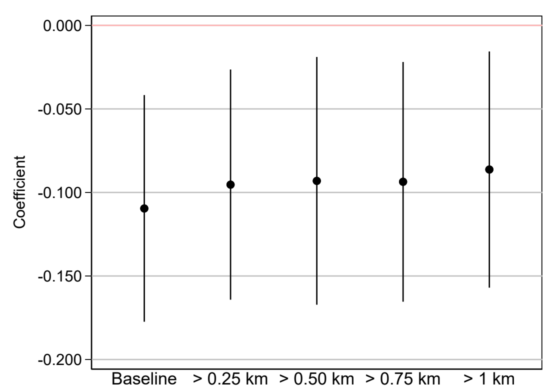
C. Test scores: Math



D. Test scores: Reading



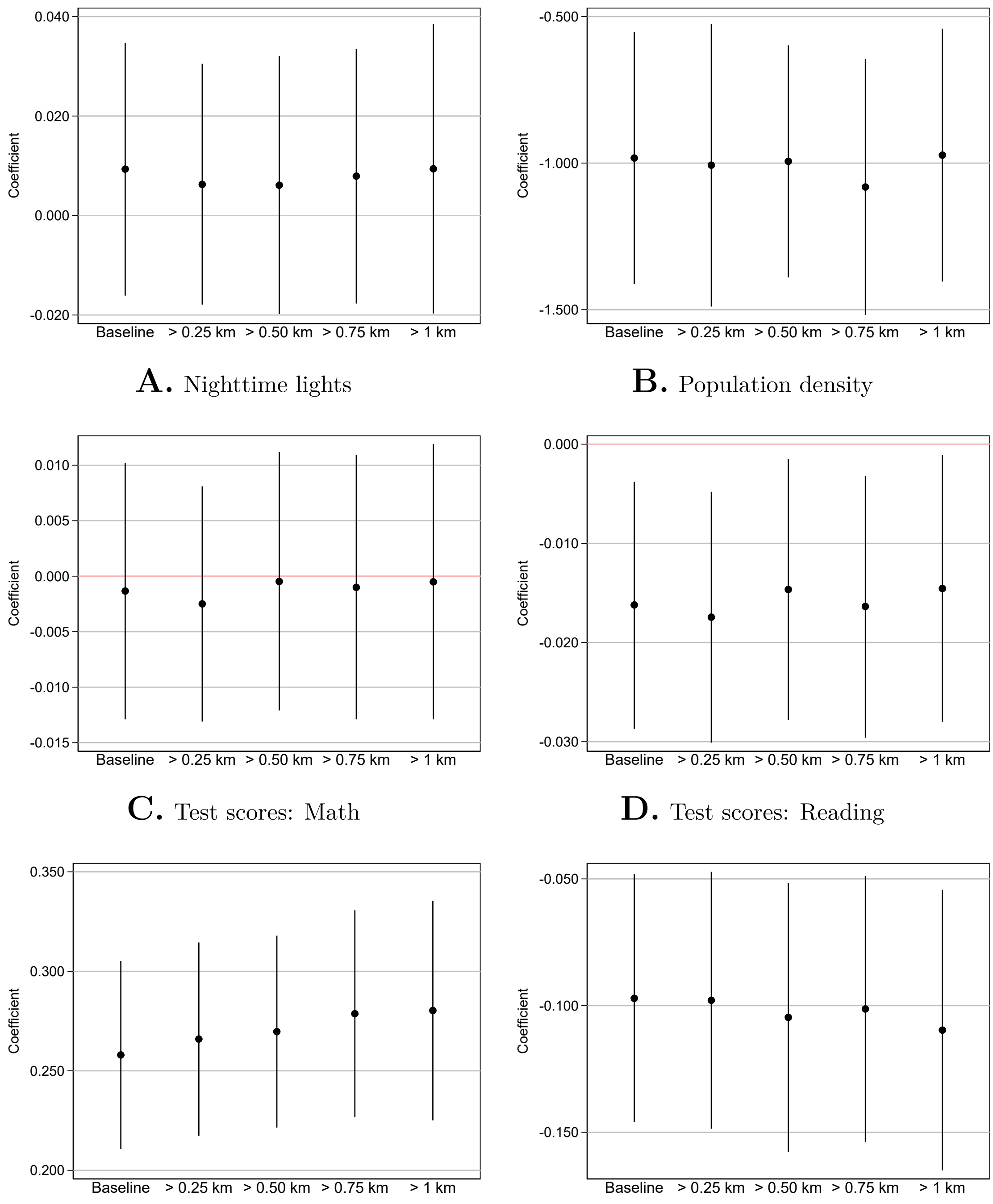
E. Forest loss



F. Coca

Notes: This figure presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. We present the overall ATT from our baseline specification in Panel A from Table 2 and excluding events closest to villages at 250 m, 500 m, 750 m, and 1 km. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining

Figure A30. Military demining during peace: Excluding events to closest village



A. Nighttime lights

B. Population density

C. Test scores: Math

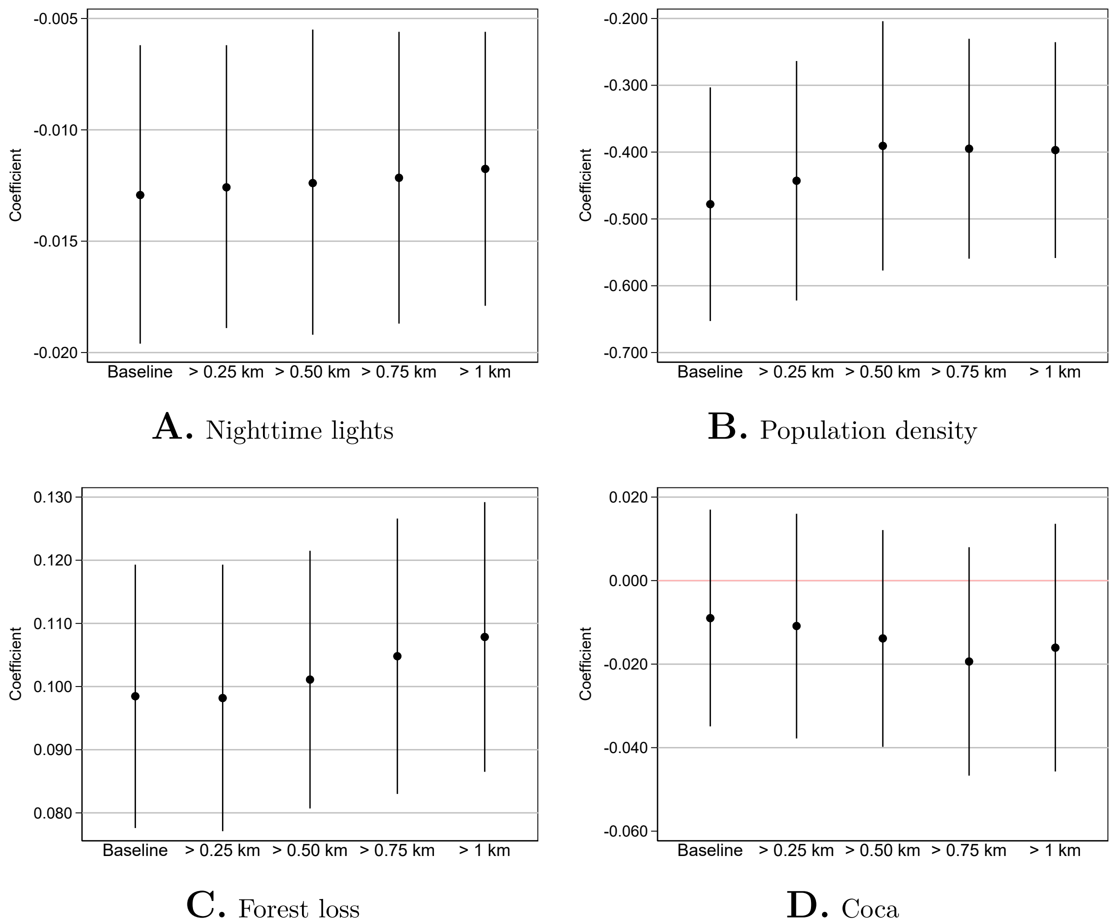
D. Test scores: Reading

E. Forest loss

F. Coca

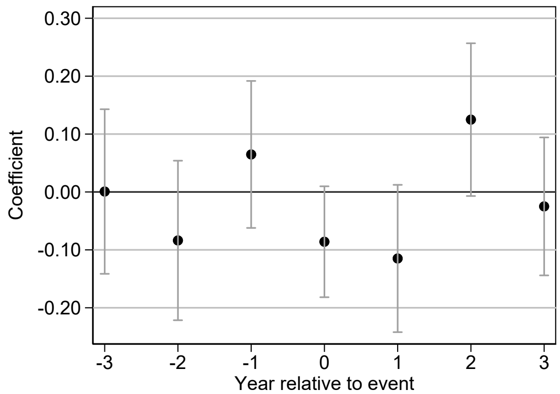
Notes: This figure presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. We present the overall ATT from our baseline specification in Panel A from Table 3 and excluding events closest to villages at 250 m, 500 m, 750 m, and 1 km. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining

Figure A31. Military demining during peace: Excluding events to closest village

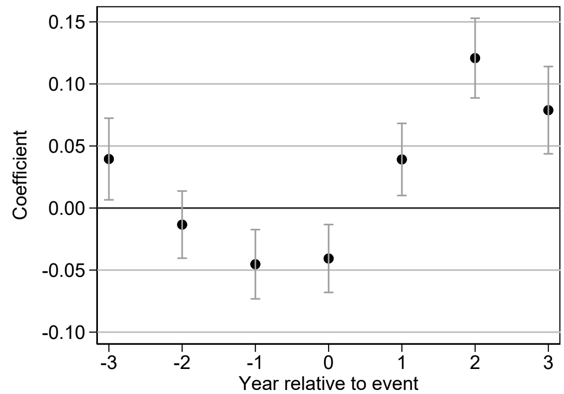


Notes: This figure presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. We present the overall ATT from our baseline specification in Panel A from Table 4 and excluding events closest to villages at 250 m, 500 m, 750 m, and 1 km. We present the point estimates as well as the 95% confidence interval. The outcomes were computed using a radius of 5km around the demining

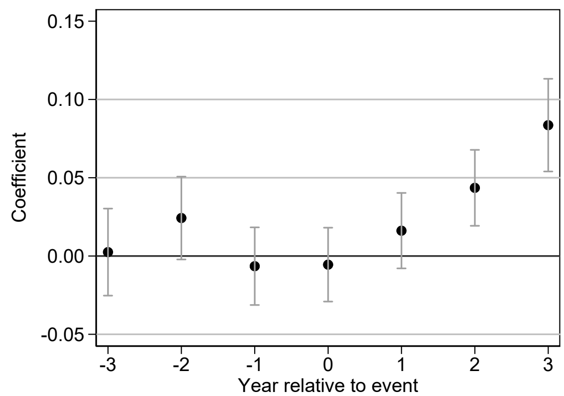
Figure A32. Demining and fires



A. Humanitarian demining during peace lights



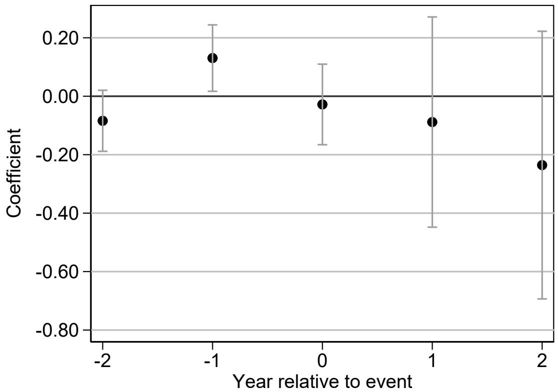
B. Military demining during peace



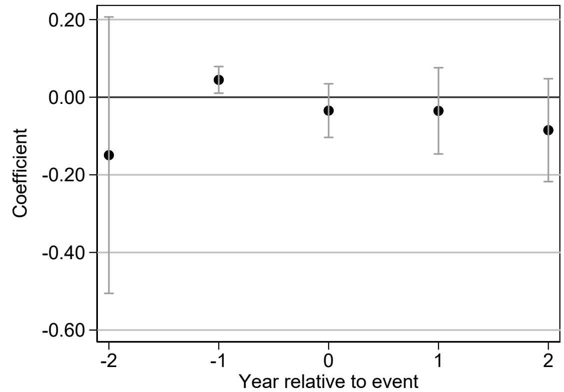
C. Military demining during conflict

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of demining during peace. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

Figure A33. Demining and illegal mining
Humanitarian demining during peace

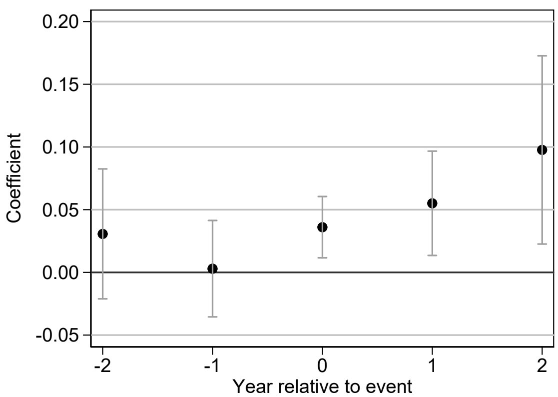


A. Area illegal gold mining

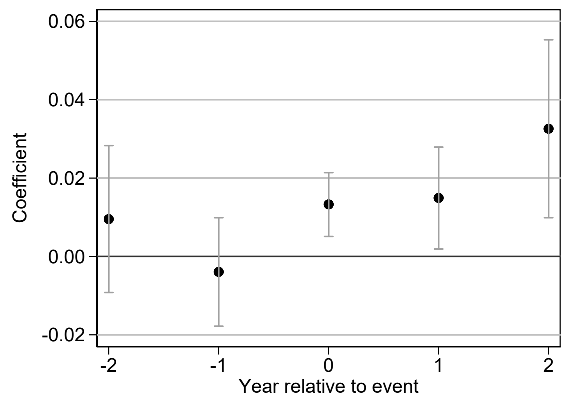


B. Illegal gold mining

Military demining during peace



C. Area illegal gold mining



D. Illegal gold mining

Notes: This figure presents the event study coefficients following Callaway and Sant'Anna (2020) for the treatment of demining during peace. We present the point estimates as well as the 95% confidence interval. Standard errors clustered at the event level. The outcomes were computed using a radius of 5km around the demining.

Table A1. Two-way fixed effects decomposition and weights

During:	(1) Peace Humanitarian	(2) Peace Military	(3) Conflict Military
Panel A: Bacon decomposition			
Treated (T) vs Never treated (C)	0.847	0.267	0.550
Early treated (T) vs Late treated (C)	0.100	0.461	0.339
Late treated (T) vs Early treated (C)	0.053	0.272	0.111
Panel B: Negative weights			
Share of negative weights	0.000	0.272	0.124
Share of sum of negative weights	0.000	0.166	0.061

Notes: This table presents the decomposition of the two-way fixed effects model from equation (4.1) for humanitarian demining during peace (column 1), military demining during peace (column 2), and military demining during conflict (column 3). In panel A, we present the Goodman-Bacon (2021) decomposition, (T) stand for treated units and (C) for comparison units. In panel B, we present the share of negative weights and the relevance of them following De Chaisemartin and d'Haultfoeuille (2020).

Table A2. The local effects of demining on student performances by different school degrees

	(1)	(2)	(3)	(4)	(5)	(6)
	Test scores:					
	Math			Reading		
	3°	5°	9°	3°	5°	9°
Panel A: Humanitarian demining during peace						
Post demining	0.057***	0.031**	0.043***	0.047***	0.043**	0.036***
	(0.016)	(0.015)	(0.007)	(0.015)	(0.019)	(0.008)
Panel B: Military demining during peace						
Post demining	0.000	0.010***	-0.003**	-0.003	-0.010***	-0.004**
	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)
Observations (Panel A)	7460	7460	7460	7460	7460	7460
Observations (Panel B)	90504	100560	100560	100560	100560	100560
Treated (Panel A)	294	294	294	294	294	294
Treated (Panel B)	9630	9630	9630	9630	9630	9630
Never treated (Panel A)	452	452	452	452	452	452
Never treated (Panel B)	426	426	426	426	426	426
Average dep var (Panel A)	0.161	0.137	0.039	0.156	0.169	0.042
Average dep var (Panel B)	0.096	0.064	0.017	0.092	0.092	0.018

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020). Panel A presents the results for humanitarian demining during peace, and panel B for military demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A3. Robustness to "group" overall ATT

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Humanitarian demining during peace						
Post demining	0.099***	0.759**	0.051**	0.062***	-0.033	-0.073**
	(0.036)	(0.295)	(0.020)	(0.021)	(0.059)	(0.035)
Panel B: Military demining during peace						
Post demining	0.017	-0.977***	-0.003	-0.018***	0.269***	-0.107***
	(0.013)	(0.205)	(0.006)	(0.006)	(0.025)	(0.023)
Panel C: Military demining during conflict						
Post demining	-0.014***	-0.463***	–	–	0.045***	-0.025**
	(0.003)	(0.096)			(0.009)	(0.012)
Observations (Panel A)	7460	7460	6960	6960	7460	7460
Observations (Panel B)	90504	100560	69340	69370	100560	100560
Observations (Panel C)	213000	213000	–	–	213000	213000
Treated (Panel A)	294	294	283	283	294	294
Treated (Panel B)	9630	9630	6641	6641	9630	9630
Treated (Panel C)	15150	15150	–	–	15150	15150
Never treated (Panel A)	452	452	413	413	452	452
Never treated (Panel B)	426	426	293	296	426	426
Never treated (Panel C)	2600	2600	–	–	2600	2600
Average dep var (Panel A)	1.343	34.407	0.207	0.222	3.290	0.636
Average dep var (Panel B)	0.973	33.381	0.149	0.168	3.721	2.392
Average dep var (Panel C)	0.435	26.349	–	–	3.403	1.728

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020). Panel A presents the results for humanitarian demining during peace, panel B for military demining during peace, and panel C for military demining during conflict. *Post demining* is the weighted average across cohorts of the cohort average treatment effects with weights proportional to the cohort size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. Panel Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A4. Bias from hypothesized linear pre-trend

	(1) Estimate	(2) Slope	(3) Unconditional bias	(4) Conditional bias
Panel A: Humanitarian demining during peace				
Nighttime lights	0.120	0.026	0.064	0.058
Population density	0.938	0.444	1.109	1.081
Test scores: Math	0.067	0.019	0.048	0.046
Test scores: Reading	0.081	0.020	0.050	0.046
Forest loss	-0.031	0.058	0.145	0.136
Coca	-0.110	0.046	0.114	0.115
Panel B: Military demining during peace				
Nighttime lights	0.009	0.003	0.010	0.009
Population density	-0.983	0.080	0.200	0.207
Test scores: Math	-0.001	0.004	0.010	0.010
Test scores: Reading	-0.016	0.004	0.011	0.011
Forest loss	0.258	0.012	0.030	0.029
Coca	-0.097	0.011	0.028	0.029
Panel C: Military demining during conflict				
Nighttime lights	-0.013	0.003	0.006	0.006
Population density	-0.478	0.039	0.098	0.109
Forest loss	0.098	0.012	0.031	0.032
Coca	-0.009	0.012	0.030	0.029

Notes: This table presents the estimated parameter from our baseline specification in Panel A from Tables 2 to 4 and the main estimates based on Roth (2021). In column 2, we present the pre-trend that has a 50% power of being detected given the precision of the estimates in the pre-period. In column 3, we present the average bias suggested by this trend, while in column 4, the bias from the adjusted pre-trend that takes into account the pre-testing bias that arises from the fact that the analysis shown is conditional on passing a pre-test.

Table A5. Robustness to other estimation methods: Humanitarian demining

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Borusyak et al. (2021)						
Post demining	0.071**	0.203	0.042***	0.041***	0.108**	-0.119***
	(0.036)	(0.456)	(0.015)	(0.016)	(0.048)	(0.037)
Panel B: De Chaisemartin and d'Haultfoeuille (2020)						
Post demining	0.095***	0.528**	0.061***	0.071***	0.002	-0.084***
	(0.028)	(0.214)	(0.023)	(0.020)	(0.042)	(0.024)
Panel C: Wooldridge (2021)						
Post demining	0.071*	0.202	0.042***	041***	0.108**	-0.119***
	(0.036)	(0.457)	(0.015)	(0.016)	(0.049)	(0.037)
Observations	7460	7460	6960	6960	7460	7460
Treated	294	294	283	283	294	294
Never treated	452	452	413	413	452	452
Average dep var	1.343	34.407	0.207	0.222	3.290	0.636

Notes: This table presents the overall ATT using two different models for the treatment of humanitarian demining during peace. The outcomes were computed using a radius of 5km around the demining. In Panel A, we present the imputation method suggested by Borusyak et al. (2021). We estimate the model for the window of three year around the event. In Panel B, we present the model suggested by De Chaisemartin and d'Haultfoeuille (2020) computing the ATT for the three years after the the treatment. In Panel C, we present the ATT suggested by Wooldridge (2021) where the estimated coefficient is a weighted average of group-year dummies after treatment. Standard errors are clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A6. Robustness to other estimation methods: Military demining during peace

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Borusyak et al. (2021)						
Post demining	0.039***	-1.524***	0.010*	-0.004	0.097***	-0.153***
	(0.015)	(0.253)	(0.006)	(0.006)	(0.018)	(0.028)
Panel B: De Chaisemartin and d'Haultfoeuille (2020)						
Post demining	0.030***	-0.719***	-0.002	-0.019***	0.145***	-0.090***
	(0.011)	(0.155)	(0.004)	(0.005)	(0.016)	(0.022)
Panel C: Wooldridge (2021)						
Post demining	0.039**	-1.524***	0.010*	-0.004	0.096***	-0.153***
	(0.015)	(0.253)	(0.006)	(0.006)	(0.018)	(0.028)
Observations	90504	100560	69340	69340	100560	100560
Treated	9630	9630	6641	6641	9630	9630
Never treated	426	426	293	296	426	426
Average dep var	0.973	33.381	0.149	0.168	3.721	2.392

Notes: This table presents the overall ATT using two different models for the treatment of military demining during peace. The outcomes were computed using a radius of 5km around the demining. In Panel A, we present the imputation method suggested by Borusyak et al. (2021). We estimate the model for the window of three year around the event. In Panel B, we present the model suggested by De Chaisemartin and d'Haultfoeuille (2020) computing the ATT for the three years after the the treatment. In Panel C, we present the ATT suggested by Wooldridge (2021) where the estimated coefficient is a weighted average of group-year dummies after treatment. Standard errors are clustered at the event level. Standard errors are clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A7. Robustness to other estimation methods: Military demining during conflict

	(1) Nighttime Lights	(2) Population density	(3) Forest Loss	(4) Coca
Panel A: Borusyak et al. (2021)				
Post demining	-0.020***	-0.716***	0.017*	0.018
	(0.003)	(0.103)	(0.009)	(0.014)
Panel B: De Chaisemartin and d'Haultfoeuille (2020)				
Post demining	-0.014***	-0.424***	0.043***	-0.020*
	(0.003)	(0.064)	(0.010)	(0.012)
Panel C: Wooldridge (2021)				
Post demining	-0.020***	-0.716***	0.017**	0.018
	(0.003)	(0.103)	(0.009)	(0.014)
Observations	213000	213000	213000	213000
Treated	15150	15150	15150	15150
Never treated	2600	2600	2600	2600
Average dep var	0.435	26.349	3.403	1.728

Notes: This table presents the overall ATT using two different models for the treatment of military demining during conflict. The outcomes were computed using a radius of 5km around the demining. In Panel A, we present the imputation method suggested by Borusyak et al. (2021). We estimate the model for the window of three year around the event. In Panel B, we present the model suggested by De Chaisemartin and d'Haultfoeuille (2020) computing the ATT for the three years after the the treatment. In Panel C, we present the ATT suggested by Wooldridge (2021) where the estimated coefficient is a weighted average of group-year dummies after treatment. Standard errors are clustered at the event level. Standard errors are clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A8. Spillover effects of humanitarian demining during peace: Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Buffer of 3 km						
Post demining	0.101**	1.053***	0.034	0.062**	-0.094	-0.061***
	(0.041)	(0.375)	(0.026)	(0.027)	(0.066)	(0.024)
Panel B: Buffer of 5 km						
Post demining	0.114**	1.019**	0.047*	0.072***	-0.061	-0.069***
	(0.045)	(0.425)	(0.027)	(0.026)	(0.068)	(0.026)
Panel C: Buffer of 7 km						
Post demining	0.105**	0.938**	0.058**	0.080***	-0.007	-0.076***
	(0.045)	(0.411)	(0.028)	(0.027)	(0.059)	(0.027)
Observations	7460	7460	6960	6960	7460	7460
Treated	294	294	283	283	294	294
Never treated	452	452	413	413	452	452
Average dep var	1.343	34.407	0.207	0.222	3.290	0.636

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The outcomes were computed using a radius of 5km around the demining. Panel A, B, and C present the results controlling with an indicator that takes the value one if there was a demining event within a buffer of 3, 5, and 7 Km the year before the demining. In the case of the never treated the dummy takes the value if there was a demining event the year before within a buffer of 3km/5km/7km. We include the covariate following Sant'Anna and Zhao (2020) doubly robust method. We include the covariate following Sant'Anna and Zhao (2020) doubly robust method. Bootstrap standard errors clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level

Table A9. Spillover effects of military demining during peace: Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Buffer of 3 km						
Post demining	0.015	-0.614***	0.006	-0.010	0.207***	-0.118***
	(0.013)	(0.200)	(0.006)	(0.007)	(0.025)	(0.027)
Panel B: Buffer of 5 km						
Post demining	0.028*	-0.325*	0.002	-0.015**	0.155***	-0.111***
	(0.015)	(0.183)	(0.006)	(0.007)	(0.024)	(0.029)
Panel C: Buffer of 7 km						
Post demining	0.038**	-0.224	0.003	-0.012	0.127***	-0.085***
	(0.015)	(0.194)	(0.007)	(0.008)	(0.026)	(0.029)
Observations	90504	100560	69340	69370	100560	100560
Treated	9630	9630	6641	6641	9630	9630
Never treated	426	426	293	296	426	426
Average dep var	0.973	33.381	0.149	0.168	3.721	2.392

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The outcomes were computed using a radius of 5km around the demining. Panel A, B, and C present the results controlling with an indicator that takes the value one if there was a demining event within a buffer of 3, 5, and 7 Km the year before the demining. In the case of the never treated the dummy takes the value if there was a demining event the year before within a buffer of 3km/5km/7km. We include the covariate following Sant'Anna and Zhao (2020) doubly robust method. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level

TABLE A10. Spillover effects of military demining during conflict: Covariates

	(1) Nighttime Lights	(2) Population	(3) Forest Loss	(4) Coca
Panel A: Buffer of 3 km				
Post demining	-0.009***	-0.422***	0.115***	-0.003
	(0.003)	(0.093)	(0.010)	(0.014)
Panel B: Buffer of 5 km				
Post demining	-0.010***	-0.373***	0.119***	0.003
	(0.003)	(0.088)	(0.011)	(0.014)
Panel C: Buffer of 7 km				
Post demining	-0.011***	-0.354***	0.119***	0.003
	(0.004)	(0.095)	(0.011)	(0.014)
Average dep var	0.435	26.349	3.403	1.728
Observations	213000	213000	213000	213000
Treated	15150	15150	15150	15150
Never treated	2600	2600	2600	2600

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The outcomes were computed using a radius of 5km around the demining. Panel A, B, and C present the results controlling with an indicator that takes the value one if there was a demining event within a buffer of 3, 5, and 7 Km the year before the demining. In the case of the never treated the dummy takes the value if there was a demining event the year before within a buffer of 3km/5km/7km. We include the covariate following Sant'Anna and Zhao (2020) doubly robust method. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level

Table A11. Spillover effects of humanitarian demining during peace: Excluding treated buffers

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Buffer of 3 km						
Post demining	0.109***	0.699	0.054**	0.058**	0.062	-0.129***
	(0.042)	(0.454)	(0.025)	(0.024)	(0.055)	(0.047)
Panel B: Buffer of 5 km						
Post demining	0.091**	0.829*	0.063**	0.072***	0.083	-0.134**
	(0.040)	(0.449)	(0.026)	(0.026)	(0.058)	(0.055)
Panel C: Buffer of 7 km						
Post demining	0.099**	0.877*	0.079***	0.087***	0.068	-0.139**
	(0.043)	(0.521)	(0.028)	(0.026)	(0.065)	(0.056)
Observations (Panel A)	6600	6600	6110	6110	6600	6600
Observations (Panel B)	6390	6390	5900	5900	6390	6390
Observations (Panel C)	6210	6210	5720	5720	6210	6210
Treated (Panel A)	208	208	198	198	208	208
Treated (Panel B)	187	187	177	177	187	187
Treated (Panel C)	169	169	159	159	169	169
Never treated (Panel A)	452	452	413	413	452	452
Never treated (Panel B)	452	452	413	413	452	452
Never treated (Panel C)	452	452	413	413	452	452
Average dep var (Panel A)	1.311	33.197	0.205	0.221	3.297	0.703
Average dep var (Panel B)	1.307	32.964	0.204	0.220	3.291	0.716
Average dep var (Panel C)	1.313	32.868	0.203	0.220	3.288	0.728

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The outcomes were computed using a radius of 5km around the demining. Panel A, B, and C presents the results excluding from the sample treated buffers with at least one demining in the previous year of the event around 3 km, 5km, and 7km to the demining, respectively. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level

Table A12. Spillover effects of military demining during peace: Excluding treated buffers

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Buffer of 3 km						
Post demining	0.007	-0.548**	0.004	-0.002	0.188***	-0.076**
	(0.015)	(0.272)	(0.009)	(0.009)	(0.028)	(0.032)
Panel B: Buffer of 5 km						
Post demining	-0.001	-0.384	0.006	0.005	0.175***	-0.050
	(0.019)	(0.282)	(0.010)	(0.011)	(0.032)	(0.032)
Panel C: Buffer of 7 km						
Post demining	-0.007	-0.328	0.009	0.011	0.197***	-0.023
	(0.020)	(0.319)	(0.011)	(0.012)	(0.034)	(0.037)
Observations (Panel A)	53082	58980	39170	39170	58980	58980
Observations (Panel B)	43542	48380	32110	32090	48380	48380
Observations (Panel C)	38007	42230	27890	27860	42230	42230
Treated (Panel A)	5472	5472	3624	3621	5472	5472
Treated (Panel B)	4412	4412	2918	2913	4412	4412
Treated (Panel C)	3797	3797	2496	2490	3797	3797
Never treated (Panel A)	426	426	293	296	426	426
Never treated (Panel B)	426	426	293	296	426	426
Never treated (Panel C)	426	426	293	296	426	426
Average dep var (Panel A)	0.971	34.491	0.158	0.178	3.550	2.244
Average dep var (Panel B)	0.977	34.402	0.159	0.180	3.497	2.222
Average dep var (Panel C)	0.974	34.205	0.160	0.181	3.468	2.204

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The outcomes were computed using a radius of 5km around the demining. Panel A, B, and C presents the results excluding from the sample treated buffers with at least one demining in the previous year of the event around 3 km, 5km, and 7km to the demining, respectively. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level

TABLE A13. Spillover effects of military demining during conflict: Excluding treated buffers

	(1) Nighttime Lights	(2) Population	(3) Forest Loss	(4) Coca
Panel A: Buffer of 3 km				
Post demining	-0.013***	-0.428***	0.056***	-0.019
	(0.004)	(0.099)	(0.013)	(0.016)
Panel B: Buffer of 5 km				
Post demining	-0.018***	-0.606***	0.008	0.002
	(0.004)	(0.119)	(0.016)	(0.019)
Panel C: Buffer of 7 km				
Post demining	-0.019***	-0.795***	-0.028	0.010
	(0.005)	(0.119)	(0.017)	(0.021)
Average dep var (Panel A)	0.395	24.879	3.349	1.706
Average dep var (Panel B)	0.401	25.390	3.331	1.696
Average dep var (Panel C)	0.414	26.142	3.331	1.690
Treated (Panel A)	9110	9110	9110	9110
Treated (Panel B)	6554	6554	6554	6554
Treated (Panel C)	4836	4836	4836	4836
Never treated (Panel A)	2600	2600	2600	2600
Never treated (Panel B)	2600	2600	2600	2600
Never treated (Panel C)	2600	2600	2600	2600
Observations (Panel A)	140520	140520	140520	140520
Observations (Panel B)	109848	109848	109848	109848
Observations (Panel C)	89232	89232	89232	89232

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The outcomes were computed using a radius of 5km around the demining. Panel A, B, and C presents the results excluding from the sample treated buffers with at least one demining in the previous year of the event around 3 km, 5km, and 7km to the demining, respectively. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level

TABLE A14. Robustness to only using never treated as controls

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Humanitarian demining during peace						
Post demining	0.113***	0.924**	0.064***	0.079***	-0.043	-0.105***
	(0.036)	(0.367)	(0.020)	(0.021)	(0.054)	(0.036)
Panel B: Military demining during peace						
Post demining	0.004	-0.888***	0.003	-0.004	0.259***	-0.129***
	(0.018)	(0.340)	(0.009)	(0.010)	(0.031)	(0.038)
Panel C: Military demining during conflict						
Post demining	-0.018***	-0.606***	–	–	0.081***	0.014
	(0.004)	(0.121)			(0.011)	(0.016)
Observations (Panel A)	7460	7460	6960	6960	7460	7460
Observations (Panel B)	90504	100560	69340	69370	100560	100560
Observations (Panel C)	213000	213000	–	–	213000	213000
Treated (Panel A)	294	294	283	283	294	294
Treated (Panel B)	9630	9630	6641	6641	9630	9630
Treated (Panel C)	15150	15150	–	–	15150	15150
Never treated (Panel A)	452	452	413	413	452	452
Never treated (Panel B)	426	426	293	296	426	426
Never treated (Panel C)	2600	2600	–	–	2600	2600
Average dep var (Panel A)	1.343	34.407	0.207	0.222	3.290	0.636
Average dep var (Panel B)	0.973	33.381	0.149	0.168	3.721	2.392
Average dep var (Panel C)	0.435	26.349	–	–	3.403	1.728

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020). Panel A presents the results for humanitarian demining during peace, panel B for military demining during peace, and panel C for military demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include only the never treated. The outcomes were computed using a radius of 5km around the demining. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A15. Robustness to excluding never treated as controls

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Humanitarian demining during peace						
Post demining	0.069	1.026	0.176***	0.211***	0.271**	-0.267***
	(0.112)	(0.831)	(0.043)	(0.040)	(0.137)	(0.091)
Panel B: Military demining during peace						
Post demining	0.014	-0.871***	0.012*	-0.008	0.174***	-0.039
	(0.015)	(0.226)	(0.006)	(0.007)	(0.023)	(0.025)
Panel C: Military demining during conflict						
Post demining	-0.006*	-0.308***	–	–	0.137***	-0.033**
	(0.003)	(0.096)			(0.010)	(0.014)
Observations (Panel A)	2940	2940	2830	2830	2940	2940
Observations (Panel B)	86670	96300	66410	66410	96300	96300
Observations (Panel C)	181800	181800	–	–	181800	181800
Treated (Panel A)	294	294	283	283	294	294
Treated (Panel B)	9630	9630	6641	6641	9630	9630
Treated (Panel C)	15150	15150	–	–	15150	15150
Average dep var (Panel A)	1.429	38.005	0.212	0.223	3.312	0.338
Average dep var (Panel B)	0.981	33.375	0.150	0.169	3.708	2.299
Average dep var (Panel C)	0.425	25.971	–	–	3.386	1.710

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020). Panel A presents the results for humanitarian demining during peace, panel B for military demining during peace, and panel C for military demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls exclude the never treated. The outcomes were computed using a radius of 5km around the demining. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

TABLE A16. Robustness to allow for one-year anticipation

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: Humanitarian demining during peace						
Post demining	0.100**	0.953	0.035**	0.032*	0.124**	-0.190***
	(0.040)	(0.649)	(0.018)	(0.020)	(0.056)	(0.055)
Panel B: Military demining during peace						
Post demining	-0.004	-1.877***	0.008	-0.010	0.123***	-0.119***
	(0.015)	(0.272)	(0.005)	(0.006)	(0.023)	(0.027)
Panel C: Military demining during conflict						
Post demining	-0.022***	-0.718***	–	–	0.083***	-0.001
	(0.004)	(0.111)			(0.010)	(0.016)
Observations (Panel A)	7460	7460	6960	6960	7460	7460
Observations (Panel B)	90504	100560	69340	69370	100560	100560
Observations (Panel C)	213000	213000	–	–	213000	213000
Treated (Panel A)	294	294	283	283	294	294
Treated (Panel B)	9630	9630	6641	6641	9630	9630
Treated (Panel C)	15150	15150	–	–	15150	15150
Never treated (Panel A)	452	452	413	413	452	452
Never treated (Panel B)	426	426	293	296	426	426
Never treated (Panel C)	2600	2600	–	–	2600	2600
Average dep var (Panel A)	1.343	34.407	0.207	0.222	3.290	0.636
Average dep var (Panel B)	0.973	33.381	0.149	0.168	3.721	2.392
Average dep var (Panel C)	0.435	26.349	–	–	3.403	1.728

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020). We allow for an anticipation of the treatment of one-year. Panel A presents the results for humanitarian demining during peace, panel B for military demining during peace, and panel C for military demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A17. Robustness to different radiuses: Humanitarian demining during peace

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: 3 km radius						
Post demining	0.201***	0.907**	0.039	0.058**	0.013	-0.117***
	(0.046)	(0.442)	(0.026)	(0.023)	(0.057)	(0.027)
Panel B: 4 km radius						
Post demining	0.159***	0.910**	0.081***	0.093***	-0.021	-0.118***
	(0.039)	(0.410)	(0.021)	(0.021)	(0.054)	(0.032)
Panel C: 6 km radius						
Post demining	0.087***	0.941***	0.101***	0.110***	-0.023	-0.122***
	(0.031)	(0.347)	(0.018)	(0.023)	(0.051)	(0.039)
Panel D: 7 km radius						
Post demining	0.061**	1.120***	0.076***	0.091***	-0.035	-0.135***
	(0.026)	(0.352)	(0.020)	(0.022)	(0.044)	(0.041)
Observations	7460	7460	6960	6960	7460	7460
Treated	294	294	283	283	294	294
Never treated	452	452	413	413	452	452
Average dep var (Panel A)	1.266	32.578	0.137	0.147	2.249	0.415
Average dep var (Panel B)	1.309	33.354	0.166	0.179	2.830	0.533
Average dep var (Panel C)	1.371	35.842	0.211	0.229	3.684	0.727
Average dep var (Panel D)	1.396	37.372	0.223	0.244	4.018	0.807

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of humanitarian demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. Panels A, B, C, and D present the results where dependent variable was computed using a radius of 3, 4, 6, and 7km around the event, respectively. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A18. Robustness to different radiuses: Military demining during peace

	(1)	(2)	(3)	(4)	(5)	(6)
			Test scores:			
	Nighttime Lights	Population density	Math	Reading	Forest loss	Coca
Panel A: 3 km radius						
Post demining	0.019	-1.193***	-0.002	-0.019**	0.300***	-0.134***
	(0.015)	(0.335)	(0.007)	(0.007)	(0.025)	(0.026)
Panel B: 4 km radius						
Post demining	0.014	-1.021***	-0.001	-0.014**	0.290***	-0.108***
	(0.013)	(0.257)	(0.006)	(0.007)	(0.025)	(0.025)
Panel C: 6 km radius						
Post demining	0.003	-0.945***	-0.002	-0.018***	0.246***	-0.087***
	(0.012)	(0.196)	(0.006)	(0.006)	(0.023)	(0.026)
Panel D: 7 km radius						
Post demining	-0.005	-0.947***	0.006	-0.001	0.246***	-0.075***
	(0.012)	(0.193)	(0.005)	(0.006)	(0.023)	(0.025)
Observations	90504	100560	69340	69370	100560	100560
Treated	9630	9630	6641	6641	9630	9630
Never treated	426	426	293	296	426	426
Average dep var (Panel A)	0.958	37.058	0.069	0.078	2.670	1.828
Average dep var (Panel B)	0.968	34.944	0.088	0.099	3.255	2.130
Average dep var (Panel C)	0.974	32.171	0.116	0.131	4.103	2.625
Average dep var (Panel D)	0.975	31.400	0.129	0.145	4.427	2.834

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. Panels A, B, C, and D present the results where dependent variable was computed using a radius of 3, 4, 6, and 7km around the event, respectively. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A19. Robustness to different radiuses: Military demining during conflict

	(1) Nighttime Lights	(2) Population	(3) Forest Loss	(4) Coca
Panel A: 3 km radius				
Post demining	-0.016***	-0.552***	0.074***	-0.036***
	(0.004)	(0.130)	(0.011)	(0.012)
Panel B: 4 km radius				
Post demining	-0.015***	-0.533***	0.094***	-0.020
	(0.003)	(0.102)	(0.011)	(0.013)
Panel C: 6 km radius				
Post demining	-0.011***	-0.424***	0.099***	-0.001
	(0.003)	(0.077)	(0.010)	(0.014)
Panel D: 7 km radius				
Post demining	-0.011***	-0.414***	0.092***	0.008
	(0.003)	(0.072)	(0.010)	(0.014)
Observations	213000	213000	213000	213000
Treated	15150	15150	15150	15150
Never treated	2600	2600	2600	2600
Average dep var (Panel A)	0.424	29.553	2.339	1.251
Average dep var (Panel B)	0.430	27.580	2.928	1.507
Average dep var (Panel C)	0.440	25.550	3.797	1.923
Average dep var (Panel D)	0.446	25.221	4.134	2.101

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for the treatment of military demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. Panels A, B, C, and D present the results where dependent variable was computed using a radius of 3, 4, 6, and 7km around the event, respectively. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A20. Robustness to outliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
					Test scores:							
	Nighttime Lights		Population density		Math		Reading		Forest loss		Coca	
Winsorizing at:	1%	3%	1%	3%	1%	3%	1%	3%	1%	3%	1%	3%
Panel A: Humanitarian demining during peace												
Post demining	0.145***	0.148***	1.025***	1.011***	0.067***	0.067***	0.081***	0.081***	-0.030	-0.026	-0.101***	-0.072**
	(0.035)	(0.034)	(0.364)	(0.336)	(0.023)	(0.022)	(0.021)	(0.020)	(0.056)	(0.049)	(0.032)	(0.035)
Panel B: Military demining during peace												
Post demining	0.008	0.005	-0.983***	-1.343***	-0.001	-0.001	-0.016***	-0.016**	0.257***	0.253***	-0.083***	-0.023
	(0.013)	(0.013)	(0.214)	(0.186)	(0.006)	(0.006)	(0.006)	(0.006)	(0.026)	(0.024)	(0.025)	(0.025)
Panel C: Military demining during conflict												
Post demining	-0.013***	-0.012***	-0.478***	-0.295***	–	–	–	–	0.100***	0.098***	-0.004	0.003
	(0.003)	(0.003)	(0.092)	(0.067)					(0.011)	(0.010)	(0.014)	(0.013)
Observations (Panel A)	7460	7460	7460	7460	6960	6960	6960	6960	7460	7460	7460	7460
Observations (Panel B)	90504	90504	100560	100560	69340	69340	69370	69370	100560	100560	100560	100560
Observations (Panel C)	213000	213000	213000	213000	–	–	–	–	213000	213000	213000	213000
Treated (Panel A)	294	294	294	294	283	283	283	283	294	294	294	294
Treated (Panel B)	9630	9630	9630	9630	6641	6641	6641	6641	9630	9630	9630	9630
Treated (Panel C)	15150	15150	15150	15150	–	–	–	–	15150	15150	15150	15150
Never treated (Panel A)	452	452	452	452	413	413	413	413	452	452	452	452
Never treated (Panel B)	426	426	426	426	293	293	296	296	426	426	426	426
Never Treated (Panel C)	2600	2600	2600	2600	–	–	–	–	2600	2600	2600	2600
Average dep var (Panel A)	1.341	1.332	33.598	33.103	0.207	0.207	0.222	0.222	3.288	3.280	0.632	0.610
Average dep var (Panel B)	0.969	0.961	33.381	29.951	0.149	0.149	0.168	0.168	3.718	3.711	2.390	2.377
Average dep var (Panel C)	0.429	0.417	26.349	22.547	–	–	–	–	3.399	3.392	1.723	1.711

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020). Panel A presents the results for humanitarian demining during peace, panel B for military demining during peace, and panel C for military demining during conflict. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. Odd columns present the results for the dependent variable winsorized at 1% and even columns at 3%. Bootstrap standard errors clustered at the municipality level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A21. The local effects of demining on fires

	(1)	(2)	(3)
During:	Peace		Conflict
	Humanitarian	Military	Military
Post demining	-0.048	0.033**	0.049***
	(0.049)	(0.014)	(0.010)
Observations	7460	100560	213000
Treated	294	9630	15150
Never treated	452	426	2600
Average dep var	0.592	0.879	0.865

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for fires for the three demining treatments. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. Bootstrap standard errors clustered at the event level. * is significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level.

Table A22. The local effects of demining during peace on illegal gold mining

	(1)	(2)	(3)	(4)
Demining:	Humanitarian		Military	
	Area illegal gold mining	Illegal gold mining	Area illegal gold mining	Illegal gold mining
Post demining	-0.103	-0.048	0.059***	0.019***
	(0.146)	(0.046)	(0.020)	(0.006)
Observations	2020	2020	11604	11604
Treated	53	53	2475	2475
Never treated	452	452	426	426
Average dep var	0.216	0.065	0.415	0.084

Notes: This table presents the overall ATT following Callaway and Sant'Anna (2020) for forest loss using the humanitarian and military demining treatments during peace. *Post demining* is the weighted average of all group-time average treatment effects with weights proportional to group size. The set of controls include not yet treated and never treated. The outcomes were computed using a radius of 5km around the demining. * significant at the 10% level, ** is significant at the 5% level, *** is significant at the 1% level