FEAR TO VOTE: EXPLOSIONS, SALIENCE, AND ELECTIONS

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Abstract. We study how antipersonnel landmines thwart democratic accountability and the consolidation of post-conflict democratic institutions. We do so by exploiting the randomness in the timing of landmine explosions relative to election days, comparing the electoral outcomes of voting polls located close to a pre-election explosion with those of polls near a post-election blast. We show that landmine explosions are salient stimuli that produce fear, reducing political participation. While the turnout reduction takes place across the ideological spectrum, we document that the explosions induce shifts in the political preferences of individuals who do vote, which are inconsistent with retrospective voting.

Keywords: Landmine explosions, conflict, voting, salience, fear.

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1 Introduction

Antipersonnel landmines are explosives hidden underground and prevalent in dozens of countries. They cause thousands of fatal victims every year and pose a risk to millions more.[1] By limiting access to markets, agricultural investment, and schooling, landmines constitute a colossal development challenge in many conflict and post-conflict settings. The recovery of Ukraine, for instance, will be hindered by the countless landmines and unexploded ordnance (UXO) left behind by Russian troops in about a third of the country's territory (covering an area equivalent to the size of Florida).[2]

While scholars have only recently begun to study the economic consequences of mine removal efforts (e.g., Chiovelli et al., 2019 and Prem et al., 2023a), our understanding of the political consequences of the explosives currently planted remains limited. Nonetheless, the consolidation of post-conflict democracies may be threatened by the prevalence of landmines and UXO. Indeed, as this paper demonstrates, mine explosions depress political participation and drive electoral choices in ways that are detrimental to electoral accountability.[3] We study the case of Colombia, which due to its prolonged civil war history, ranks third in the number of landmine victims per year after Syria and Afghanistan.[4]

Unlike other forms of violence, exerted strategically by criminal groups to achieve specific goals, landmine explosions are fortuitous, and cannot be triggered remotely or at will. In fact, landmine explosions are technically referred to as 'accidents'. Therefore, by comparing the voting patterns of voting polls close to areas of (endogenous) landmine presence, but relying on the precise timing of landmine explosions relative to election days, we can isolate the electoral effects of landmine explosions. We leverage geo-located administrative data on all anti-personnel landmine explosions, along with a novel data set on the coordinates of all voting polls in rural Colombia to make exactly this comparison, effectively adopting a Regression Discontinuity Design (RDD).

We find that antipersonnel landmines that burst in the vicinity of voting polls within a month prior to (local, presidential, and congress) elections have a large negative impact on

[1]Landmines detonate upon contact or proximity to moving bodies such as people or vehicles. Civilians are particularly at risk when the precise location of minefields is unknown. In 2022, about half of all civilian landmine victims were children (Landmine Monitor, 2023).

[2]See, e.g., `https://rb.gy/ujkcar`, `https://rb.gy/nklsel`, and `https://rb.gy/vlfwqa`.

[3]For Przeworski et al. (1999), electoral accountability requires widespread participation from voters who, even if imperfectly, can discern if governments are promoting their best interest and reward or sanction them accordingly. In turn, by anticipating the judgment of voters, governments will act in the best interest of the people. From this perspective, "retrospective voting" helps enforce electoral accountability (Fiorina, 1978), and achieve representation (Key, 1966).

[4]Colombia is the country with the highest number of victims of *improvised* anti-personnel mines. Unlike the type of industrial mines that are prevalent in Ukraine, these are more unstable and damaging homemade explosives, that are harder to detect and remove without risking an explosion (Landmine Monitor, 2019).

political participation, relative to explosions that occur close to polls within a month afterward. Specifically, they depress turnout at the voting poll level by at least 13 percentage points (p.p.), 23% relative to the mean. We argue that this finding can be explained by the exacerbation of short-term emotions (particularly fear) caused by landmine explosions. To substantiate this, we leverage a nationally representative political behavior survey and show that individuals who report landmine accidents as a new risk to their community were less likely to vote in the last election (conditional on being frequent voters and living in conflict-affected areas). Moreover, the majority of non-voters reported *fear* as their primary reason for abstaining.[5]

At the same time, we rule out three alternative mechanisms: i) that landmine accidents damage the road network and reduce the access to voting polls; ii) that they exacerbate other types of violence in the proximity of voting polls and prior to the election; iii) that they reduce the trust that citizens have on local institutions, making them less likely to participate in the electoral process.

Establishing that landmine explosions hurt electoral participation by creating fear is critical for the consolidation of post-conflict democracies, especially given that, in the absence of demining or controlled explosions–which are costly and dangerous–these explosives can remain active for decades. By prioritizing survival considerations over their political preferences or the performance of politicians, fearful voters may act in ways detrimental to democratic accountability: while *retrospective voting* theories assume that voters reward or punish politicians based on their assessment of government performance (Barro, 1973; Ferejohn, 1986; Canes-Wrone et al., 2001), research in psychology suggests that emotional shocks can blind voters from political factors (Schwarz and Clore, 1983).

We also explore the reasons why landmine explosions cause fear. This is important for two reasons. From a policy perspective, it can shed light on whether the provision of information about potential landmine hazards in post-conflict settings would suffice to offset the detrimental effect of landmine accidents on electoral participation, especially given the large costs implied by comprehensive demining campaigns (Prem et al., 2023a; Perilla et al., 2024). From a theoretical perspective, it may inform the behavioral mechanisms that connect violence shocks with electoral participation. Conceptually, there are two distinct channels why landmine blasts produce fear: on the one hand, they may convey key *information* about risk. For instance, explosions could hint at the likely presence of other landmines–or the group that placed them. Thus, the risk of future victimization may translate into fear, generating

[5]Conversely, by exploiting variation in the adoption of humanitarian demining campaigns across Colombia as well as geo-located information of the targeted areas, we find suggestive evidence that voting polls located near areas that benefited from landmine clearance experience an increase in turnout.

(conscious) actions to reduce it. This mechanism yields two testable implications: first, if landmine explosions are recurrent, the *additional* information gathered from the marginal explosion is smaller and the observed behavioral responses should become smaller as explosions accumulate; second, to the extent that the source of the perceived victimization risk remains present, the behavioral response of an explosion should also linger.

On the other hand, due to their prominence, contrast with surroundings, and often surprising nature, landmine explosions are *salient* stimuli (Bordalo et al., 2022). Put differently, the unpredictability in the timing of landmine explosions, together with their capacity to produce damage and even kill, makes blasts salient. Salience, in turn, shifts people's attention 'bottom-up' (i.e., automatically and involuntarily) and distorts behavior *in the short-run* relative to current goals and expectations.

We provide empirical support for the second mechanism by showing that: i) the turnout reduction is larger the closer the explosion is to election day; ii) (using grid-level Facebook mobility data) the mobility reduction after a landmine explosion is immediate, large, and short-lasting (which is consistent with the short-term distortion of salience, even in the presence of a lingering risk); iii) the turnout reduction remains unchanged after controlling either for the history of landmine explosions in the affected area (i.e., accounting for the bulk of prior information) or for the underlying risk of future explosions; iv) the magnitude of the effect is very similar if the election is national or local, or irrespective of a range of victim characteristics (so what matters for behavior is only the explosion).

In addition to exploring the effect of landmine explosions on political participation, we examine their effect on the voting patterns of citizens who cast their vote despite of the blast. We document that landmine accidents reduce the poll-level vote share of left-wing candidates by 22 p.p. Importantly, we show that this is not mechanically driven by the reduction in political participation. This would be the case if, after a landmine explosions, individuals chose to abstain based on their political ideology. The absence of evidence in favor of this mechanism is reassuring, as it would be conceptually inconsistent with the bottom-up salience explanation of the reduction in turnout.

Rather, this finding is consistent with the observation that in Colombia, those largely responsible for placing antipersonnel landmines were left-wing guerrillas, particularly the *Revolutionary Armed Forces of Colombia* (FARC from the Spanish acronym, see section 2). Moreover, it is also consistent with the explosion being salient: The psychology literature highlights the impact of salient stimuli in driving attention selection (Itti et al., 1998). This implies that bottom-up sensory salience increases the probability that certain events are remembered (Rajaram, 1998; Pedale and Santangelo, 2015). In our context, even if the local community is aware of the threat of minefields–and the identity of the perpetrator–an explosion makes it salient that left-wing guerrillas are to be blamed, so they use their vote to punish the left. Because this is irrespective of the democratic left being traditionally dissociated from the guerrillas (Fergusson et al., 2021), it adds to the argument that explosions undermine democratic accountability.[6]

Our RDD strategy stands on a number of assumptions, for which we provide validating empirical evidence. First, consistent with the lack of manipulation of the timing of landmine accidents relative to the election, we show that the temporal distribution of explosions is statistically indistinguishable before and after election day. Similarly, we show that the landmines that go off prior to the election are not located closer to voting polls, relative to those that burst afterward. Third, we show that a large number of voting poll-level and (more aggregated) municipal-level characteristics are balanced around the (election day) cutoff. Importantly, these include all our main outcomes measured on the same voting poll in the previous elections, a placebo that alleviates sorting concerns. The balanced characteristics also include various measures of violence (such as geo-located homicides). Our findings are also robust to a battery of tests and alternative specifications, including controlling for the amount of rainfall around voting polls during the month leading to the election (which may change soil conditions and therefore the sensibility of landmines to approaching ground objects), and addressing the challenges of using discrete running variables in RD settings (Kolesár and Rothe, 2018; Imbens and Wager, 2019).

We contribute to research in various fields. First, recent literature has documented the significant economic and social costs of antipersonnel landmines, affecting health and educational outcomes (Arcand et al., 2015; Merrouche, 2011), and increasing poverty (Merrouche, 2008). Relatedly, Chiovelli et al. (2019) and Prem et al. (2023a) have found that humanitarian demining campaigns both increase short-term economic activity (as proxied by night lights) and enhance long-term development prospects (by boosting schooling and learning outcomes). We contribute to this literature by studying the electoral effects of landmine explosions and documenting their threat to post-conflict democratic consolidation.

A second strand of the related development literature studies the long-term economic consequences of the U.S.-led counter-insurgent aerial bombings in Southeast Asia from 1955 to 1975 (Miguel and Roland, 2011; Dell and Querubin, 2018; Lin, 2022; Riaño and Valencia Caicedo, 2024). While these studies primarily focus on economic and development outcomes, our paper introduces a novel perspective by examining the political consequences

[6]In addition, the psychology literature also suggests that emotions are interconnected and particularly that anger is often the go-to reaction after experiencing fear (Tsai and Young, 2010; Nussbaum, 2019). The implication for our context is that voters who approach the polling station after a blast are angry, and engage in negative reciprocity.

of explosions. Furthermore, the long-term effects of buried aerial UXO likely represent only a fraction of those resulting from landmines, which are not only cheaper to manufacture but also intentionally concealed underground. In fact, landmine contamination is still a problem in around 60 countries, while unexploded aerial bombs are currently prevalent only in Laos and Cambodia, and recently in Ukraine.

Third, we contribute to the idea that retrospective voting can be limited by circumstances where voters experience significant emotional shifts due to factors unrelated to the incumbent's performance (see the recent review of Healy and Malhotra, 2013). Indeed, voters may reward or punish politicians based on their emotional reactions to external stimuli, which can induce feelings of happiness, sadness, or fear. In particular, voters experiencing negative emotional states might erroneously attribute their feelings to the incumbent, thereby affecting their voting decisions (Schwarz and Clore, 1983). In this sense, our paper adds to the view that emotional (as well as cognitive) biases may undermine democratic accountability.[7]

Relatedly, our paper also connects to recent political economy papers on how the fear caused by epidemics (e.g., Campante et al., 2020 and Mansour et al., 2022), repression (e.g., Bautista et al., 2023, Iwanowsky and Madestam, 2023, and Young, 2019), or by terror attacks (e.g., Vasilopoulos et al., 2019) affects political participation and the support of specific political parties. However, while these shocks could also be interpreted as salient, the findings of these and related papers are mostly mediated by political manipulation and media amplification. This implies that salience is likely confounded by strategic responses to the stimulus. Our setting, in which information about landmine explosions spreads rapidly and locally, and by and large via word of mouth (with the urban mass media rarely covering episodes of landmine explosions), allows us to minimize this possibility.

Finally, our paper is somewhat related to the research on how organized criminal groups use violence to affect electoral outcomes (e.g., Robinson and Torvik, 2009; Montalvo, 2011; Collier and Vicente, 2012; Acemoglu et al., 2013; De Feo and De Luca, 2017; Condra et al., 2018 and Alesina et al., 2019). We show that, by generating fear, a form of violence that is not electoral in principle can also have large effects on electoral outcomes. Another advantage of leveraging landmine explosions is that our treatment is largely homogeneous and comparable across space and time.

[7]It also relates to the literature on behavioral economics that studies how emotions influence choices (Chichilnisky, 2009; Chanel and Chichilnisky, 2009; Nguyen and Noussair, 2014; Kassas et al., 2022). We show that violence-induced fear can affect consequential behaviors such as political participation. We also contribute to the research on the behavioral consequences of salience (Bordalo et al., 2012, 2013, 2020). Because of their fortuitousness, landmine explosions are salient stimuli that make individuals decide under the veil of fear.

2 Context

2.1 Violence and landmines Colombia's conflict started in the mid-1960s, when the FARC and the *National Liberation Army* (ELN) were founded. The conflict became three-sided in the 1970s when self-defense and paramilitary organizations–which eventually became illegal in 1989–were armed and trained by the military in counter-insurgency. Both guerrilla and paramilitary groups fight for territorial control. One key strategy of the guerrilla (and especially the FARC) to secure the strongholds and to protect illegal crops is the employment of anti-personnel landmines. In fact, the main milestone in the fabrication and planting of improvised mines in Colombia came in 2008, when FARC's secretariat launched a strategy aimed at increasing the production and utilization of artisanal landmines.[8] By 2017, the area contaminated with landmines was officially estimated to be around 11,400 acres (Landmine Monitor, 2017), which is equivalent to almost 80% of the size of Manhattan. Civilian communities are neither unaware of the approximate location of suspected mined fields, nor of the responsibility of the guerrillas in placing them. This, however, does not prevent the occurrence of accidental explosions throughout the country, both because of uncertainty about the exact location of landmines and due to the explosives drifting around due to heavy rain or floods.[9]

2.2 Democracy and elections Local elections in Colombia were introduced in the late 1980s.[10] These include mayors, city councils, governors, and state assembly (the state-level legislature).[11] They are all elected on the same day, in October, with the term starting in January of the following year. Local election years, however, do not coincide with those of national elections. At the local level, executive bodies follow a majoritarian rule, and legislative bodies proportional representation.

At the national level, there are both presidential and congressional elections. The latter includes the lower chamber, with regional constituencies, and the Senate, with national representation. Both presidential and congressional elections take place every four years and during the same year. While legislators are elected in March by proportional representation and take their seats in July, presidential elections include two rounds, both by majoritarian rule (in May and June). The elected president takes office in August. Ultimately, these institutional details shape the number and frequency of elections during our sample period, which covers 2003 to 2019. Our sample includes four presidential and congressional elections (from 2006 to 2018) and five local elections (from 2003 to 2019).

[8] See Appendix Figure A1 for the internal secret memorandum–in the original Spanish–that Commander 'Alfonso Cano' addressed to all fronts of the organization.
[9] See, e.g., `https://shorturl.at/ilGPY` (last accessed 02/12/2024).
[10] Appendix A provides a historical context that discusses how and why local elections were introduced.
[11] In some cities, other lower-level executive bodies are also elected.

Colombia uses a secret ballot for all elections and has never implemented electronic voting. Until January 2003, new voters (people turning 18 and receiving a national ID card) were registered in the municipality issuing the national ID and had to actively enroll in a poll of their preference in order to vote there (as opposed to a default location designated by the municipality). Since January 2003, new voters are automatically registered in the poll nearest their residence address. During a window that ends two months prior to an election, voters can enroll in a poll of their choice (MOE, 2022).

2.3 The interplay between conflict and elections Criminal organizations that operate under democratic regimes have incentives to employ violent means to shape the political process for obtaining favorable policies, receiving a share of public contracts, or directly benefiting from public procurement, among others. To this end, criminal groups may attempt to exert influence at different stages, including the selection of candidates, the electoral process, and the behavior and choices of elected officials. Colombian armed groups are no exception. The most prominent example is that of paramilitary militias, which have traditionally been an illegal arm of local economic and political elites to silence the new political challengers, especially left-wing candidates, activists, and sympathizers (Steele, 2017; Steele and Schubiger, 2018; Fergusson et al., 2021).

Most guerrilla fronts, on the other hand, question the legitimacy of elections but refrain from attempting to influence them.[12] A few, however, try to sabotage the electoral process by: threatening or kidnapping candidates that they associate with the paramilitary or judge as corrupt or clientelistic; threatening election juries; destroying ballots and other electoral material, and preventing voters from reaching the polls (Peña, 2000). Consistent with this, Arjona (2016) argues that, in the regions in which they exert governance, guerrillas often ban turnout in elections. This contrasts with the practice of paramilitaries, which usually 'make' communities vote for the candidate of their preference.[13]

There is, however, no evidence that placing landmines is part of the strategy of any group in their quest to shape either election outcomes or policy choices. This comes as no surprise, given the fact that establishing landmine fields requires a minimum degree of territorial control, but that once control is established, there are other, more cost-beneficial, tractable, and accurate ways to influence the outcome of the electoral process.

[12]While the FARC co-founded an apolitical party in the late 1980s (the *Patriotic Union*, UP from the Spanish acronym), by the early 1990s the two organizations split, and UP became an independent political party.
[13]Gallego (2018) shows that while FARC violence decreases turnout, paramilitary violence reduces political competition.

3 Data

3.1 Elections and voting Colombia's electoral authority is the National Civil Registry, which organizes and oversees all national and local elections, and engages in a pre-count of ballots at the end of each election in order to provide readily preliminary information about results. The institution maintains poll-level aggregates in its archives and, for this project, we geo-located these data and built a poll/election-level data set covering the period 2003-2019.[14] The data include the poll's vote potential and the number of votes obtained by each candidate. The National Civil Registry selects the location of voting polls, which are usually located at parks, parking lots, or school yards. The location of polls very rarely changes.

Panel A of Figure A2 shows the spatial distribution of the 12,109 voting polls that were enabled for the 13 elections that constitute our sample.[15] Polls' location closely maps population density which moves along Colombia's three branches of the Andes Cordillera. In turn, the Pacific coast (the west-most strip of the country) and especially the Amazon region (in the south and southeast of the country) are scarcely populated and host very few polls.

Our main outcome variable is the turnout rate of each poll/election, defined as the total votes cast divided by the poll's vote potential. We also explore the effect of landmine blasts on the composition of votes. To that end, we compute the number of votes for the incumbent party, for parties across the ideological spectrum, and for parties that have been shown to have strong ties with illegal paramilitary groups.[16] We then converted these totals in rates using either the total votes cast in each poll/election or the poll's vote potential.

3.2 Landmine explosions As a signatory of the 1997 Ottawa Convention, which forbids the employment, storage, production, and transfer of anti-personnel mines, Colombia adopted in 2002 the Information Management System for Mine Action (IMSMA) of the Geneva International Centre for Humanitarian Demining (GICHD). IMSMA is a registry of all explosions of landmines and other explosive artifacts and of all demining events. It provides geo-located data on landmine explosions in a consistent way since 2001. It also provides a brief description of the accident from which, using text analysis, we recover information about the resulting victims.

Panel B of Figure A2 shows the spatial distribution of the 5,653 landmine explosions that

[14] We managed to geo-locate 98% of the voting polls using Google's Geocoding API. The remaining 2% had inaccuracies in addresses.

[15] For 2003 we have only poll-level electoral data for a subset of departments, which however account for over a third of the country's population. Our results are robust to dropping this election year.

[16] For the ideology of parties, we rely on the classification of Fergusson et al. (2021). For the connections with paramilitaries, we focus on parties for which at least one-third of their elected congress members were prosecuted because of ties with paramilitary groups (Valencia, 2007). Appendix Table A1 summarizes the parties classified as left-wing or right-wing, as well as those classified as having ties with paramilitaries.

occurred during our sample period. However, in our baseline sample, we keep only landmine explosions that took place within 4Km-radius circle around a voting poll and over a 90-day window around the election day. We, however, perform two key refinements that make our estimation more accurate but do not drive our findings. First, we drop the landmine explosions that occurred within 1Km of the poll, and focus on the subsequent donut from 1 to 4Km. We do so because the geo-location of landmines that explode very close to the urban center of a village is approximated to the village's centroid. Thus, by removing blasts very close to voting polls we make sure that this source of measurement error does not affect our inference.[17] Second, to the extent that there might be some small uncertainty regarding the reported versus the actual date of an explosion (if, for instance, weekend blasts are not recorded before the next working day) we exclude explosions that occur three days around the election date. This, however, has no effect on our findings.

Ultimately, these refinements reduce our sample to 495 voting polls (4.5% of the country's total), in 173 municipalities (15%). These polls were affected by 520 landmine explosions (9.2% of the total blasts during the sample period). This leads to 1,136 unique observations of the type: voting poll-explosion-year.[18] These explosions yielded, on average, 1.6 total victims (fatal or injured), 48% of them involved a civilian, and 22% led to at least one victim being killed (see Appendix Figure A4).

Finally, we use a range of additional variables as controls as well as to test the RDD assumption of local continuity in terms of pre-treatment poll-level and municipal-level characteristics between voting polls with explosions before elections and polls with explosions afterward. Moreover, we bring in additional data sources to further explore the mechanisms behind our main results. We describe these, together with their source, in Appendix B.

4 Empirical strategy

Landmines are placed strategically in the territory to protect strongholds, illegal crops, and smuggling routes. Therefore, the naive comparison of voting patterns in places with and without landmine explosions would likely be contaminated by a range of confounders. Instead, we rely on an RDD that uses as a running variable the day of a landmine explosion

[17] In Appendix Table A2, we show the robustness of our results (both in terms of size and significance) to not having this sample restriction. Moreover, the 4Km radius was defined based on the shortest path between two points along an ellipsoid. However, our results are robust to compute the radius based on the shortest path between two points while taking into account the ruggedness of the terrain.

[18] Appendix Figure A3 overlays the geo-location of voting polls and landmine explosions in the estimation sample.

relative to the election day.[19] Our treatment rule is:

$$T_i = \begin{cases} T_i = 0 & \text{if } x_i > 0 \\ T_i = 1 & \text{if } x_i < 0 \end{cases} \tag{4.1}$$

where i is an explosion and x_i reflects the day relative to the election day. That is, a negative value of x_i indicates that explosion i took place x days before an election, which yields T_i, the treatment status, equal to one.[20] Moreover, if a voting poll experienced explosions at both sides of the discontinuity within the same election cycle, we keep it in our sample only as treated. However, our results are robust to dropping these cases.[21]

That the running variable takes discrete values –the number of days since the election may be problematic if only a few values are observed, because it leads to large extrapolations for the days close to the election. However, in our case, there are 104 different explosion days over a 60-day window around the elections, so this is not a major concern (Cattaneo et al., 2020). Moreover, in the robustness section, we report the result of a data-driven RD analysis suggested by Imbens and Wager (2019) for these types of settings. In addition, we also show the robustness of our results to implementing the local randomization approach suggested by Cattaneo et al. (2020). Our main estimation equation takes the form:

$$y_{impe} = \alpha_e + \beta \times T_i + \gamma_1 \times f(x_i) + \gamma_2 \times T_i \times f(x_i) + \varepsilon_{impe}. \tag{4.2}$$

where y_{impe} is an electoral outcome for poll station p in municipality m, computed for election e, and associated with explosion i. $f(x_i)$ is a polynomial of the day of explosion relative to the election day. α_e is an election fixed effect, which implies that our estimates compare outcomes in poll stations exposed to explosions shortly before and shortly after *the same* election. Finally, ε_{impe} corresponds to the idiosyncratic error term. Given the discrete nature of the running variable, we present the heteroskedasticity-robust standard errors suggested by Kolesár and Rothe (2018). Moreover, we also report standard errors clustered at the running variable level, as suggested by Lee and Card (2008), as well as errors clustered at the municipality level that account for spatial and temporal correlation for voting polls within the same municipality.

Our parameter of interest, β, captures the electoral outcome of interest in voting polls close to a landmine explosion that occurred just before the election relative to the same outcome

[19] Note that even if our running variable is defined as time with respect to a given event, our design differs from the standard *regression discontinuity in time* (RDiT). In our setting, the outcome variable is measured on the same day that is used to compute the relative time of the running variable, thus not being subject to the issue of serially correlated outcomes that may affect RDiT strategies (Hausman and Rapson, 2018).

[20] Note that a given poll station can be both in the treatment and control group but never in the same election year.

[21] In our main specification, we only keep explosions that occurred within a 4Km radius of a poll station. Naturally, we then test the robustness of this choice.

in polls exposed to a landmine blast that took place shortly afterward. To interpret β as a causal parameter, we require two key assumptions: 1) landmine explosions are not manipulated to take place disproportionally shortly before elections; and 2) the covariates that are potentially correlated with either the treatment or outcome variables must vary smoothly around the cut-off. In the next subsection, we discuss a range of tests implemented to address the validity of these (as well as additional) assumptions.

To estimate equation (4.2), we follow Cattaneo et al. (2020) and estimate the RDD non-parametrically using polynomials of orders one and two. We also weight observations according to their distance to the cut-off (using triangular kernel weights) as well as by the total number of potential voters of each poll station.[22] Additionally, we follow Calonico et al. (2014) and Cattaneo et al. (2020) and employ an optimal data-driven bandwidth selection procedure that minimizes the asymptotic mean square error (MSE). However, because MSE bandwidths produce non-robust confidence intervals, we report robust standard errors and confidence intervals at the 95% level together with the conventional point estimate within the MSE optimal bandwidth. We also explore the sensitivity of our estimates to changing the size of the bandwidth.

4.1 Validity of the empirical design We start by exploring whether landmines could have been manipulated to burst just before elections. This could be the case if landmines were a tool commonly used to disrupt elections and their explosion could be provoked at will. However, as discussed in Section 2, there are no accounts of this being the case. Following Cattaneo et al. (2018), we complement this qualitative evidence with a formal statistical manipulation test based on density discontinuity around the (election day) cut-off. Panel A of Figure 1 reports the distribution of explosions over a time window of up to 80 days around the election, 2.5 (4) times the optimal bandwidth when fitting a linear (quadratic) polynomial of the running variable. We find no statistically significant evidence of systematic manipulation over this period (`p-value` 0.71).[23] The evidence of lack of manipulation is robust to implementing the test suggested by McCrary (2008) to check for sorting around the threshold (`p-value` of 0.25). Moreover, given the discrete nature of our running variable, we also estimate the test suggested by Frandsen (2017) and, again, fail to reject that the density is continuous around the cut-off (`p-value` of 0.60).

A different way of manipulation in our setting could arise if organized criminal groups seeking

[22]As shown by Cattaneo et al. (2020), using triangular weights and their suggested optimal bandwidth leads to the best properties of the RDD estimate. In a robustness exercise, we present the results using uniform weights that weigh equally all the observations within the optimal bandwidth. As for the second weight, it allows us to give a similar weight to each voter, instead of treating equally two poll stations with a very different potential number of voters. Our results are, however robust to dropping this weight.

[23]Similar results are found using shorter windows (60, 40, or 20 days) around the election day (`p-values` 0.72, 0.29, and 0.75, respectively).

to alter electoral outcomes could trigger landmine explosions closer to poll stations before the elections relative to afterward. We test this in Panel B of Figure 1, which reports the distribution of the distance from a landmine explosion to the closest voting poll, according to the timing of the explosion. The empirical distribution prior to elections is plotted left to the 0 cut-off (the location of the poll). These two distributions are no different from one another. Importantly, moreover, when implementing the manipulation test of Cattaneo et al. (2018) (on the baseline distance of 4Km), we find no statistically significant discontinuity.[24]

Even if the timing of the explosion is as good as random, a third form of manipulation would occur if the *planting* of landmines took place in the vicinity of voting polls differentially prior to the elections relative to after. While this is much harder to test due to the lack of data on the location of unexploded landmines (let alone the timing of their placement), we provide both qualitative and indirect quantitative evidence that this is not the case. We exploit the fact that, at the end of 2014 and amid peace negotiations with the government, FARC declared a permanent ceasefire and stopped any bellicose activity, including planting new landmines.[25] Rather, it started collaborating with the government to reveal the location of minefields (Perilla et al., 2024). Exploiting this temporal change in the use of landmines by FARC (the main landmine user in our context), we explore a period heterogeneity and fail to find any differential effect before and after the ceasefire (see Column 2 of Table A3).[26]

The second main assumption is related to potential differences in poll station, explosion characteristics, or municipal-level variables that could be correlated with the treatment assignment, thus confounding the effect of landmine explosions on electoral outcomes. We formally address this concern in Tables 1 and A4, where we present differences in poll station and municipality characteristics (either time-invariant or measured before the election). The structure of both tables is as follows: Column 1 presents the average of the characteristics for the non-treated observations. Column 2 reports the outcome of univariate regressions within the optimal bandwidth.[27] And Column 3 reports the RDD estimate for each of these characteristics (based on equation 4.2).

We do not find, in either of the latter two columns, any statistical difference across a wide range of pre-election political characteristics. This is true at the explosion, voting poll, and

[24]The `p-value` of this test is 0.3, and when estimating the test suggested by McCrary (2008) is 0.55.

[25]For details about the causes, scope, and consequences of the ceasefire, see Prem et al. (2020, 2021, 2023b).

[26]Table A3 explores this, as well as other potential heterogeneities of the effect of landmine explosions on turnout. To that end, we estimate a linear regression on the sub-sample that lies within the optimal bandwidth associated with the linear polynomial and using triangular kernel weights and election-year fixed effects. For reference, the baseline effect of explosions on turnout –estimated following the procedure just described–is reported in Column 1.

[27]This bandwidth comes from the optimal MSE for turnout when using a linear polynomial (see Column 1 of Table 2).

municipality level.[28] Importantly, we find no evidence of differences in our main outcomes (as measured in the previous election, within the same voting poll), or a differential incidence of homicides (measured at the poll level), or in any of several conflict variables measured (at the municipality level) either in the year before the election or the *day* of the election. These results alleviate concerns regarding both sorting and a differential targeting of these areas by illegal armed groups as well as regarding any difference in voting poll characteristics that could be correlated with differential mobility of people.

Finally, in Appendix Table A5, we present poll and municipality-level characteristics for observations: i) in sample; ii) out of sample but affected by explosions; iii) the rest. We find no major differences between (i) and (ii), which alleviates concerns about the external validity of the sample of municipalities affected by landmines, and supports the idea that the timing of the explosion is random. However, between (i) and (iii), there are major differences in terms of the size of the voting polls, the incidence of conflict, and other socioeconomic dimensions, which are consistent with the rural nature of the Colombian conflict.

Overall, these findings support the idea that, in this context, our research design is suitable for a causal interpretation of the effect of landmine explosions on electoral outcomes.

5 Results

5.1 Landmine explosions and electoral participation Table 2 summarizes the main estimates of the effects of landmine explosions on poll-level turnout. These are obtained from estimating equation (4.2) non-parametrically, following Cattaneo et al. (2020).[29] Columns 1 and 2 fit a local linear polynomial, and Columns 3 and 4 fit a quadratic polynomial. Even columns control for the log of votes' potential of each voting poll.

We find that landmine explosions that take place in the few days prior to an election discourage political participation. Specifically, based on the even columns, they depress turnout by between 13 and 36 p.p. (22 and 62% of the sample mean).[30] Taking into account that the average voting poll in our estimation sample hosts 610 potential voters and that the average turnout in control voting polls is 59.7%, these magnitudes imply that, on average, between

[28]We also compute a randomization inference for the joint significance test for both poll and municipality-level characteristics, finding `p-values` of 0.92 and 0.96, respectively.

[29]We report robust p-values along with the corresponding 95% confidence interval, as well as two additional p-values that depend on how we cluster the standard errors. Those labeled [1] are associated with standard errors clustered at the running variable level, as suggested by Lee and Card (2008). Those labeled [2] refer to municipal-level clusters. All our findings are robust to any of these decisions regarding inference.

[30]Alternatively, instead of computing the poll-level turnout, which divides the total votes by the voting poll's vote potential, we can measure political participation with the (log of) total votes cast in each poll. We report these results in Appendix Table A6, finding similar results.

76 and 134 fewer citizens voted in each affected voting poll.[31] Panels A and B of Figure 2 graphically illustrate the effect of a landmine blast on electoral participation, respectively for polynomials of orders one and two. Each dot represents the average turnout within bins of equal size of days to the election. Linear and quadratic fits (based on the raw, unbinned data) are depicted together with the bin averages. A statistically significant jump in turnout rate across the threshold is evident in both figures.

Note that the magnitude of the effect of landmine explosions on turnout rates varies with the size of the optimal bandwidth, which in turn depends on the degree of the local polynomial and on the included controls. Indeed, the optimal bandwidth, estimated following Calonico et al. (2014), ranges between 19.6 and 32 days. Appendix Table A7 estimates the same specifications but fixing the bandwidth to the optimal value with a linear polynomial (32 days, Columns 1 to 4) and to the one with a quadratic polynomial (19.6 days, Columns 5 to 8). This significantly reduces the dispersion in the estimated magnitude, making the point estimate of each polynomial model always lying within the 95% confidence interval of each other. The fact that smaller bandwidths are associated with larger turnout reductions–which is also evident when examining Figure 3–is consistent with the interpretation that landmine explosions constitute salient shocks that have large but temporary effects of people's behavior. We come back to this in section 6.1.[32]

To better understand the magnitude of the coefficients, we first note that our estimates rely on voting poll-level variation and, thus are highly local. This calls for caution when comparing the magnitude of the effects with what has been found in the literature for different treatments that affect turnout, which in turn rely on municipal or district-level variation. To make the size of our estimates more comparable, we perform a back-of-the-envelope calculation that takes into account the size of the affected voting polls as compared with the size of the municipality, as well as how many of the voting polls are affected by landmine explosions. This allows us to compute the municipality equivalence of our estimates. Based on the model with a linear polynomial, we find that an explosion reduces municipal turnout by 0.64 p.p.[33] Since rainfall has been shown to reduce political participation (see e.g., Gomez et al., 2007) we also estimate the effect of rainfall on turnout in our sample, as a way to benchmark our findings of the effects of landmine explosions. In Appendix Table A8, we find

[31] Further, because the average total number of victims from landmine explosions (both killed and injured) in our sample is 1.6, this implies that direct (killed or injured) and indirect (relatives and friends) victimization are extremely unlikely to drive the reduction in turnout due solely to incapacitation. Indeed, for this to be the case, on average every landmine victim should lead to between 48 and 84 voters abstaining.

[32] By the same token, Panels C and D vary the radius of the estimation buffer around poll stations. The magnitude of the turnout reduction is largely robust to the estimation buffer.

[33] Panel A of Appendix Figure A5 reports our original (poll-level) estimates, the computed municipality equivalent, and those found by selected papers.

that a one standard deviation increase in rainfall around a voting poll leads to a decrease in turnout of 2 p.p. This is equivalent to 16% of the effect found for landmine explosions.

5.2 Landmine explosions and voting outcomes Landmine explosions also change the electoral behavior of the portion of potential voters who actually vote. These results are reported in Table 3. Focusing on the RD estimates that fit a linear polynomial, we show the effect of an explosion on: i) the support for the incumbent presidential party (Columns 1 and 2), ii) the share of votes for left-wing parties (Columns 3 and 4), and iii) the share of votes for parties with proven ties with illegal paramilitary groups (see section 3). These shares are computed over two alternative denominators: the poll-level vote potential (odd columns) and the number of votes cast in each election/poll (even columns). The optimal bandwidth changes across columns, and so does the number of effective observations.[34]

We find weak evidence that landmine explosions reduce the vote share of candidates from the national incumbent party (Columns 1 and 2). The point estimate suggests a reduction of about 3 p.p., which is, however, not statistically significant. Instead, there is robust evidence that explosions cause a substantial decrease in the vote share of left-wing parties (Columns 3 and 4), which ranges from 22 to 31 p.p. depending on the denominator used to compute the share. We document that a non-negligible part of these votes (between 3 and 9 p.p. depending on the denominator of the vote share) goes to parties that have proven alliances with illegal right-wing militias (Columns 5 and 6). These findings are robust if we control for the poll-level vote potential (Panel A of Table A9 in the Appendix) or if we fit a quadratic polynomial instead (Panel B).[35]

In Appendix Table A11, we explore in more detail what happens after a landmine explosion with the votes that the left loses. The first thing to note is that not all parties with paramilitary ties are coded as right-wing by Fergusson et al. (2021). Therefore, when exploring the effect of landmine explosion on the share of votes for right-wing candidates, we also find a significant increase (between 2 and 9 p.p., Columns 1 and 2). However, this seems to be driven by the support of right-wing parties that, in addition, have paramilitary ties. This is because we find no effect on the support of non-paramilitary-related right-wing parties (Columns 3 and 4). For completeness, we also explore the effect of landmine explosions on the support of center (neither left- nor right-wing) candidates. The support for these parties increases, although it is not robust to the denominator used to compute the vote share

[34]Note that candidate selection should not be a concern in our context, given that the final list of candidates disputing an office closes three months before the election day, well before any estimation bandwidth. Moreover, in Appendix Table A4, we show balance in terms of the number of candidates in local elections, as well as regarding their party composition.

[35]They are also robust to using only the sub-sample of parties that actually participated in an election (thus assigning a missing to all other parties rather than a zero). See Appendix Table A10.

(Columns 5 and 6).

Figure 4 portrays the graphical counterpart of the main estimates of the effect of landmine explosions on voting outcomes. Panels A and B focus on the effect of landmine blasts on the support for incumbent parties at the national level, C and D on the vote share of the left, and E and F on the vote share of parties allied with paramilitaries.[36] Finally, Figure A6 shows the robustness to different bandwidths (a window ranging from 10 to 45 days) of the effect of landmine explosion on, respectively, the vote share of the incumbent party, the vote share of the left, and the vote share of pro-paramilitary right-wing parties. From this exercise, we can draw two conclusions: first, the effect of landmine explosions on the vote share of the national incumbent party is mostly null; second, as with the case of political participation, the size of the reduction in the support for the left is decreasing in the size of the bandwidth. Again, this is suggestive that the mechanism is the salience of the explosions, which in this case, makes people more likely to recall that the guerrilla is responsible for the placement of landmines (and as a consequence, they punish the democratic left in the polls). We discuss this mechanism in detail in section 6.2.[37]

To understand the magnitude of the estimated effects, we perform two exercises. First, a back-of-the-envelope calculation explores the extent to which landmine blasts could have distorted aggregate municipal electoral results.[38] We find that landmine explosions lead to a reduction (increase) in the vote share for the left-wing (paramilitary-related) parties at the municipal level of 0.3 (0.001) p.p. Further, using all the close races where a left-wing candidate lost by a close margin in conflict-affected municipalities during the last 20 years, these estimates imply that, in the absence of landmine explosions, electoral outcomes would have been different in 38% of the close races.

Second, we follow DellaVigna and Kaplan (2007) to compute the explosion-led *persuasion rate* (the share of voters who are persuaded by the explosion to change their vote).[39] We find that landmine accidents persuaded 8.6% of left-wing voters to vote for parties outside the left, and 3.1% of non-paramilitary-related party voters to vote for such parties. These magnitudes are in the middle-to-low range of what has been found in the literature.[40]

5.3 Additional robustness We conduct a wide set of empirical exercises to assess the robustness of our findings. Appendix E motivates all the robustness tests that we perform, and discusses their nature and obtained results. Here we limit the discussion to a brief

[36]The left column (Panels A, C, and E) computes the shares over the poll's vote potential and the right column over the number of votes cast.

[37]Similarly, Figure A7 shows the robustness to estimation buffers of different radii around the polls.

[38]Section C in the Appendix provides more details about this calculation.

[39]See Appendix D for a detailed explanation.

[40]Figure A5, Panel B presents the persuasion rates of different media-related treatments.

summary. We document that both the decrease in turnout rates and that in the vote share for left-wing parties are robust to a wide set of empirical exercises. However, as pointed out before, the decrease in the vote share of the incumbent and the increase in the vote share of paramilitary-related parties are less robust and, thus should be interpreted with caution.

First, our results are robust to eliminating the baseline weight by the poll's vote potential and to changing the triangular kernels by a uniform kernel weight. Second, they are also robust to studying only instances with one landmine explosion in the 60 days prior to elections, and to using only one explosion per poll. Third, they are unchanged after refining the comparison set of voting polls in various ways. Fourth, the results are robust to controlling for the amount of rainfall around voting polls during the month before the election, which is important because rainfall can both reduce turnout and facilitate the drifting of landmines underground. Fifth, they remain the same after the inclusion of pre-determined controls following Belloni et al. (2014). Sixth, they survive using ellipsoid instead of Euclidean distance of the computation of the estimation buffer. Seventh, our results are robust to adjusting the estimation to take into account the fact that the running variable in our RDD is discrete (see Imbens and Wager, 2019), and to estimate our main model using the local randomization estimation suggested by Cattaneo et al. (2020).

6 Mechanisms

6.1 Landmine explosions and political participation

6.1.1 Explosions generate fear. We argue that landmine explosions depress electoral participation by creating fear. Specifically, driven by survival considerations, frightened individuals reduce their mobility to avoid a fatal accident, which hurts political participation. This is especially important given the fact that, due to the rural nature of our treatment, the share of citizens who must walk relatively long distances to vote is rather large. To provide evidence for this idea, we leverage a nationally representative political culture survey from Colombia's National Statistics Department that allows us to correlate (the risk of) landmine explosions and electoral participation. Indeed, in the 2017 and 2021 waves, the survey instrument included a question on what were the main threats to the security of the respondent's community during the last 12 months, with landmine accidents being one of the predefined answers.[41] We correlate choosing this option with an indicator of whether the respondent voted in the last elections. Moreover, conditional on responding 'No' to the voting question, we also correlate the landmine accidents' response with a dummy that equals one if the main

[41]Unfortunately, since the survey lacks geographic identifiers we cannot merge the location of the respondent with our data set on landmine explosions.

reason for abstention was fear.[42]

Table 4 summarizes these correlations. Columns 1 and 2 show that respondents who perceived that landmine accidents were a new security threat to the community during the last year were 4p.p. (i.e., 7.3% relative to the mean) less likely to have voted in the last elections, controlling, respectively, for the frequency of voting and for other individual characteristics.[43] In turn, Columns 3 and 4 show that respondents who perceived landmine accidents as a threat and did not vote in the last election were 16p.p. (i.e., 479%) more likely to respond that the main reason for abstention was fear.[44]

As complementary evidence, we show that humanitarian demining increases political participation.[45] For that, we leverage geo-located information on humanitarian mine removal activities along with its temporal variation to construct grids of 5×5 Km, which we merge with grid-level measures of pre-election cumulative demining episodes and political participation. We then estimate a panel regression with grid and municipality×year-of-election fixed effects and find that a grid that moves from zero to three episodes of humanitarian demining (the latter being the median cumulative demining conditional on at least one episode), experiences a turnout surge of between 1 and 2 p.p. (see Panel A of Appendix Table A13).[46]

6.1.2 Alternative mechanisms. We rule out three alternative potential mechanisms of why landmine explosions decrease political participation. First, landmine blasts may cause a violence spiral and hence reduce the safety willingness to go to vote. This could happen, for instance, if the military arrived in the affected area to confront the group held responsible for placing the explosive. We show evidence against the empirical validity of this hypothesis with two different tests: i) At the municipality level–for lack of more disaggregated data–Table 1 suggests there was no differential surge in attacks by illegal groups between treated and control areas, neither two weeks before nor during the day of the election; ii) At the buffer level, using geo-coded data on the universe of homicides in Colombia from 2012 on-wards, we build a balanced panel of the voting polls of our main sample and estimate–during the two

[42] The question on voting in the last election appears before that of community threats in the survey questionnaire. This should alleviate concerns about the recalling of the violent event driving the voting response.

[43] These are gender, age, household access to utilities, and the respondent's level of education. Importantly, Appendix Table A12 suggests that this negative correlation is not present for respondents who identified other security threats to their community, including forced displacement, land dispossession, and stigmatization.

[44] These correlations do not just reflect the difference in responses by people affected or not by conflict. In fact, in Columns 5 to 8 we repeat the same exercise but focus on the smaller sub-sample (10%) of individuals who stated to have ever been victimized by conflict. The results are remarkably similar.

[45] Demining activities were launched at the beginning of peace negotiations with the FARC and are conducted by certified NGOs that clear contaminated areas until there is no suspicion of landmines anymore. The areas to be demined are prioritized based on the pre-2013 number of landmine victims (Prem et al., 2023a).

[46] In Appendix Table A14, we find that there is an increase in voting for the national government's party after demining, consistent with voters rewarding the incumbent for increasing safety in the area through a pertaining ti the national government. Moreover, we document an increase in the vote share of the left.

months before elections–a staggered difference-in-differences model with weekly variation to identify the effect of landmine explosions on homicides. Specifically, the outcome in this test is a dummy that captures the occurrence of a homicide in week t within 4km or 8km from a voting poll. In turn, the treatment is the occurrence of an explosion before the election.[47] Voting polls that were affected by an explosion after an election serve as never-treated units. We implement a TWFE model and the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020). We find no effect of landmine explosions in the incidence of homicides in the vicinity of voting polls (see Appendix Table A15 and Figures A8 and A9).

Second, explosions may increase the costs of voting by damaging the road network in affected areas. This is especially plausible in contexts such as rural Colombia, where the road network is characterized by narrow semi-paved lanes.[48] To formally explore this possibility, we use the geo-located road network compiled by Prem et al. (2023a) to compute the demeaned distance of all the spots where a landmine exploded to the nearest road. We interact this continuous measure with the indicator of an explosion happening before the election and find that the heterogeneous effect is small in magnitude and not statistically significant (see Column 4 of Table A3).[49] We also perform a more stringent test based on a categorization of roads according to how important they are within the road network to access a specific polling station. To that end, we use two different definitions: i) We code a landmine explosion as affecting the road connectivity to a poll station if it occurred within 50 (or 100) meters from a road that belongs to the shortest path distance between the spot of the explosion and the voting poll;[50] ii) We identify the explosions that occurred within 50 (or 100) meters from a 'primary' road leading to a voting poll.[51] In Appendix Table A16, we exclude from the main sample the explosions that meet either of these two definitions and find effects of landmine accidents on turnout that are very similar to those obtained in the baseline specification.

Third, landmine explosions could lead to a general disappointment about the government's capacity to handle violence, thus decreasing trust in democratic institutions and depressing political participation. We test this idea indirectly in two different ways. First, we look at the share of blank votes, a widely recognized proxy of protest voting (Alvarez et al.,

[47]To avoid a mechanical relationship in case the explosion caused lethal casualties that are then counted as homicides, we exclude homicides that occurred one day around the explosion.

[48]Indeed, Condra et al. (2018) show that, in Afghanistan, rebels deploy assaults to damage the road network to prevent voters from accessing voting polls.

[49]In addition. we find similar (null) results when using different types of roads depending on their quality and size (Columns 5 to 7).

[50]Here, the shortest path distance is defined as being above the median of the empirical distribution considering all the roads that need to be taken to access the poll station.

[51]In Colombia, primary roads are those that connect municipalities or else connect a municipality with a main highway.

2018).[52] Columns 9 and 10 of Appendix Table A11 show that landmine explosions have no effect on the proportion of blank votes. Second, we explore a set of questions about 'trust in elected offices' at the local level (i.e., mayors and governors) from the political culture survey discussed earlier. In Appendix Table A17, we present the results from estimating our preferred specification, which includes individual controls and focuses on the sub-sample of individuals who have been exposed to conflict. We find no systematic evidence of a correlation between trust and reporting that landmine accidents were a new risk to one's community in the past 12 months.

6.1.3 Fear: information or salience? After establishing that landmine explosions depress political participation due to fear, a follow-up question is why is this the case. There are two possibilities. The first is that explosions are informative, as they update people's perception of the risk (to one's own safety) to go out and engage in a range of activities, including voting. The second is that, due to their prominence and often surprising nature, landmine explosions are salient and hence, by exacerbating short-term emotions, change people's behavior bottom-up (i.e., automatically and involuntarily) in the short-run, relative to current goals and expectations (Bordalo et al., 2022).

While both alternatives have the same observable implication, namely that (either consciously or involuntarily) people would reduce their mobility to increase their safety, the first has two testable implications. On the one hand, if explosions are recurrent, the additional information gathered from the marginal explosions is decreasing and hence behavioral responses to the blasts should be smaller. On the other hand, if the underlying risk revealed by the explosion is persistent (e.g., because minefields are still active or armed groups are still a threat), the behavioral response to the explosion should also linger. These implications inform some of the empirical tests that we implement to partially distinguish what drives fear.[53] This distinction is important for at least two reasons. From a theoretical point of view, it may inform the behavioral processes that connect violent (as well as other types of) shocks with electoral participation and more generally with mobilization. From a policy perspective, it can inform how to optimally address the landmine threat that endures after conflict termination. In particular, it can shed light on whether the provision of information about the location of potential landmine hazards would at least partially boost electoral

52 In the Colombia context, the blank vote is largely seen as a vehicle to express dissatisfaction and frustration with the political institutions (Palacio Vélez, 2022). Constitutionally, a victory of the blank vote means that the election must be repeated with an entirely different set of candidates. This has in fact happened in a handful of local elections.

53 The evidence discussed so far, however, already points to the empirical relevance of the salience mechanism. Indeed, recall that the proximity of an explosion to an election day results in a greater decrease in political participation, the effect being three times as large for explosions within a ten-day window as compared with a 40-days window. These heterogeneous effects are consistent with the idea that salience effects are short-lasting (Bordalo et al., 2022; Dessaint and Matray, 2017; Kunreuther et al., 1978).

participation in affected areas.

To test if individuals previously more exposed to explosions may react less to a new blast (given that they are already informed about the surrounding security risks), we take our main specification and add as covariates (or interact with the treatment variable to test for heterogeneous effects) either the recent history of landmine explosions or a proxy of the underlying risk of a landmine explosion around the voting poll.[54] Panels A and B of Table 5 report our findings, respectively for the covariates and the heterogeneous effect approach.[55] The control/interaction term of recent landmine explosions is included both in the extensive (Columns 1, 3, and 5) and the intensive (Columns 2, 4, and 6) margins. Columns 1 and 2 (3 and 4) [5 and 6] include past explosions 3 to 9 (3 to 12) [3 to 15] months before the election day. Column 7 focuses on the risk proxy. We find no change in the coefficient of the treatment when adding past explosions/latent risk as covariates (Panel A) and no significant heterogeneous effect when adding them interacted with the treatment (Panel B). If anything, most interaction terms are negative, which suggests that, instead of updating their information set about underlying security risks, people who have been more exposed to landmine explosions in the past, may recall (traumatic) memories associated with them. Coupled with the current (re-)victimization, this may exacerbate fear and generate a larger behavioral reaction (Enke et al., 2023; Marsh, 2022; Bordalo et al., 2023, 2022).

To test whether the duration of the behavioral response is consistent with the span of the underlying risk (which would be consistent with the explosions-as-information alternative), we computed people's mobility using raster data from Facebook that measures the number of people moving each day between tiles of 350^2 m (about $1{,}150^2$ ft).[56] With it, we explore the extent to which mobility changes after a landmine explosion. In particular, given the random timing of the blasts along with their staggered nature, we estimate a staggered difference-in-differences model that leverages the timing of each treated tile and uses as *never treated* either all the other tiles of the country or only those affected by conflict in the past.[57] We estimate this model using both two-way fixed effects (TWFE) and the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020), and plot the coefficients of the dynamic

[54]For the latter, we use the number of explosions that took place around the voting poll during the two years after the election. Both variables are computed within the same estimation buffer.

[55]See footnote 26 for details on how we estimate these heterogeneities.

[56]The data is available daily from June 2021 to March 2022, a period with no elections (and outside our sample period). To state the obvious caveat, it only records the movement of individuals who have Facebook on their smartphone and do not opt out from their location being tracked. A second caveat is that the data only covers the Andean natural zone, which is Colombia's most populated and ranges from the border with Ecuador and Peru to the Atlantic Ocean. However, it is also the area with a higher density of landmine explosions and voting polls (see Figure A3).

[57]We define conflict-affected tiles as those located in the surrounding of previously demined areas, or in areas identified as still in danger of a landmine explosion.

specification in Appendix Figure A10, together with the average ATTs in Appendix Table A18. Overall, we find that landmine accidents lead to a drop in the standardized measure of mobility of around 0.4 standard deviations, which is concentrated within the first weeks after the explosion (with mobility returning to the pre-explosion levels five weeks afterward). Again, this immediate, large, and short-lasting effect is consistent with fear being driven by the salience of landmine explosions rather than their provision of information.

As an additional (albeit more suggestive) piece of evidence consistent with this interpretation, we explore potential heterogeneities of the effect of landmine accidents on turnout parametrized by the characteristics of the victims resulting from the explosions and by the type of election at stake (whether local or national). In Appendix Table A19, we find that the treatment and a dummy of whether the associated victim was a female (Column 1), was a civilian (relative to from the military, Column 2), was killed by the explosion (instead of injured, Column 3), or was a child (under 18, Column 4) is small and not statistically significant. This is also the case of an indicator of whether the election is local (Column 5). That the behavioral reaction is independent of the type of victim and the type of election shows that it responds to bottom-up and emotional reasons, rather than to strategic considerations associated with the information provided by the explosion and related to the identity of the victim or the importance of the election.

6.2 Landmine explosions and voting behavior

6.2.1 Salience, fear, and anger Recall from section 2 that, during the Colombian conflict, the left-wing guerrillas–and notably the FARC–were the main responsible party for fabricating and placing antipersonnel landmines. Local communities have largely been aware of this, as the placement of landmines (which are mainly utilized to secure land and illegal activities from enemies) requires a minimum level of territorial control. In such a context, the salience of landmine explosions increases the probability that affected individuals remember the responsibility of the guerrillas. Indeed, in laboratory experiments, salient stimuli have been shown to cause attention selection and to increase the probability of remembering events that are connected with them (see, e.g. Itti et al., 1998 and Pedale and Santangelo, 2015).

A different branch of the psychology and behavioral literature argues that emotions often come in bundles, with specific emotions being closely connected in a sequential manner to other previously experienced ones. This is the case of anger, which is often the byproduct of fear (Tsai and Young, 2010; Nussbaum, 2019). Individuals who are shocked with fear portray a first reaction, which is involuntary and short-lived: they withdraw from the source of the emotion. Note that, in our context, this is consistent with the short-term mobility reduction and the depression of political participation. A second and subsequent emotion is anger. Angry individuals return to the source of the shock and seek revenge.

Based on these observations, we posit that, as in the case of the fall in turnout, the main mechanism of the reduction in the vote share of the left is the salience of the explosions, which after a short-term involuntary state of fear evolves into a state of retaliatory anger. Therefore, in the absence of a political party that represents the illegal guerrillas, voters of explosions-affected communities are more likely to punish the democratic left. Moreover, for a fraction of such voters, the electoral punishment gets amplified as they actually turn to supporting parties historically associated with counter-insurgent paramilitary groups, which actively promote a violent strategy against guerrillas. The fact that, in the context of the Colombian conflict, these groups have been responsible for atrocities against civilians such as massacres implies that this punishing behavior is driven by a short-term emotional response. Ultimately, this behavior is consistent with the literature on negative reciprocity and punishment (Fehr and Gächter, 2000, 2002), especially with the type of retaliation that is triggered by exposure to violence (Zeitzoff, 2014).

6.2.2 Alternative mechanisms. Our findings regarding the behavior of voters could be explained by a composition effect of the documented reduction in turnout. This would be the case if, after a landmine blast, voters self-selected into casting their vote based on their political ideology, and specifically if left-wing supporters were differentially less likely to vote after an explosion. We explore this alternative in different ways. First, we estimate a version of Table 4 that tests for heterogeneous effects using individual information from the political culture survey respondents. Specifically, we interact the dummy on whether landmine accidents were a new problem to the community during the last year with the respondent's self-reported political ideology. If the effects of landmine accidents on voting behavior were coming from a composition effect, we should then expect a larger negative correlation between the threat of landmine accidents and the decision to vote in the last election for respondents who identify as left-wing. Columns 1 to 4 of Appendix Table A20 suggest that this is not the case: the correlation coefficient of the interaction is a well-identified zero. One concern with this test is that the stated political ideology of survey respondents could be affected by the exposition to landmine explosions. To partially address this concern, we study whether the blast-driven poll-level turnout reduction is different in municipalities with higher historical support for left-wing parties. Consistent with the survey evidence, we find no differential effects in traditionally more left-leaning municipalities (Column 5).

Second, we follow DellaVigna and Kaplan (2007) and include turnout as a "bad control" in the voting RDD regression model. We find that the point estimates change very little when adding this control (see Appendix Figure A11). As a more formal test, we follow Acharya et al. (2016) and estimate a *g-sequential* mediation analysis that treats turnout as a mediator in the relationship between landmine explosions and voting behavior.[58] Once we account for the indirect effect through turnout, we find no major change in the effect of landmine explosions on voting. Overall, this evidence suggests that the documented effect of the pre-election landmine accidents on voting patterns is not likely to be driven by a change in the composition of voters.

A second alternative mechanism relates to potential campaigning strategies induced by the blats and carried out deferentially by specific parties or candidates. In the absence of geo-located data on political rallies in rural Colombia, we test this idea indirectly by looking at the social media activity of candidates. Specifically, we identified the Twitter accounts of all mayoral candidates in the 2015 and 2019 local elections, as Twitter penetration in Colombia was low prior to 2015. Over that period, we found the Twitter accounts of 23 percent of the 542 candidates running for mayor in the municipalities of our sample. We scraped their tweets and performed text analysis during the pre-election window to look for colloquial and technical terms related to landmines, landmine accidents, and demining.[59] Upon completion, we only found *three* tweets related to a landmine explosion. These mentions were referring to the generic problems of landmines in Colombia, thus not related to any specific blast. By not referring to a specific location, if anything, these few instances should equally affect treated and control units. In any case, this suggests that, at least in our sample, the behavior of political candidates on Twitter seems rather unresponsive to landmine accidents.

Illegal political practices, such as vote buying and electoral fraud may be a related alternative mechanism. If the cost of voting increases for individuals in areas affected by a landmine blast, the price to mobilize them to the polling station should also go up. Observationally, and under the assumption that reported electoral offenses are longitudinally correlated with real offenses, this would imply a differential reduction in the number of electoral offenses in affected areas. Albeit suggestively, we test this hypothesis in Panel C of Appendix Table A4, where we look at the mean difference of electoral offenses in municipalities of our treated group relative to those of our control group. Overall, we find no evidence of differential electoral offenses, which is consistent with the idea that the incentives to obtain votes illegally did not change because of the explosion.

[58]The main assumption behind this method is that there is no omitted variable that affects both the relationship between explosions and voting behavior and the relationship between turnout and voting behavior, conditional on being exposed to an explosion before the election.

[59]We took the technical terms from the glossary of demining terms in Colombia (see https://rb.gy/ptfiyv, last accessed 02/08/2023).

7 Conclusions

This paper studies the effect of quasi-random accidental landmine explosions on voting-poll-level electoral outcomes related to political participation and party support. Empirically, the randomness of landmine explosions allows us to study causal effects in an RDD framework, by comparing the voting patterns of voting polls located close to where a landmine exploded shortly before elections to those of voting polls in the vicinity of landmines that exploded just afterward. We find that landmine explosions deteriorate political participation and decrease the vote share of the parties implicitly associated with the groups held responsible for the fabrication and placement of landmines. Moreover, we document that the main mechanism is a salience-driven fear, that refrains some potential voters from going to the voting poll by prioritizing survival considerations, and makes some actual voters seek (electoral) retaliation.

These findings have important implications for the consolidation of democracies in post-conflict settings that featured territorial contestation. They also have implications for the prioritization of post-conflict reconstruction funding and priorities from international donors. On the one hand, by detaching voting decisions from people's political preferences or from their assessment of politicians' performance–and making voting decisions hinge on short-term emotions–landmine explosions may hamper electoral accountability. Indeed, electoral accountability relies on a retrospective voting electorate that is capable of discerning whether governments act in their best interest and has the tools to punish politicians who deviate from that (Przeworski et al., 1999). Moreover, while the effect of one single explosion is rather local and short-lasting, the aggregate effect of hundreds of yearly explosions (tens of thousands if taking into account the about 60 countries where landmines still prevail) is indeed worrisome. If landmine fabrication and planting completely stopped, at the current demining rate it would take over a thousand years to strip the entire planet of its landmine stockpile.[60]

On the other hand, inasmuch as the salience of landmines creates fear independently of people's prior information about the underlying victimization risk, short-term information campaigns that communicate explosion hazards in places with suspected presence of landmines may fail to enhance electoral participation and enhance the ability to decide based on retrospective voting. Instead, our findings suggest that the international community should emphasize comprehensive short-term demining campaigns.

[60]See https://landminefree.org/facts-about-landmines/ (last accessed 02/13/2024).

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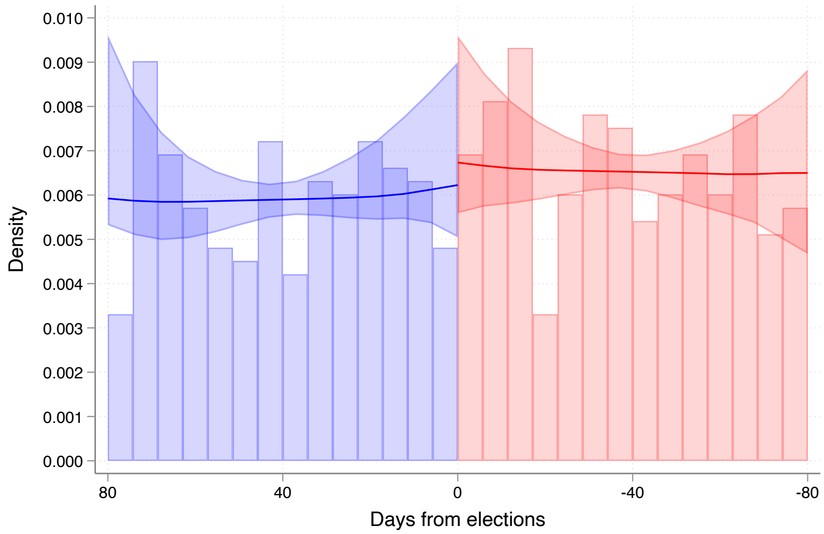
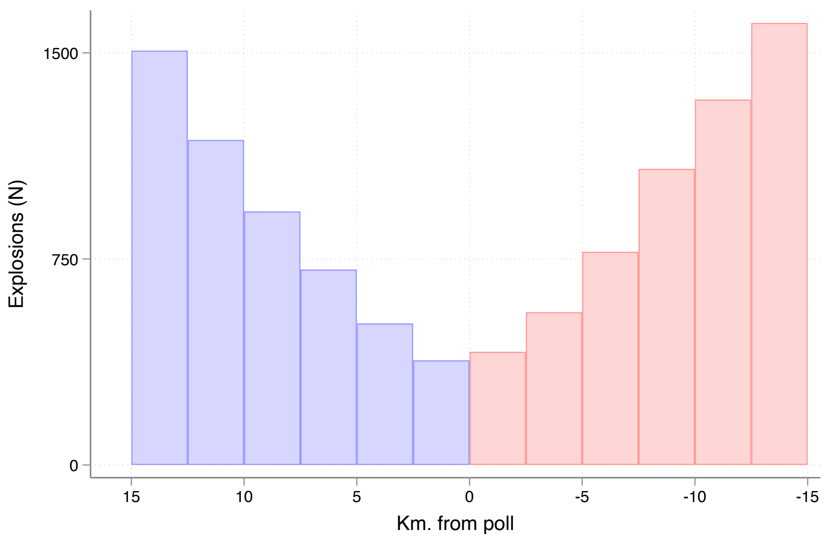
FIGURE 1. Explosions Distribution



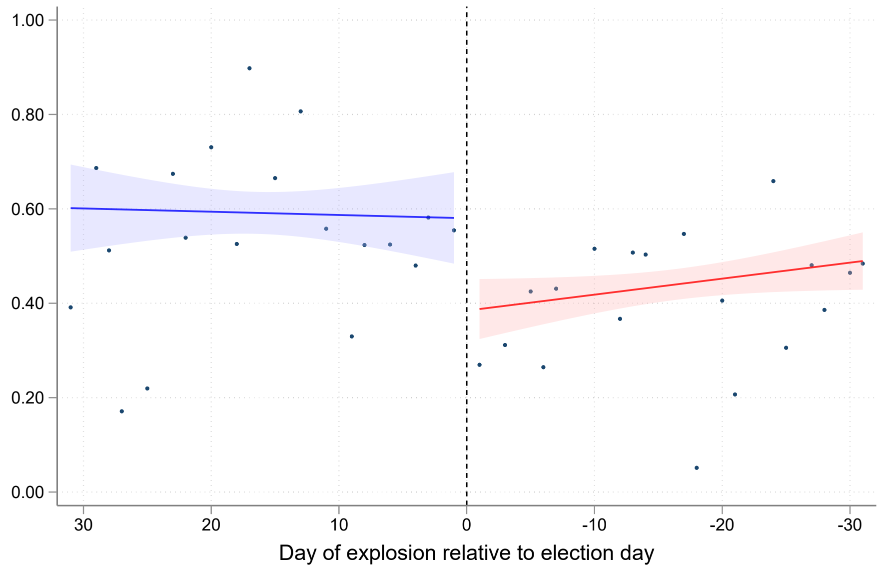
A. Across Days



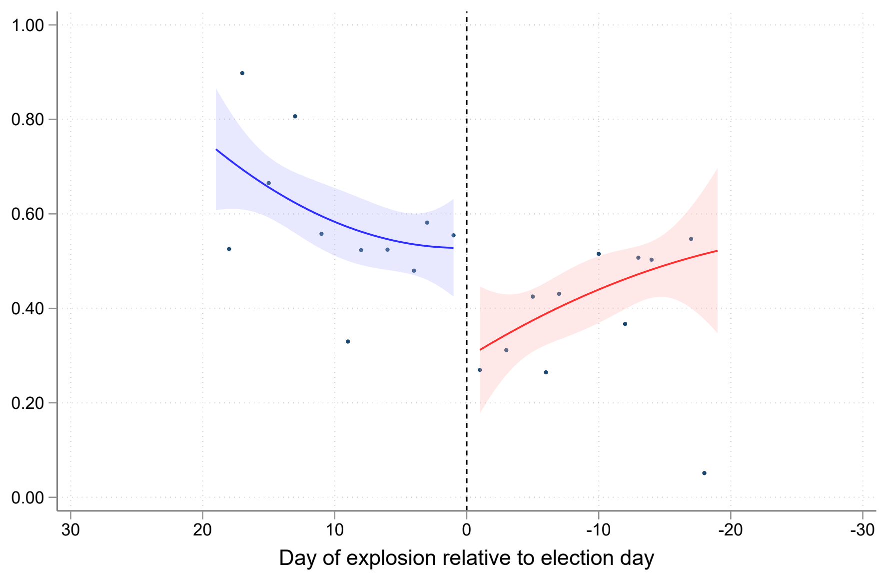
B. Over Distance

Notes: This figure shows the distribution of explosions around election day and their proximity to voting polls in Colombia. Panel A presents the Cattaneo et al. (2018) manipulation test of the density of explosions around election day, using a bandwidth of 80 days, a triangular kernel, and a local polynomial of order one. We obtain a p-value of 0.71 for the null hypothesis of continuity in the distribution around the cut-off. Conducting the same test with bandwidths of 60, 40, and 20, yields `p-values` of 0.72, 0.29, and 0.75, respectively. Following the approach of McCrary (2008), we obtain a p-value of 0.22 for a bandwidth of 80, and 0.25, 0.15, and 0.21 for bandwidths of 60, 40, and 20, respectively. We also implement Frandsen (2017) density test specific to discrete running variables, and we obtain a p-value of 0.60. Panel B shows the distribution of explosions over the distance to a voting poll within 60 days of election day. Negative distances represent the distance of the explosion to a voting poll before the election day, while positive distances represent explosions that occurred afterward. The bins have a width of 2.5km. A manipulation test based on Cattaneo et al. (2018) yields a p-value of 0.38 for a bandwidth of 4km around the voting poll, indicating that the null hypothesis of continuity in the distribution around the cut-off is not rejected.

Figure 2. RDD Estimates for Turnout



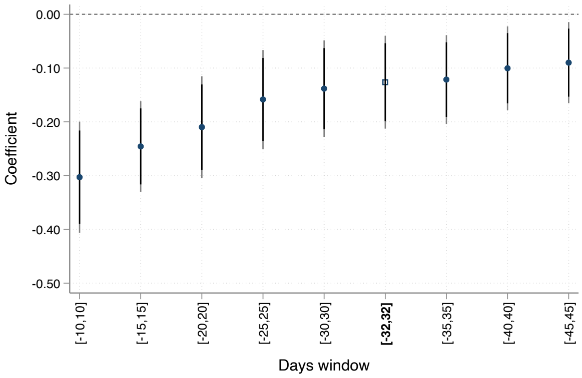
A. Linear



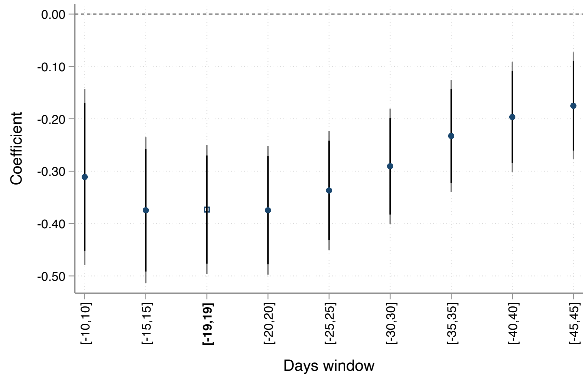
B. Quadratic

Notes: This figure plots a graphical representation of the regression discontinuity design for turnout, with observations displayed within the MSE optimal bandwidth. Panel A shows a linear polynomial approximation, while Panel B uses a quadratic approximation.

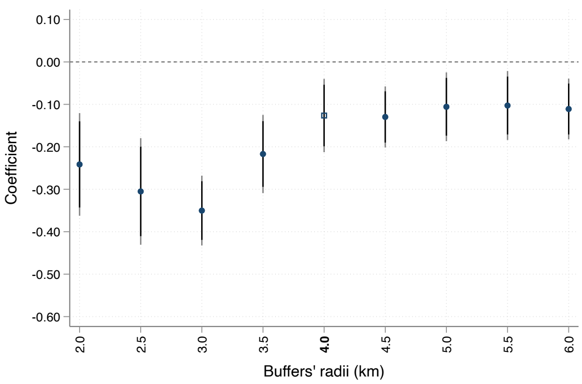
Figure 3. Turnout and Explosions Over Different Bandwidths and Buffers' Radii



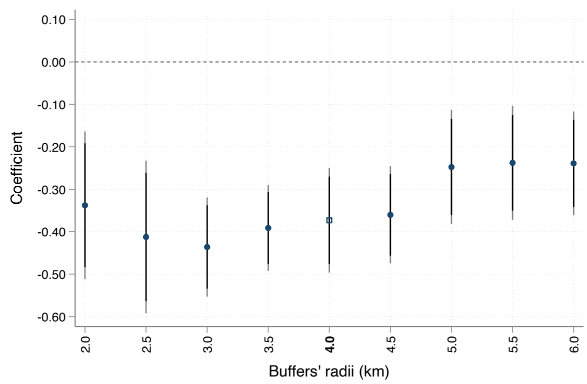
A. Bandwidth: Linear



B. Bandwidth: Quadratic



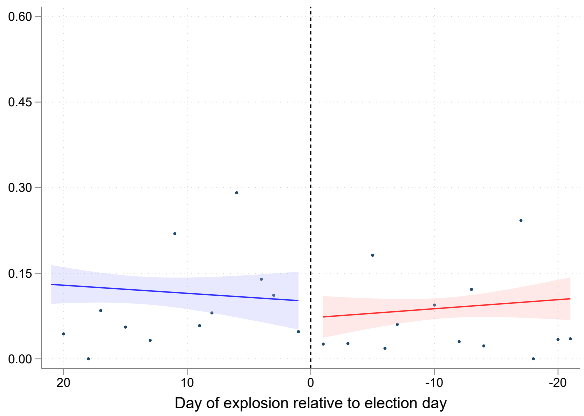
C. Buffer's Radio: Linear



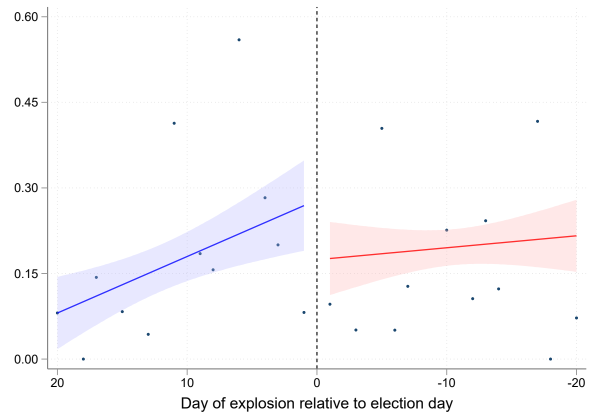
D. Buffer's Radio: Quadratic

Notes: This figure plots local linear and quadratic estimates of the average treatment effects on turnout around the cut-off, using triangular kernel weights and optimal MSE bandwidth, for different time windows (Panels A and B) and buffers' radii (Panels C and D). We also present the point estimates from our baseline specification in Table 2, along the 90% and 95% confidence intervals. All estimations are weighted by the potential voters registered in the poll.

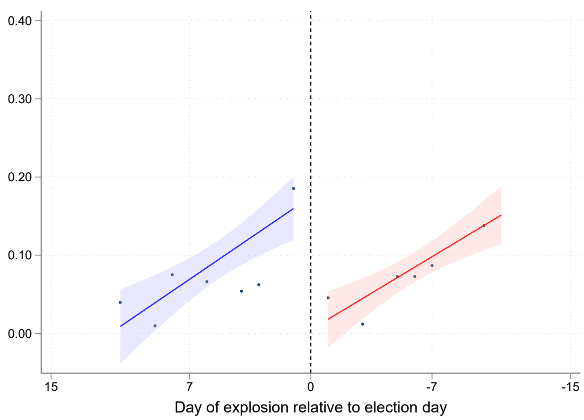
FIGURE 4. The Effect of Explosions on Voting Behavior



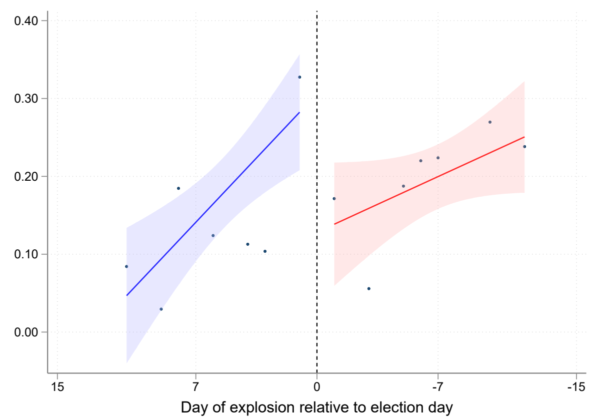
A. Incumbent Over Potential



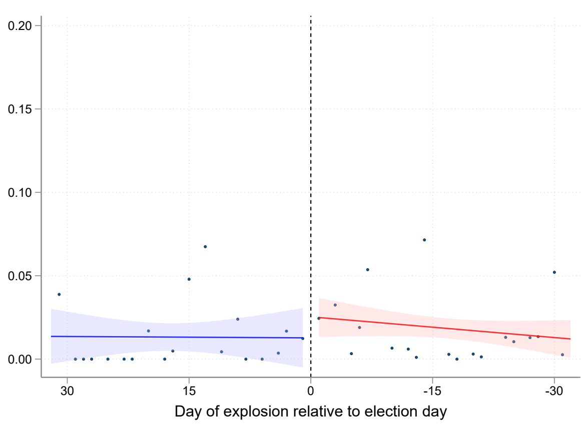
B. Incumbent Over Votes



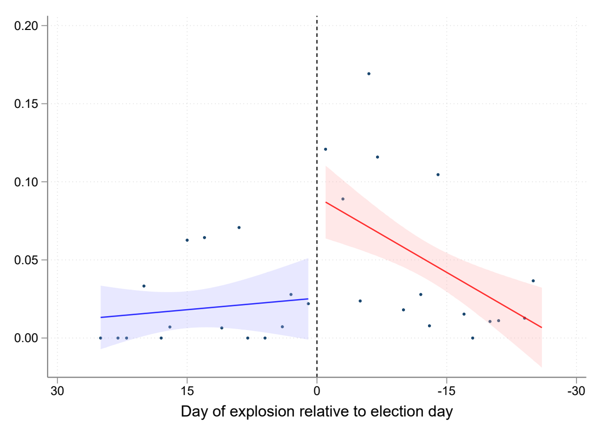
C. Left-wing Over Potential



D. Left-wing Over Votes



E. Paramilitary Over Potential



F. Paramilitary Over Votes

Notes: This figure plots a graphical representation of the regression discontinuity design for voting, with observations displayed within the MSE optimal bandwidth. In Panel A and B, we show the estimates using the vote share for the incumbent over the registered and actual voters, respectively. Panel C and D use the share of left-wing party voters over registered and actual voters, while panels E and F use the share of voters for paramilitary-related parties over registered and actual voters. All panels with linear polynomial approximation.

Table 1. Differences by Treatment Status

	Mean Control	Difference in Mean	RDD Estimate
	(1)	(2)	(3)
Panel A: Poll Station Level			
Turnout (pre)	0.51	-0.00	0.03
	(0.27)	(0.04)	[-0.05, 0.34]
Incumbent vote share (pre)	0.08	-0.01	0.03
	(0.11)	(0.02)	[-0.01, 0.11]
Left vote share (pre)	0.11	-0.01	-0.12
	(0.17)	(0.03)	[-0.17, 0.02]
Paramilitaries vote share (pre)	0.04	-0.02	0.01
	(0.08)	(0.01)	[-0.02, 0.08]
Ln potential voters	5.73	0.13	0.36
	(0.97)	(0.10)	[-0.23, 0.86]
Political competition (pre)	0.50	0.01	0.09
	(0.22)	(0.03)	[-0.12, 0.23]
Homicides (pre)	0.02	0.00	0.01
	(0.11)	(0.01)	[-0.04, 0.04]
Latent explo. risk (1 year)	0.30	-0.07	0.00
	(0.46)	(0.09)	[-0.11, 0.30]
Rainfall (30 days pre-election)	1.96	0.55	0.66
	(2.74)	(0.58)	[-0.51, 3.33]
Panel B: Explosion Level			
Female Victim	0.12	-0.02	-0.12
	(0.33)	(0.07)	[-0.88, 0.24]
Civilian Vicitm	0.49	0.08	0.09
	(0.51)	(0.10)	[-0.61, 0.70]
Dead victim	0.15	0.13*	0.17
	(0.36)	(0.08)	[-0.12, 0.41]
Victim Under 18	0.12	0.03	0.09
	(0.33)	(0.07)	[-0.13, 0.28]
Panel C: Municipality Level			
Any Attack	0.37	0.09	-0.06
	(0.48)	(0.07)	[-0.37, 0.08]
Any Attack (election day)	0.08	0.00	-0.02
	(0.27)	(0.01)	[-0.13, 0.01]
Any Attack (2 weeks pre-election)	0.15	-0.00	-0.06
	(0.36)	(0.04)	[-0.20, 0.12]
Police stations	0.09	0.01	0.00
	(0.07)	(0.01)	[-0.03, 0.05]
Ln potential voters	10.01	-0.23	0.35
	(1.10)	(0.22)	[-0.50, 0.45]
Any left-wing candidate	0.12	0.04	0.12
	(0.34)	(0.20)	[-2.17, 0.42]
Any paramilitary candidate	0.00	0.07	-0.01
	(0.00)	(0.07)	[-0.14, 0.31]
Any incumbent-wing candidate	0.50	-0.12	0.43
	(0.51)	(0.34)	[-2.28, 2.45]
Number of candidates	28.07	-3.37	-4.81
	(12.66)	(6.41)	[-9.52, 10.52]

Note: This table reports the differences in pre-election voting poll-level characteristics (Panel A) and municipality-level characteristics (Panel B) for explosions within 4 km from the voting poll and within the optimal MSE bandwidth between treatment and control groups. Column 1 presents the mean and standard deviation for the control group. Column 2 shows the estimated coefficient and standard error from an OLS regression of the poll or municipality characteristic and the treatment status, controlling for election fixed effects and with clustered standard errors at the municipality level. Finally, Column 3 presents the local linear estimates of the average treatment effects around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth, and adding election fixed effects. In square brackets 95% robust confidence intervals, following Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table 2. The Effect of Explosions on Political Participation

Dep. Variable:	Turnout			
	(1)	(2)	(3)	(4)
Explosion Before	-0.126***	-0.134**	-0.373***	-0.358***
Robust p-value	0.004	0.017	0.000	0.000
CI 95%	[-0.25, -0.05]	[-0.28, -0.03]	[-0.54, -0.27]	[-0.57, -0.20]
[1] p-value	0.023	0.008	0.000	0.000
[2] p-value	0.047	0.020	0.000	0.000
Election Fixed Effects	Yes	Yes	Yes	Yes
Control for Log Potential	No	Yes	No	Yes
Observations	1136	1136	1136	1136
Bandwidth Obs.	396	396	223	223
Mean	0.597	0.597	0.590	0.590
Bandwidth	32.0	31.4	19.6	19.9
(Local) Polynomial Order	1	1	2	2

Note: This table reports local linear estimates of the average treatment effects on turnout around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth. Columns 1-2 show the estimates using linear polynomials, while columns 3-4 use quadratic polynomials. We provide 95% robust confidence intervals and robust p-values, following Calonico et al. (2014). The p-value in [1] is based on robust standard errors clustered at the running variable level, as suggested by Lee and Card (2008), while [2] uses standard errors clustered at the municipality level. Bandwidth obs. indicates the number of observations in the optimal MSE bandwidth. Columns 2 and 4 include the logarithm of the number of potential voters in the poll as a covariate. All estimations are weighted by the number of potential voters registered in the poll. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. The Effect of Explosions on Voting Behavior

Dep. Variable:	Incumbent Votes Over		Left-wing Votes Over		Paramilitary Votes Over	
	Potential	Votes	Potential	Votes	Potential	Votes
	(1)	(2)	(3)	(4)	(5)	(6)
Explosion Before	-0.028	-0.032	-0.217***	-0.314***	0.028*	0.087***
Robust p-value	0.121	0.400	0.000	0.002	0.054	0.000
CI 95%	[-0.09, 0.01]	[-0.13, 0.05]	[-0.32, -0.12]	[-0.56, -0.12]	[-0.00, 0.05]	[0.04, 0.14]
[1] p-value	0.191	0.406	0.000	0.000	0.068	0.000
[2] p-value	0.263	0.431	0.000	0.000	0.112	0.002
Election Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1136	1136	1136	1136	1136	1136
Bandwidth Obs.	278	253	121	138	409	323
Mean	0.148	0.180	0.089	0.173	0.009	0.013
Bandwidth	21.8	20.9	11.4	12.7	32.4	26.9
(Local) Polynomial Order	1	1	1	1	1	1

Note: This table presents local linear estimates of the average treatment effects on voting behavior around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth. Columns 1 and 2 show the estimates using the vote share for the incumbent over the registered and actual voters, respectively. Columns 3 and 4 use the share of left-wing party voters over registered and actual voters, while columns 5 and 6 use the share of voters for paramilitary-related parties over registered and actual voters. We provide 95% robust confidence intervals and robust p-values, following Calonico et al. (2014). The p-value in [1] is based on robust standard errors clustered at the running variable level, as suggested by Lee and Card (2008), while [2] uses standard errors clustered at the municipality level. Bandwidth obs. indicates the number of observations in the optimal MSE bandwidth. All estimations are weighted by the number of potential voters in the poll and include election fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 4. Explosions, Electoral Participation, and Fear to Vote

Sample:	Full				Conflict Affected			
Dep. Variable:	Voted Last Election		Fear		Voted Last Election		Fear	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explosions Before	-0.043***	-0.039***	0.164***	0.158***	-0.049***	-0.043***	0.143***	0.142***
	(0.013)	(0.013)	(0.028)	(0.028)	(0.016)	(0.016)	(0.030)	(0.029)
Observations	16,930	16,930	6,806	6,806	1,769	1,769	971	971
R-squared	0.586	0.587	0.024	0.029	0.547	0.553	0.045	0.075
Mean Dep Variable	0.771	0.771	0.0325	0.0325	0.775	0.775	0.0803	0.0803
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: This table presents the correlation between respondents who reported being exposed to at least one landmine explosion before and their voting behavior in the previous election or their decision not to vote due to fear, utilizing data from the ECP-DANE 2017 and 2021 waves. Both outcomes are represented as dummy variables, and fear of voting is limited to those who reported not voting in the previous election. The even columns adjust for individual characteristics, such as gender, age, household utilities, and education level indicators. The sub-sample of conflict-affected respondents includes responses from victims of displacement, forced recruitment, dispossession, stigmatization, and killings. All columns are controlled for region fixed effects, and robust standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The Role of Past Exposure

Dep. Variable:	Turnout						
Z:	Explosions 3-9 Months Before		Explosions 3-12 Months Before		Explosions 3-15 Months Before		Latent
	Dummy	Total	Dummy	Total	Dummy	Total	Risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Controlling for Z							
Explosion Before	-0.105***	-0.106***	-0.096***	-0.095***	-0.096***	-0.094***	-0.122***
Robust p-value	0.000	0.000	0.001	0.000	0.001	0.000	0.000
CI 95%	[-0.31, -0.09]	[-0.33, -0.12]	[-0.29, -0.08]	[-0.31, -0.11]	[-0.29, -0.08]	[-0.31, -0.11]	[-0.35, -0.14]
Election fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1136	1136	1136	1136	1136	1136	1136
Bandwidth obs.	396	396	396	396	396	396	396
Mean	0.597	0.597	0.597	0.597	0.597	0.597	0.597
Bandwidth	32.0	32.0	32.0	32.0	32.0	32.0	32.0
B. Heterogenous Effect							
Explosion Before × Z	-0.093	0.009	-0.026	0.035	-0.023	0.021	0.029*
	(0.077)	(0.016)	(0.063)	(0.028)	(0.060)	(0.019)	(0.016)
Explosion Before	-0.171***	-0.202***	-0.171***	-0.198***	-0.172***	-0.194***	-0.243***
	(0.048)	(0.055)	(0.046)	(0.053)	(0.046)	(0.053)	(0.054)
Z	-0.044	-0.017	-0.115*	-0.044	-0.119**	-0.029	-0.028*
	(0.051)	(0.016)	(0.061)	(0.029)	(0.056)	(0.019)	(0.017)
Observations	396	396	396	396	396	396	396
Mean dep. variable	0.592	0.592	0.592	0.592	0.592	0.592	0.592

Note: This table shows the role of past exposure in the effect of violence on political participation. Panel A of this table reports local linear estimates of the average treatment effects on turnout around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth and a linear polynomial. We provide 95% robust confidence intervals and robust p-values, following Calonico et al. (2014). Bandwidth obs. indicates the number of observations in the optimal MSE bandwidth. Panel B of this table presents the OLS regression around the cut-off estimated with triangular kernel weights and within the optimal MSE bandwidth the baseline model in column 1. The optimal bandwidth was constructed for a baseline RDD with triangular kernel weights. In all columns, we interact our treatment variable with the pre-treatment characteristic Z specified in the heading of the columns. Columns 1, 3, and 5 present the extensive margin, while columns 2, 4, 6, and 7, present the extensive margin. Columns 1 and 2 (3 and 4, 5 and 6) use the explosions between 3 and 9 (3 and 12, 3 and 15) months before the election. Column 7 uses all explosions during a 1 year period after the election. All estimations are weighted by the number of potential voters registered in the poll. *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX (For Online Publication)

Fear to Vote: Explosions, Salience, and Elections

A Historical context

Since its independence from Spain in the early nineteenth century, Colombia has often experienced internal conflicts. For instance, during the nineteenth century only, it went through nine fully-fledged national civil wars and dozens of local violent disputes (Mazzuca and Robinson, 2009). The most recent civil war officially dates to the mid 1960s, when FARC and ELN were founded. Over the next two decades, these insurgencies were followed by other –albeit smaller–guerrilla organizations as well as by right-wing paramilitary groups, that were originally armed by the state in the early 1970s and trained as self-defense organizations.

While particularly violent, even within the Latin American context, post-independence Colombia has also had an outlier democratic record (Fergusson and Vargas, 2022). It is the only Latin American country with just one single (and short-lived) autocratic interim, when General Rojas-Pinilla's ascent to power was facilitated by an ongoing partisan civil war (called *La Violencia*). National elections have been in place since 1830, and Colombia was one of the first countries in adopting universal male suffrage in 1853, even if this unprecedented franchise extension only lasted 10 years (Fergusson and Vargas, 2013).

Local elections, on the other hand, were only introduced in the mid 1980s. Before so, department governors and municipal mayors were appointed by the national executive. Paradoxically, the introduction of local elections was the result of the central government's attempt to appease the increasing violence that rural areas were then suffering. The Betancur government negotiated with the insurgents and, to signal a credible willingness to open the democratic system, it introduced local elections by plurality rule (Fergusson et al., 2021). The first such elections took place in 1988.

In this context, both guerrilla and paramilitary groups frequently attempt to shape the outcomes of elections. For instance, the heads of the paramilitary met in 2001 with over 50 local and national politicians (including senators, governors, mayors, and councilmen) to sign a secret document in which they agreed to work together to "refound the country." In essence, the idea of the *Ralito Pact* was for militias to help elect –through violence and coercion–'friendly' candidates in exchange for a lenient legislation. This is at the backbone of the 'Parapolitics' scandal that eventually documented this and other alliances between politicians and paramilitary groups, and for which tens of politicians received judicial sentences (Acemoglu et al., 2013; Fergusson et al., 2018). To grasp a hint of the extent of the political infiltration of right-wing militias, during a hearing before the Supreme Court in 2005, paramilitary leader Salvatore Mancuso famously claimed that up to 35 percent of Colombia's Congress was elected thanks to the coercive influence of the AUC.[61]

B Data description and sources

B.1 Conflict dataset The URosario Colombian Conflict Dataset was originally compiled by Restrepo et al. (2004) and updated through 2019 by Universidad del Rosario. It codes violent events recorded in the *Noche y Niebla* reports from the NGO *Centro de Investigación y Educación Popular* (CINEP) of the Company of Jesus in Colombia, which provides a detailed description of the violent event, its date of occurrence, the municipality in which it took place, the identity of the perpetrator and the count of the victims involved in the incident.

B.2 Retrospective voting survey To further test one of the mechanisms behind our results we use the Political Culture Survey, a repeated cross-section implemented by DANE every two years to study political preferences and democratic participation.[62] Specifically, in the 2017 and 2021 waves, the survey included a question about whether the respondent considered that his/her community had faced, over the previous year, a threat to people's life, liberty, integrity, or safety. The list of potential such threats, for each of which subjects respond either 'Yes' (i.e., the community has been exposed) or 'No', includes antipersonnel landmine accidents. Around 3 percent of survey respondents answer positively about the landmine explosion threat to the community. In addition, for the sub-sample of respondents that report not having voted in the last election, the survey elicits the reasons why and includes in such a list the feeling of fear. Finally, we also conduct the analysis in a sub-sample of individuals exposed to conflict. We use questions on past exposure to displacement, forced recruitment, expropriation, stigmatization, and family killings.

B.3 Roads We also use detailed information, obtained from Colombia's Geographic Bureau, on the location of the entire road network of Colombia, including all road types from primary (highways) to tertiary (intra-municipal, non-paved) roads. The geo-location of the road network, which is available for the 2012 cross-section, allows us to compute the distance of every landmine explosion to the nearest road, and therefore test whether there are differential electoral effects of the blasts when they disrupt ground mobilization of voters.

[61] See `https://rb.gy/3z0cul` (last accessed 01/30/2023).

[62] The survey is representative at the region level, of which Colombia has four (plus a fifth constituted by Bogota, the country's capital): Caribe, Central, Eastern, and Pacific. Our analysis focuses on the first three, where most of the population resides and where 70 percent of the landmines exploded during our sample period.

B.4 Facebook To test changes in mobility after landmine explosions, we use mobility information from Facebook's Data for Good. We used grid-level maps with tiles of approximately 350 × 350m, measuring standardized changes in the flow of people in each tile since 2020 to mid 2022. They collected this data as part of their initiative to better understand mobility during the COVID-19 pandemic. Then there are two limitations to the data. First, mobility was calculated for the most densely populated areas of the country (the center of the country, the Andean region). This means that we miss landmine explosions in the northern and southern parts of the country. Second, the imposition of lockdowns clearly affected mobility. Therefore, we only used data from mid-2021, when the lockdown restrictions were lifted in the country.

B.5 Homicides Geo-located data on homicides is available since 2011 from the Statistical, Criminal, Contraventional, and Operative Information System (SIEDCO from the Spanish acronym) of Colombia's National Police. These data only include the date when the homicide was registered and the coordinates where the body was found, but do not include characteristics either about the victims or the perpetrator.

B.6 Rainfall To investigate the incidence between rainfall and the effects of landmine explosions on electoral outcomes, we utilized geolocated rainfall data obtained from the Colombia Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM). IDEAM's meteorology stations are strategically positioned throughout the country to collect data. Although the polling stations and meteorology stations are not always in close proximity to each other, we employed Thiessen polygons to interpolate the rainfall data from the stations and obtain comprehensive rainfall information across the entire country.

B.7 Demining The IMSMA information system (see section 2) provides detailed georeferenced data on all humanitarian demining events and the confirmed or suspected presence of antipersonnel mines from 2013 onward. The database includes the location of all demining events and the year of occurrence. As of March 31, 2021, the database contained 2,272 hazardous areas. Of these, 1,141 had been confirmed to host landmines, and 645 had been cleared by the seven active NGOs dedicated to humanitarian demining.[63] We focus on the sample period 2013-2021 because there was no humanitarian demining in Colombia before then. In turn, as discussed in section 2, in 2013, peace negotiations with FARC were already underway, which precipitated the decision of the Colombian government to undertake humanitarian demining to comply with the Ottawa Convention. We constructed a grid for Colombia containing 5 km square squares. We counted the number of demining events before each election to build a cumulative measure of demining activity in each grid.

[63]The information on humanitarian demining provided by IMSMA coincides very accurately with that of the administrative records of the NGOs.

B.8 Satellite-based information. We use the global harmonized nighttime light (NTL) dataset constructed by Li et al. (2020).

B.9 Electoral offenses. Colombia's electoral democracy is permeated by a series of electoral crimes, especially in non-urban areas, such as vote buying and electoral fraud. To this end, the Registraduría Nacional del Estado Civil collects information on reports and investigations of electoral crimes. They have been tracking these reports at the municipal level since the 2010 national elections. Using this information, we test that the number of electoral offenses between municipalities with an explosion before and after the election is similar.

B.10 Political candidates' tweets. To test whether politicians used explosions as a tool for political campaigning, we identified all candidates (542) running for local elections in 2015 and 2019 and manually searched their Twitter accounts. We found 125 politicians' Twitter accounts and web-scraped their tweets using R's RTWEET library, collecting 6,402 tweets.

B.11 Municipality characteristics. First, we use panel data of general characteristics at the municipality level from Acevedo et al. (2014). This dataset contains information on municipality characteristics such as total population, a rurality index, and a poverty index, value added as a proxy for GDP, number of schools, and soil production.

C Municipality-level aggregation of the effects

Our baseline effects are computed at the poll station level. To suggest municipal-level aggregate counterparts we follow this procedure: First, we take the number of explosion-affected polls in each municipality with a least one affected polls.[64] Second, we multiply the number of affected polls their average potential voters and by our estimated poll-level turnout reduction (12.6 p.p. in our most conservative finding). This gives us an estimate of the potential voters lost in municipalities with at least one affected poll station. Third, we compute the share of voters lost relative to the votes' potential by dividing this figure per the municipality votes' potential. We follow similar approached to compute municipal-aggregates for the other outcomes explored in the paper.

Regarding the number of municipal-level electoral races the outcome of which would have changed in the absence of landmine explosions, we focus on all the closely contested races that left-wing parties lost in municipalities with a lest one voting poll affected by a landmine

[64] We define a poll as affected by a landmine explosion if there was at least one such explosion within the 24 days before an election and within the 4Km radius. We choose this bandwidth to ensure some homogeneity in our calculation. Indeed, 24 days is the average of the optimal bandwidths for the main outcomes.

explosion. Using the figure obtained from the procedure described in the previous paragraph, we compute the share of the close races that would have had different electoral results in the absence of the explosion.

D Persuasion rates

We use the model proposed by DellaVigna and Kaplan (2007) to calculate the persuasion rates based on our estimates in Tables 2 and 3. Using the left-parties estimator in Column 3, we calculate the percentage of left-party voters that may change their minds due to the explosion (i.e., they decided not to vote or vote for another party). Similarly, using the paramilitary-related parties estimator in column 5, we calculate the percentage of voters that were not planning to vote for a paramilitary-related party (including voters for other parties and non-voters) convinced to vote for paramilitary-related parties because of the explosion.

Taking the voting for paramilitary-related parties as an example, we define polls T, as polls where a landmine blast occurred within a window of 30 days before the election day, and control polls C as polls where an explosion occurred within a window of 30 days after the election (which is close to the optimal bandwidth of Column 5 in Table 3). We define $Paramilitary_{t-1}$ as the average voting share for paramilitary-related parties in the previous election before the explosion, and $Others_{t-1}$ as the average voting share for other parties. This implies that the share of non-voters is $1 - Paramilitary_{t-1} - Others_{t-1}$. Notice that these averages are not statistically different for control and treated units in elections in $t-1$ (see Table 1).

In our case, since people cannot choose if they are affected by an explosion or not, and given the small buffer around the voting poll that we use, we define the exposure rate for treated polls to be equal to one ($e_t = 1$) and control polls, for construction, are set to be equal to zero ($e_c = 0$). Finally, the parameter f is the fraction of voters that were not planning to vote for a paramilitary-related party ($1 - Paramilitary_{t-1}$) that were persuaded to vote for a paramilitary-related party after the explosion. For $j = T, C$, the two-party vote share for paramilitaries after explosions will be:

$$\text{(A1)} \qquad v_j = \frac{Paramilitary_{t-1} + (1 - Paramilitary_{t-1})e_j f}{Paramilitary_{t-1} + Others_{t-1} + (1 - Paramilitary_{t-1} - Others_{t-1})e_j f}.$$

Notice that $\alpha_j = Paramilitary_{t-1} + Others_{t-1} + (1 - Paramilitary_{t-1} - Others_{t-1})e_j f$, where α_j is the turnout in poll j. Thus, if we solve equation A1 for the difference between

$v_t - v_c$, equivalent to our $\hat{\beta}_{paras}$, the implied persuasion rate is:

$$f_{paramilitary} = \frac{v_T - v_C}{(e_T - e_C)\,(1 - Paramilitary_{t-1})} \frac{(1 - Paramilitary_{t-1})\alpha_C \alpha_T}{(Others_{t-1})} \tag{A2}$$

Here, α_C and α_T are the turnouts of control and treated polls in time t. And $v_t - v_c$ is our estimator $\hat{\beta}_{paras}$. For left parties, we repeat the same process but this time applying the persuasion rate on past left voters. Thus, our final rates of persuasion are:

$$f_{paramilitary} = \frac{\hat{\beta}_{paramilitary}}{(e_T - e_C)\,(1 - Paramilitary_{t-1})} \frac{(1 - Paramilitary_{t-1})\alpha_C \alpha_T}{(Others_{t-1})} \tag{A3}$$

$$f_{left} = \frac{\hat{\beta}_{left}}{(e_T - e_C)\,Left_{t-1}} \frac{(Left_{t-1})\alpha_C \alpha_T}{(1 - Others_{t-1})}. \tag{A4}$$

Using these equations, we estimate that a landmine explosion convinced 8.6% of past left voters affected by the explosion to vote differently or not to vote. Under the same logic, an explosion persuaded 3.05% of non-paras' potential voters to vote for them.

E Robustness

This section discusses all the robustness exercises as well as the result they yield. First, recall that in addition to triangular kernel weights, in the baseline specification, we also weight the observations by the poll's voting potential. We do so to give similar weight to each voter, avoiding penalizing poll stations with a very larger number of voters. Arguably, however, this strategy gives more weight to denser and more urban areas. However, if we eliminate this weight (keeping only the triangular kernel) our results are similar. We report these results for all the main outcomes in Column 1 of Table A21.[65] Moreover, our findings are not driven by the use of a triangular kernel (that gives more weight to observations closer to the –election day–threshold). In Column 2 of Table A21, we report our baseline estimates using a uniform kernel instead (that gives equal weight to all observations). The results are remarkably similar, both in terms of magnitude and significance.

Second, when we restrict our sample to instances in which only one landmine explosion took place within 60 days from elections (and within the vicinity buffer) our results of the effect of violence on electoral participation are very similar. This is important because, arguably, instances with more than one explosion are less unexpected or occurred in different types of voting polls, assuming that voters learn about the existence of a minefield and anticipate other blasts. The estimates for this sub-sample are reported in Column 3 of Table A21,

[65] In the Appendix, we present the robustness when using the voting over the actual voters (Table A22) as well as for a quadratic polynomial (Table A23).

finding similar results with the exception of voting for paramilitary related being not statistically significant, while the penalty for the incumbent is. Alternatively, our results are qualitatively unchanged when using only one explosion per poll (the closest to the day of the election), instead of all the explosions within the optimal bandwidth (see Table A21, Column 4).

Third, one potential concern is that the control group could also be affected by an explosion if there was an explosion before the election that occurred relatively close to that voting poll. In principle, this could lead to an underestimation of our treatment effect, given that voting polls in the control group could have also responded to a pre-election explosion. To gauge this magnitude, we re-run our main specification, excluding control voting polls that were "contaminated" by an explosion that occurred before the election, in the same election year, and was 5 or 10 km away from the control voting poll. Our results in Table A21 Columns 5 and 6 show that the effects are similar if anything larger when excluding these "contaminated" controls.[66]

Fourth, in Appendix Table A24, we control for average rainfall around the voting poll in the 30 days prior to the election. This control is important given the evidence that rain reduces turnout (Gomez et al., 2007), as well as the evidence that rainfall can move the location of mines, making them more dangerous.[67] We find similar results when adding this control which alleviates concerns about the potential confounding role of rainfall. Moreover, recall that we find no statistical difference in the average pre-election rainfall in treated and control voting polls (see Table 1).

Fifth, our results are robust to adding predetermined controls. While in principle the inclusion of covariates should not have a large effect on the magnitude of the coefficients, doing so may help improve the precision of the estimates (Lee and Lemieux, 2010; Calonico et al., 2019). The included controls vary both at the poll and at the municipality level, and we select them following Belloni et al. (2014)'s machine learning LASSO algorithm, which selects the best covariates predicting the treatment status. The estimated coefficients change very little (see Table A21, Column 7).

Sixth, the baseline results are computed over a buffer around each polling station that uses the Euclidean distance. This implicitly assumes that the earth is a regular ellipsoid. Instead, we can take into account the irregularity of the earth's surface by computing the topographic distance, which weights the regular distance by the elevation between the landmine explosion spot and the poll. The estimated effect of a landmine blast using this alternative distance

[66] In Figure A12, we present the coefficients for excluding contaminated controls using a distance for up to 20 km.

[67] See for example, `https://rb.gy/ki20h` and `https://rb.gy/j94l1` (last accessed 6/5/2023).

measure is reported in Column 8 of Table A21. The results are robust to this change, and the reduction in the support for the incumbent becomes statistically significant when computed over the poll-level vote potential.[68]

Seventh, we address the documented potential problems of implementing RD designs with a discrete running variable. Note, however, that this does not seem to be a significant challenge in our case, since we have a large enough number of days around the elections with explosions (104 explosions over 120 different days, in a 60-day window). In any case, there could remain concerns about the discrete nature of our running variable so we implement two alternative estimation procedures that the literature has proposed to address this issue. The first one is an optimized RD suggested by Imbens and Wager (2019), where instead of using a local linear regression method, we use a data-driven approach based on numerical optimization.[69] Column 9 of Table A21 reports the results. We find a similar effect for turnout and a statistically significant but smaller effect for the drop in left-wing vote share, while we find no effect for voting for the incumbent and paramilitary-related parties.[70]

The second procedure follows Cattaneo et al. (2020) and it is based on a local randomization design instead of an RDD. Instead of continuity around the cut-off, under local randomization, the main identifying assumption is that being treated or not is as if randomly assigned within a small window around the cut-off. The point estimate and p-value that this method yields within a 20-days window is reported in Column 10 of Table A21. The estimates are similar to that of the baseline specification for both turnout and voting for left-wing parties, with the effect for voting for the incumbent being statistically significant in this specification, but not for voting for paramilitary-related parties.[71]

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[68]Note that, because 4Km of topographic distance is shorter than 4Km of Euclidean distance (especially in a very mountainous terrain such as Colombia's), the number of observations is smaller and consequently the optimal bandwidth is different. This partly explains the changes in the magnitude of the estimated coefficients.

[69]For this method, it is needed to provide a bound of the second derivative of the response function. As suggested by the authors, we estimate a quadratic polynomial between the outcome of interest and the running variable and use the coefficient of the squared term multiplied by four as the bound. In Appendix Figure A13, we present the robustness of this procedure to an expansion factor of up to 24, respectively for turnout and for the outcomes related to electoral behavior.

[70]In Appendix Figure A14, we present the robustness of the results of this method to different radii.

[71]In Appendix Figures A15 and A16, we present the robustness of the results of this method to different bandwidths and radii.

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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 politica 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.

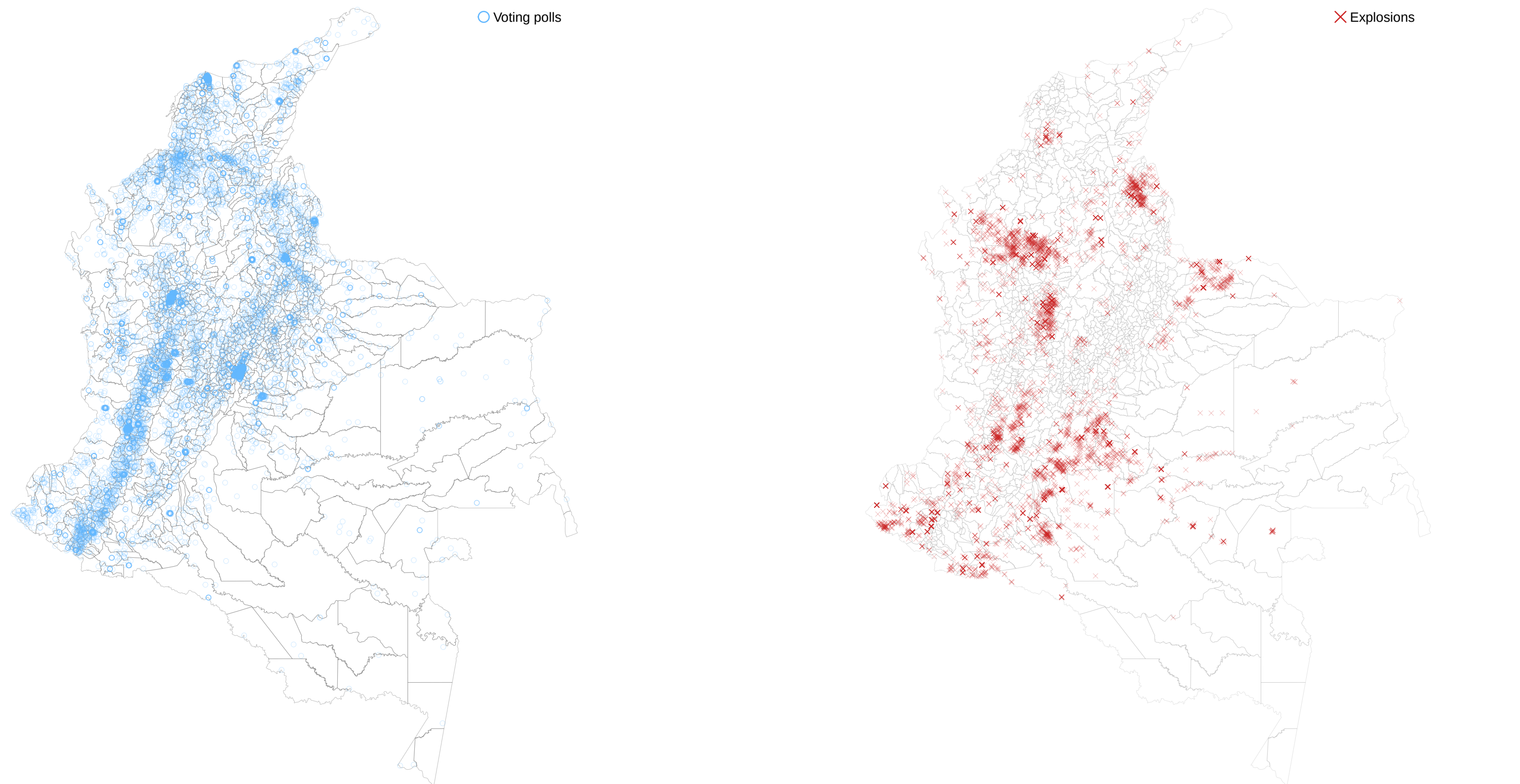
12. Los grupos encargados de la tarea telefónica se debe incrementar en todas las áreas de operaciones enemigas, está comprobado que estando lo bastando cerca de ellos arroja buenos resultados para IC.

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

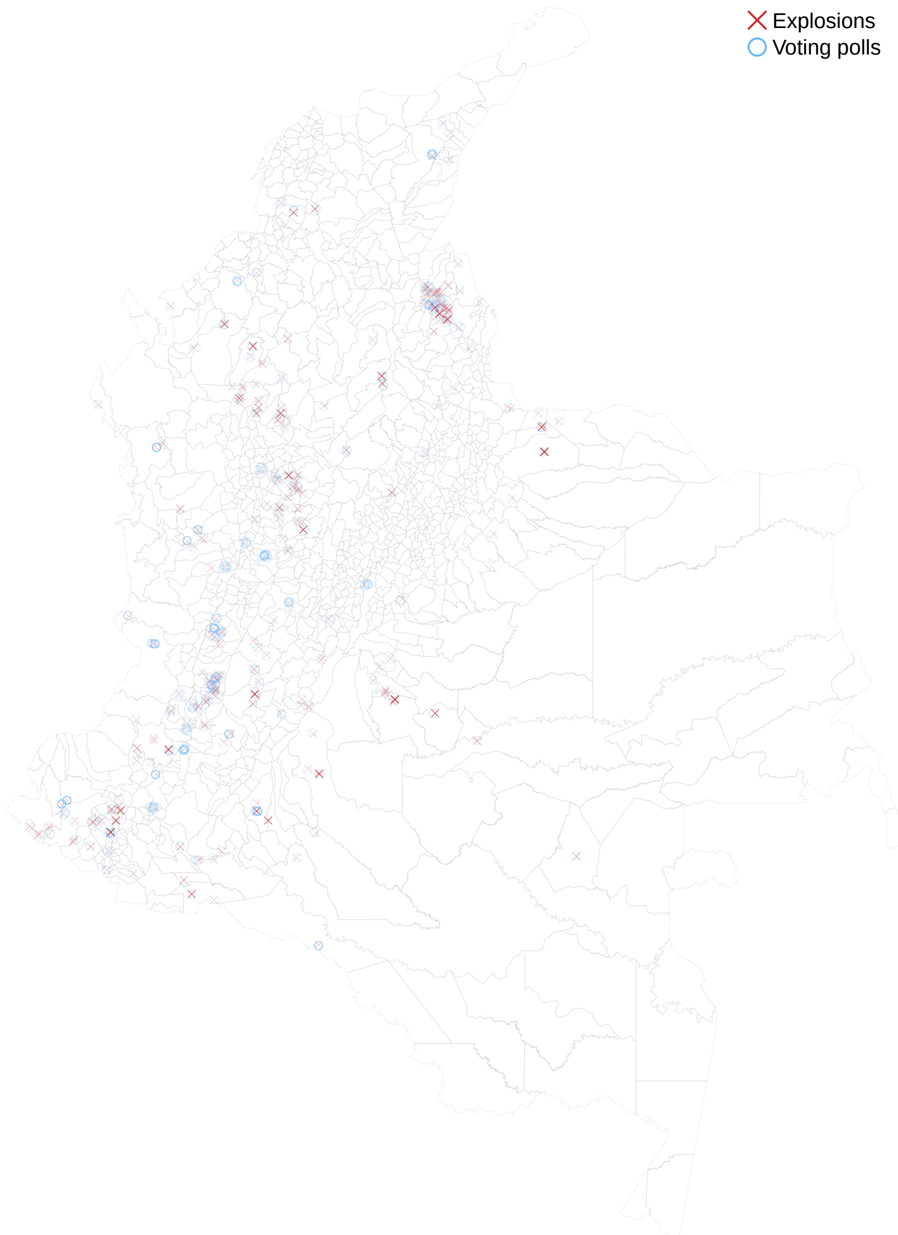
Figure A2. Voting Polls and Landmine Explosions



A. Voting Polls **B.** Landmine Explosions

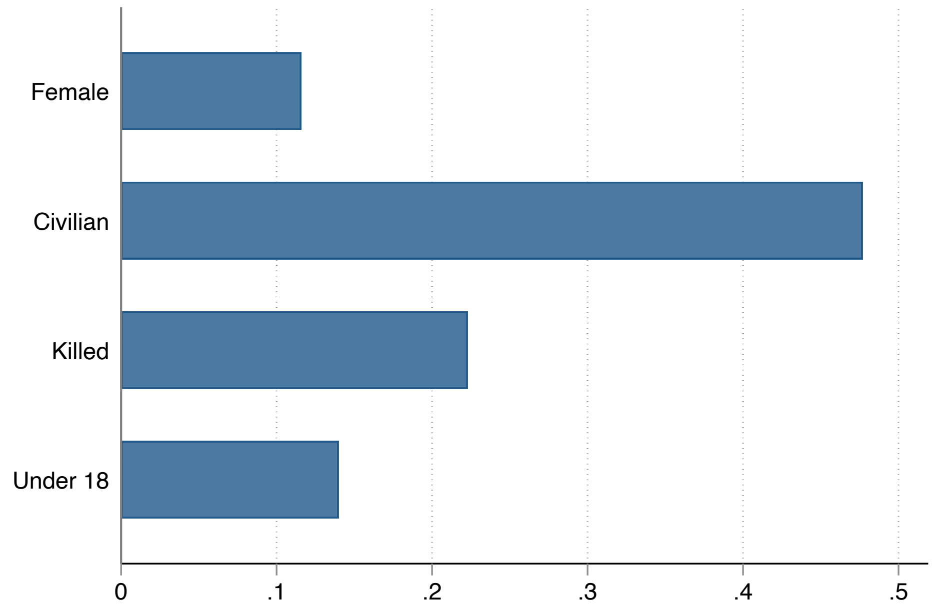
Notes: This figure shows the spatial distribution of voting polls (map on Panel A) and landmine explosions (map on panel B) between 2003 and 2019 in Colombia.

Figure A3. Landmine Explosions and Voting Polls Inside Donuts' Distance and Time Windows



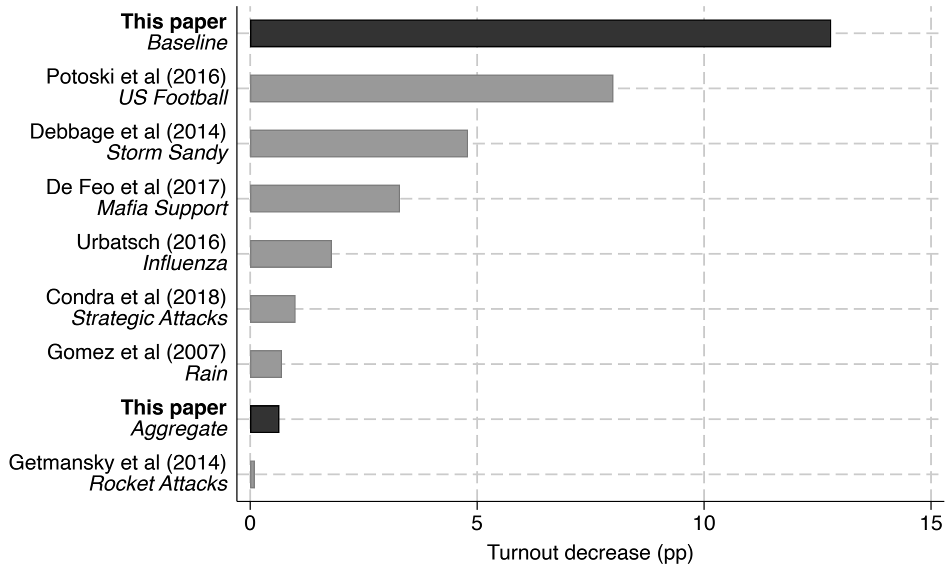
Notes: This figure shows the spatial distribution of the landmine explosions and voting polls inside donuts of 4km and 60 days around the election, between 2003 and 2019, with red dots and blue circle hollows, respectively.

Figure A4. Victims characteristics

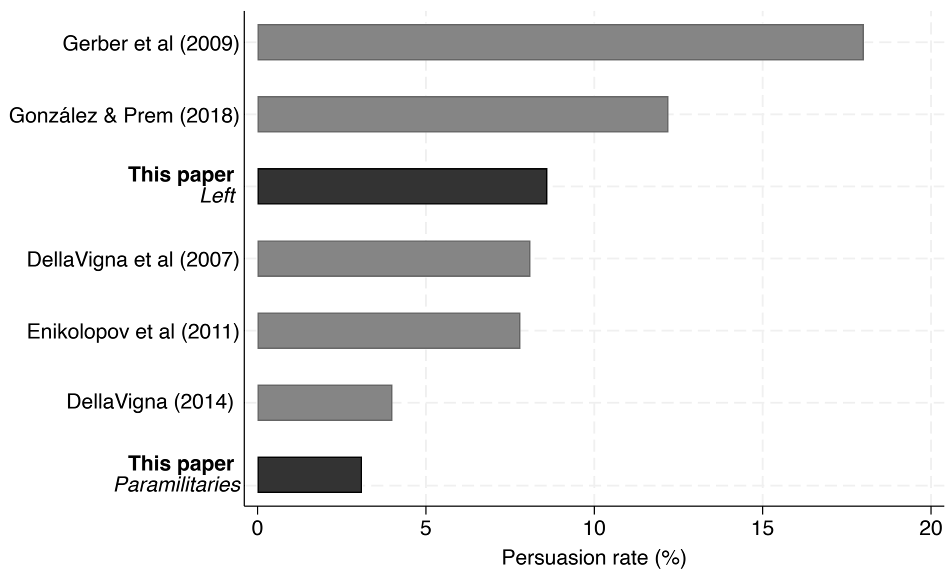


Notes: This figure presents the share of explosions in our sample with at least one victim with the characteristic mentioned on the y-axis.

Figure A5. Our Estimates in the Literature



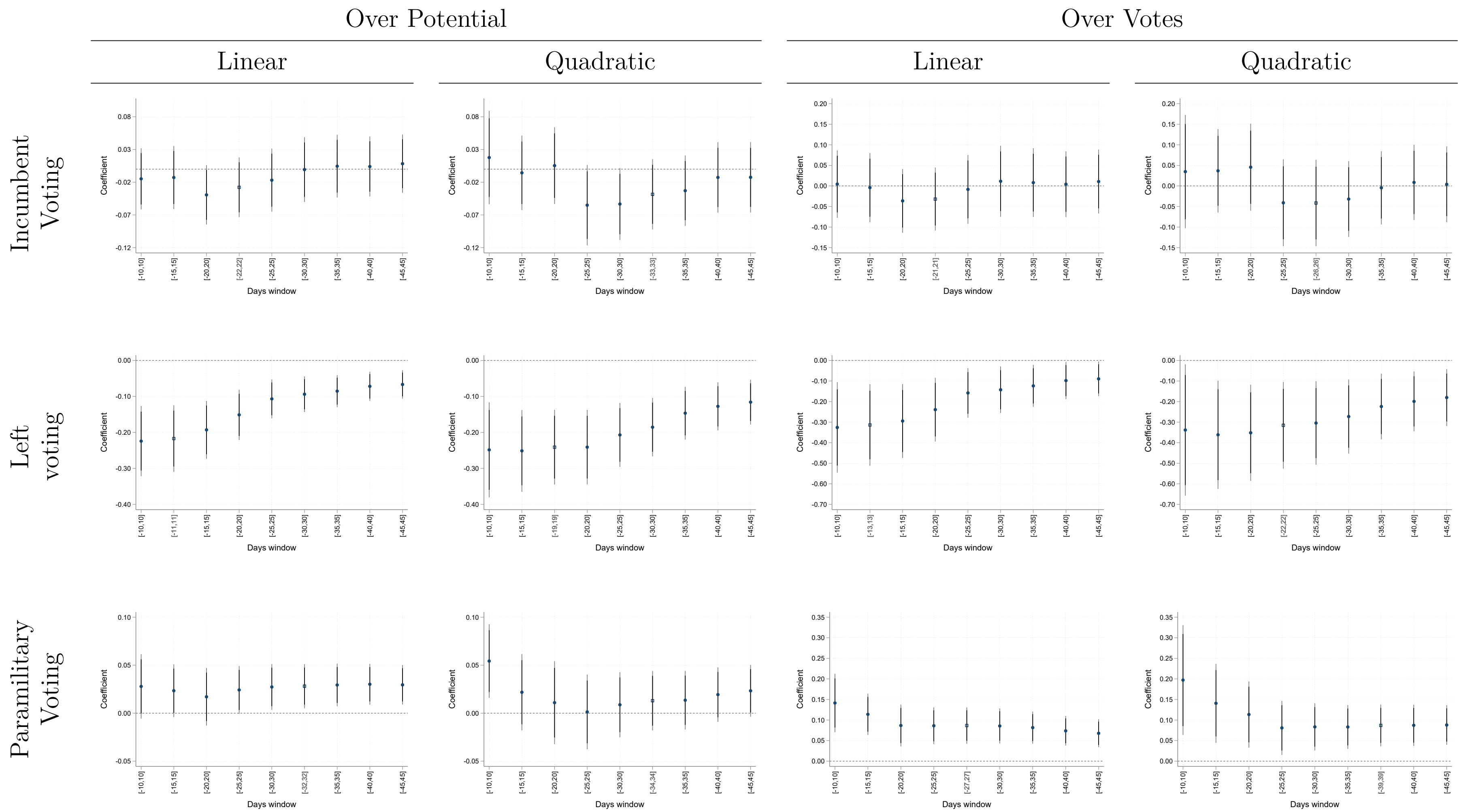
A. Turnout



B. Persuasion Rate

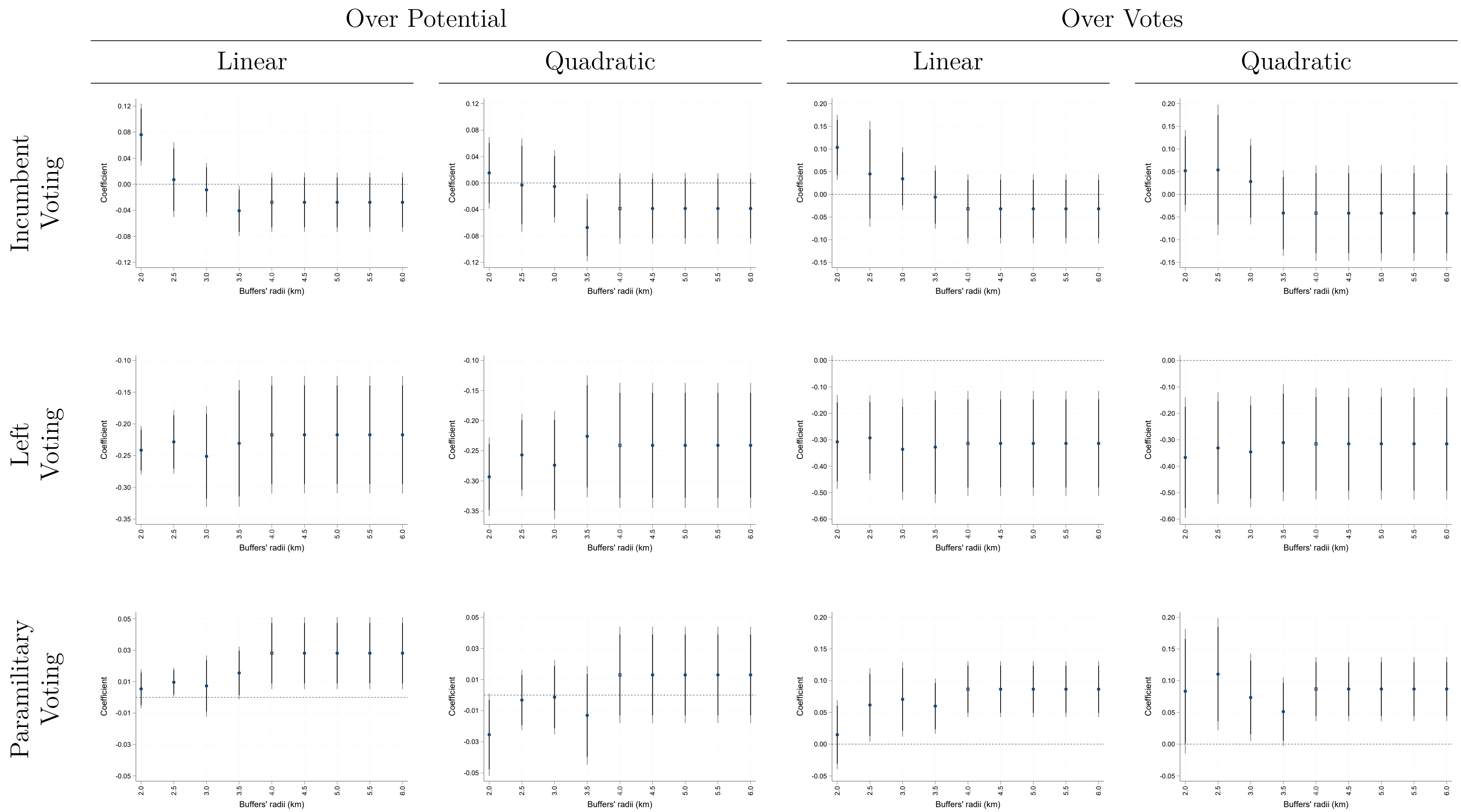
Notes: This figures plots how our estimates compare to the existing literature. In panel A, the figure presents the size of our estimates compared to other studies that relate turnout and other kind of events. De Feo and De Luca (2017); Getmansky and Zeitzoff (2014) indicate a decrease on turnout from mafia support in the electoral cycle, and rocket attacks in Israel, respectively. However, their estimates are not statistically significant. In panel B, the figure presents the size of our persuasion rates estimates compared to other studies.

Figure A6. Voting and Landmine Explosions Over Different Days Windows



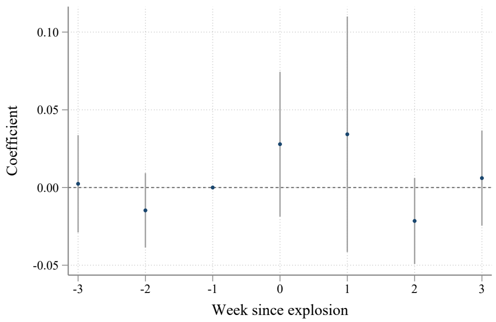
Notes: This figure plots local linear and quadratic estimates of the average treatment effects on voting behavior around the cut-off, using triangular kernel weights and optimal MSE bandwidth over different days windows. We report the estimates divided by potential voters (first two columns) and votes (last two columns). We also report the point estimates from our baseline specification in Table 2, along with 90% and 95% confidence intervals. Standard errors clustered at the municipality level. All estimations are weighted by the potential voters registered in the poll.

Figure A7. Voting and Landmine Explosions Over Different Buffers' Radii

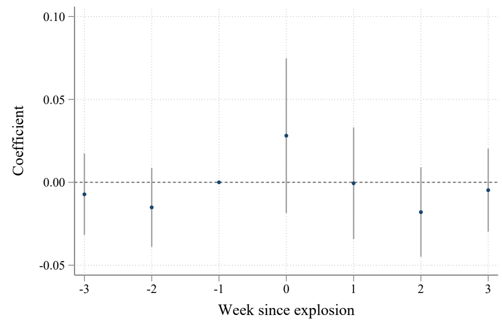


Notes: This figure plots local linear and quadratic estimates of the average treatment effects on voting behavior around the cut-off, using triangular kernel weights and optimal MSE bandwidth over different buffers' radii. We report the estimates divided by potential voters (first two columns) and votes (last two columns). We also report the point estimates from our baseline specification in Table 2, along with 90% and 95% confidence intervals. Standard errors clustered at the municipality level. All estimations are weighted by the potential voters registered in the poll.

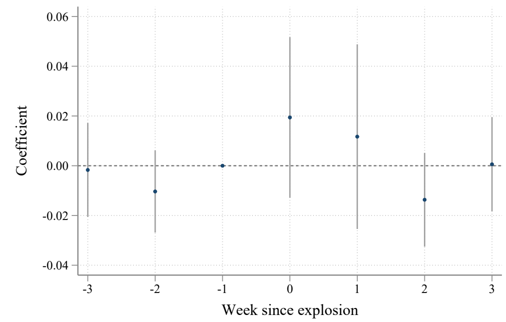
Figure A8. Homicides and Landmine Explosions: TWFE



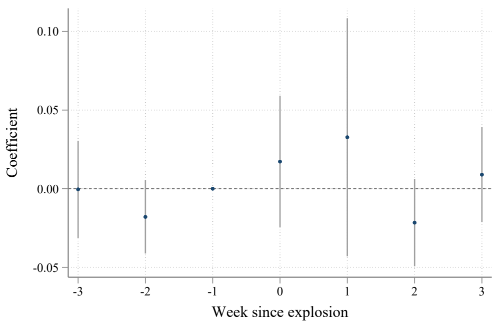
A. N. Homicides



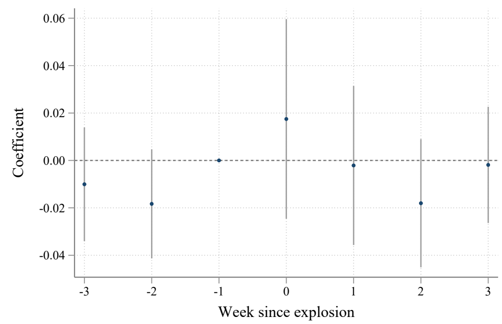
B. Any Homicide



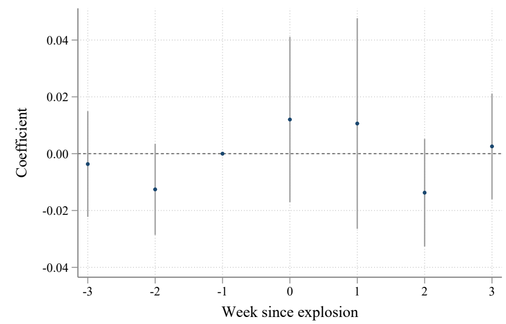
C. Ln Homicides



D. N. Homicides - BW



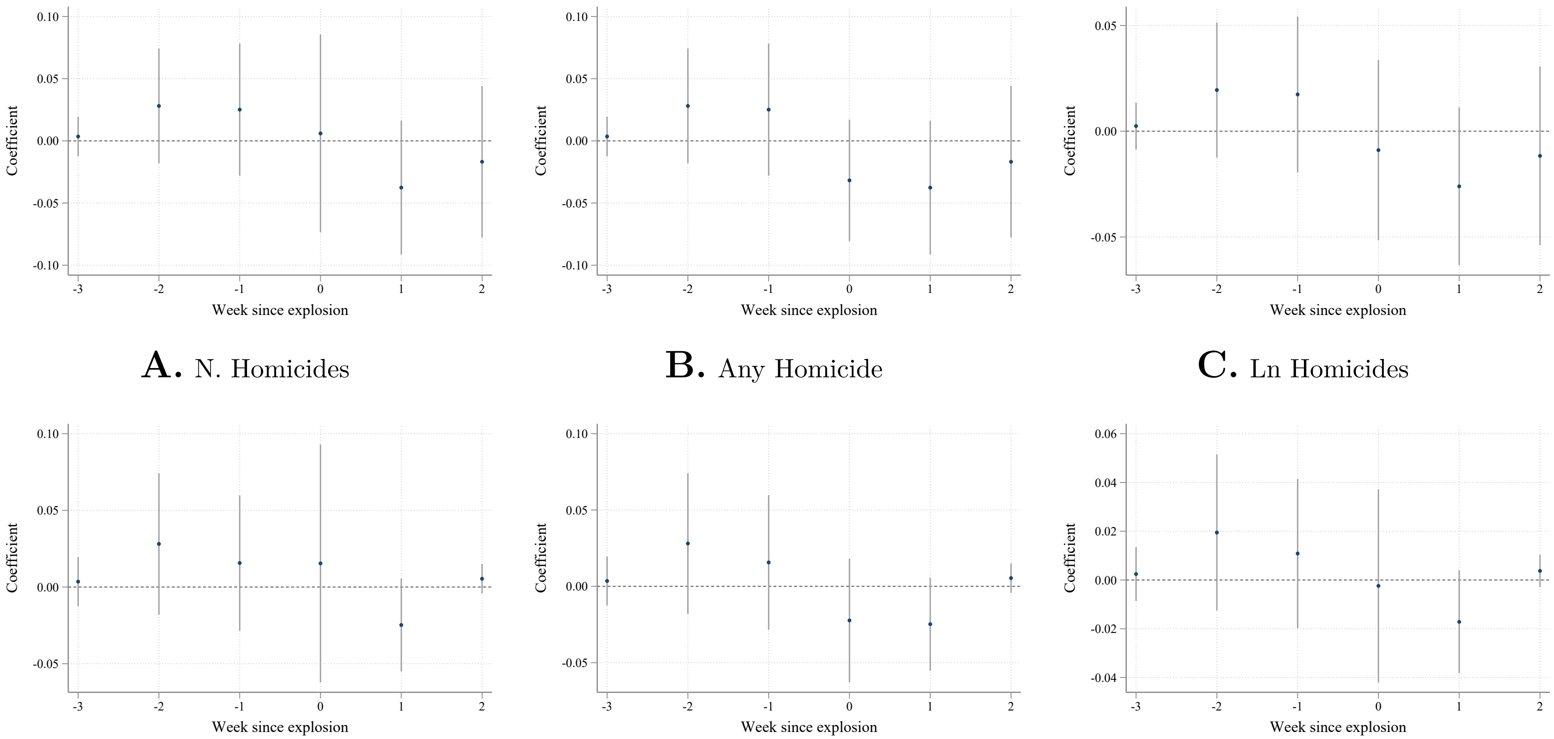
E. Any Homicide - BW



F. Ln Homicides - BW

Notes: This figure presents the event study coefficients of the effect of landmine explosions on homicides. The outcomes were computed using a radius of 4km around the voting poll. We present the point estimates as well as the 95% confidence interval. Standard errors are clustered at the poll-election level. Estimates on the first row are over the full sample, and in the second row on a model restricted to the optimal bandwidth in Column 2 of Table 2.

Figure A9. Homicides and Landmine Explosions: De Chaisemartin and d'Haultfoeuille (2020)



A. N. Homicides

B. Any Homicide

C. Ln Homicides

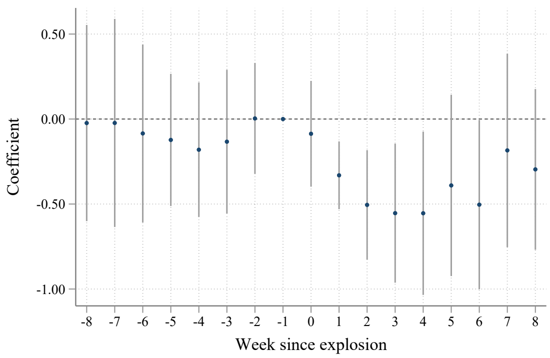
D. N. Homicides - BW

E. Any Homicide - BW

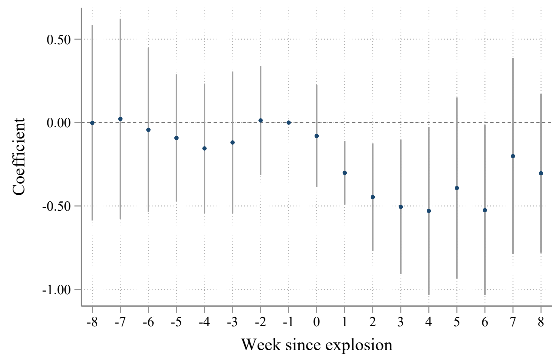
F. Ln Homicides - BW

Notes: This figure presents the event study coefficients of the effect of landmine explosions on homicides following De Chaisemartin and d'Haultfoeuille (2020). The outcomes were computed using a radius of 4km around the voting poll. We present the point estimates as well as the 95% confidence interval. Standard errors are clustered at the poll-election level. Estimates on the first row are over the full sample, and in the second row on a model restricted to the optimal bandwidth in Column 2 of Table 2. Following De Chaisemartin and d'Haultfoeuille (2020), we find that the share of ATTs that enter in the weighted sum as negative is 0%.

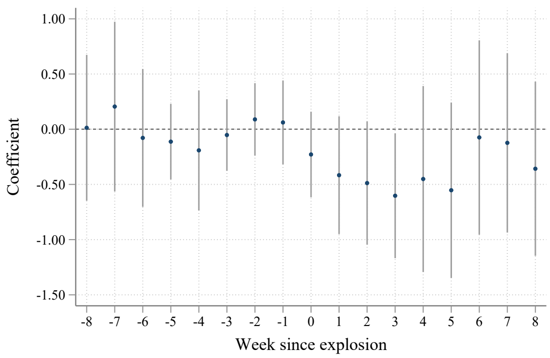
FIGURE A10. Mobility and Landmine Explosions



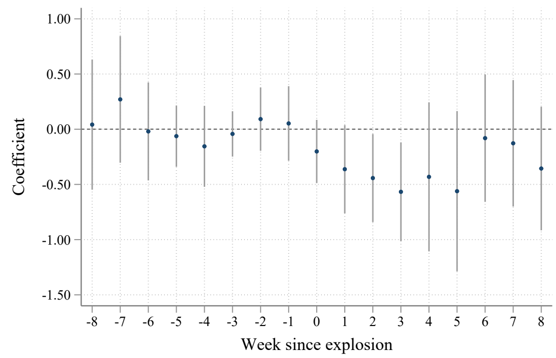
A. All Tiles



B. Conflict-affected Tiles



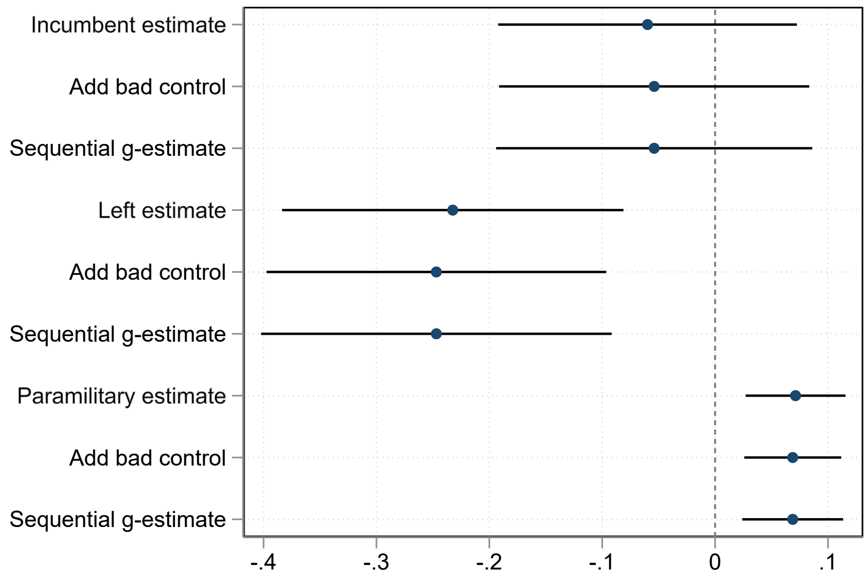
C. All Tiles



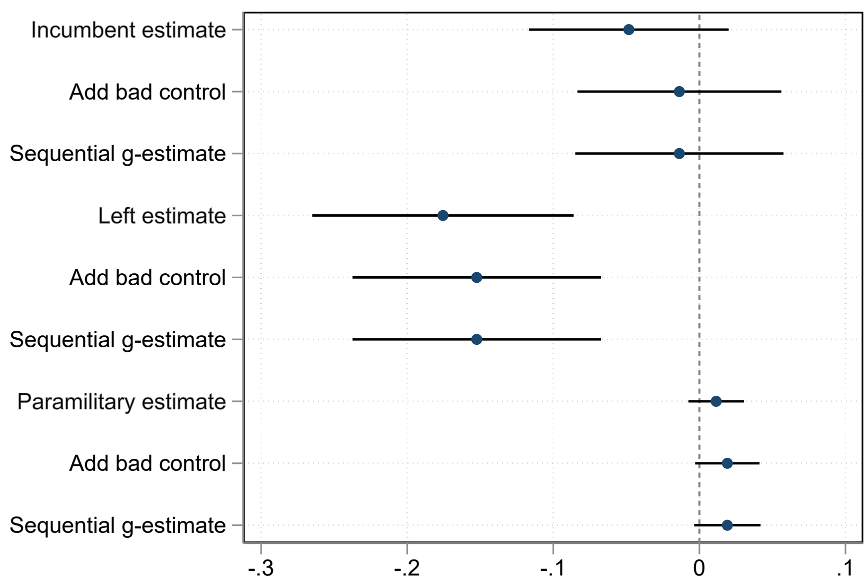
D. Conflict-affected Tiles

Notes: This figure presents the event study coefficients for the treatment of landmine explosions. We present the point estimates as well as the 95% confidence interval. Standard errors are clustered at the tile level. The outcome is the standardized average mobility in pixels from July 2021 to May 2022. The mobility was computed using Facebook population density maps at the tile level. Panels A and C present the results for the full sample with mobility data, while in Panels B and D, we restrict the sample to conflict-affected tiles as those located in the surrounding of previously demined areas, or in areas identified as still in danger of a landmine explosion. Panels A and B, we present the estimates using a Two-way Fixed Effects model, while Panels C and D, present the estimates following De Chaisemartin and d'Haultfoeuille (2020). Following De Chaisemartin and d'Haultfoeuille (2020), we find that the share of ATTs that enter in the weighted sum as negative is 12%.

Figure A11. Mediation Analysis



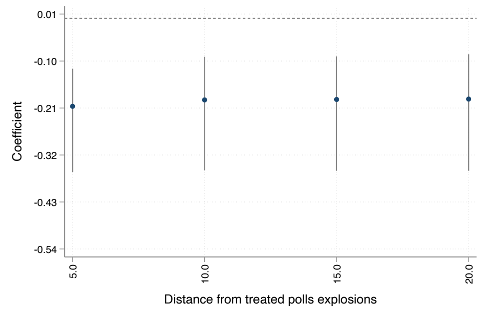
A. Over Potential Voters



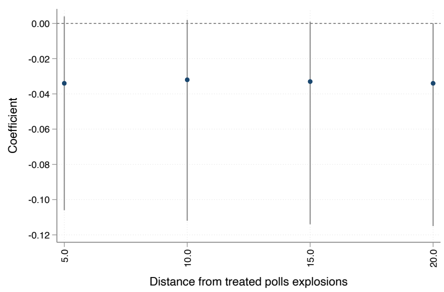
B. Over Actual Voters

Notes: This figure plots the mediation analysis for turnout in the voting behaviour estimates in Table 3. *Incumbent, Left* and *Paramilitary* estimates in Panel A present the point estimates and the 95% confidence interval for our baseline specification from column 1, 3, and 6 in Table 3, respectively. *Incumbent, Left* and *Paramilitary* estimates in Panel A (Panel B) present the point estimates and the 95% confidence interval for our baseline specification from column 1 (2), 3 (4), and 5 (6) in Table 3, respectively. *Add bad control* presents the point estimates and the 95% confidence interval for the main specification but adding the poll turnout as a control. *Sequential g-estimate* presents the point estimate and the 95% confidence interval for the sequential g-estimate suggested by Acharya et al. 2016. We construct the confidence intervals using a non-parametric bootstrap procedure that includes the two estimation stages as suggested by the authors.

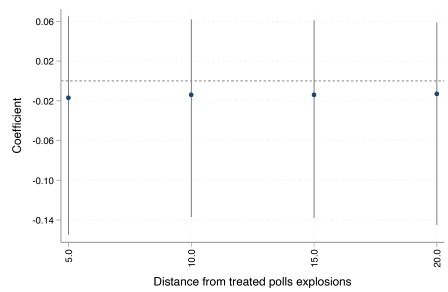
Figure A12. Excluding "contaminated" controls



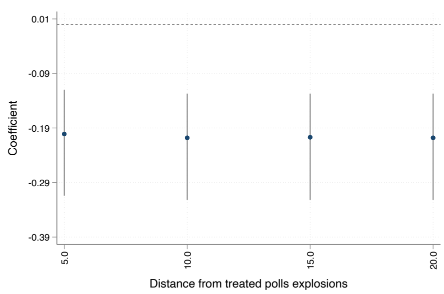
A. Turnout



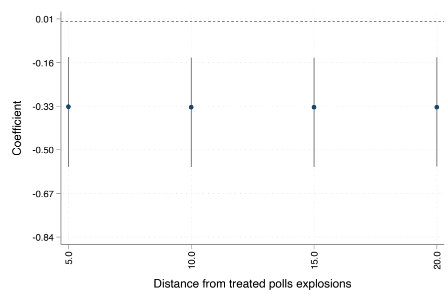
B. Incumbent Over Potential



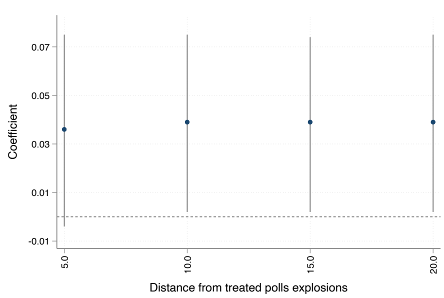
C. Incumbent Over Votes



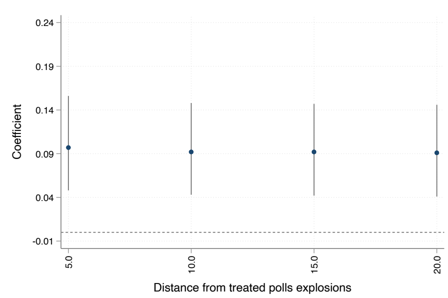
D. Left Over Potential



E. Left Over Votes



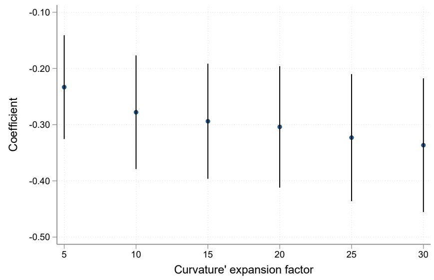
F. Paramilitary Over Potential



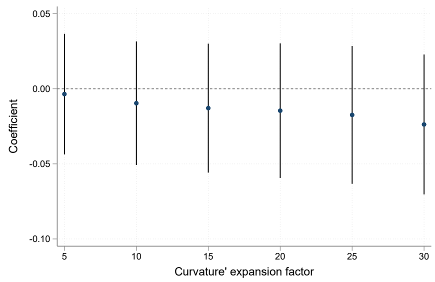
G. Paramilitary Over Votes

Notes: This figure presents our main estimates, excluding from the control polls those that were inside a buffer of 5, 10, 15, and 20 kilometers of an explosion that affected a treated poll in the year t and election j.

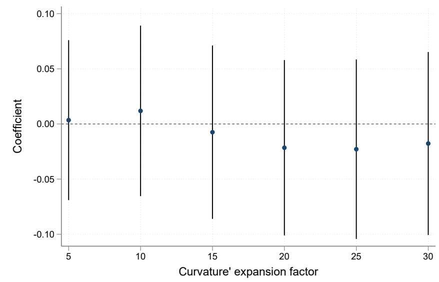
Figure A13. Curvature' Expansion Factor



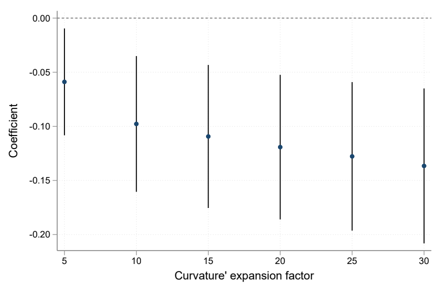
A. Turnout



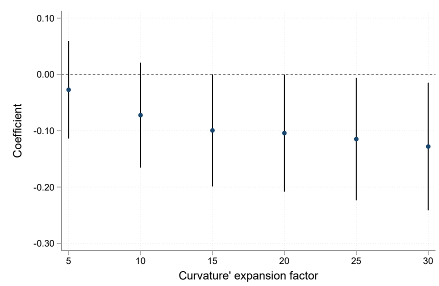
B. Incumbent Over Potential



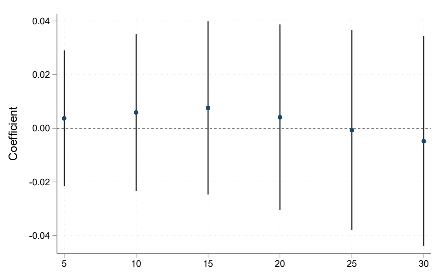
C. Incumbent Over Votes



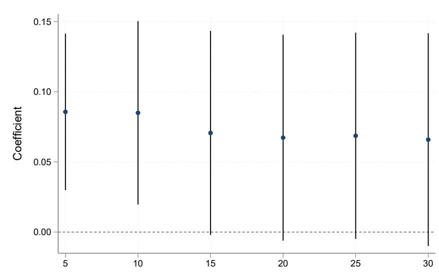
D. Left-wing Over Potential



E. Left-wing Over Votes



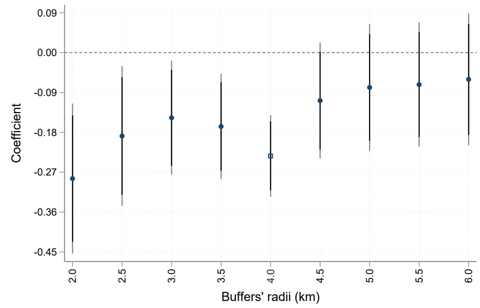
F. Paramilitary Over Potential



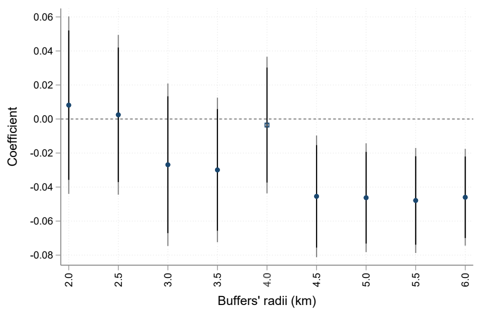
G. Paramilitary Over Votes

Notes: This figure plots the point estimate and 95% confidence intervals for the optimized-RD suggested by Imbens and Wager (2019) for variables related to political participation and voting behavior. In this case, we vary the second derivative bound of the response function. We estimate a quadratic polynomial between the outcome of interest and the running variable and use that coefficient multiplied by different expansion factors (x-axis), ranging from 5 (our baseline) up to 25.

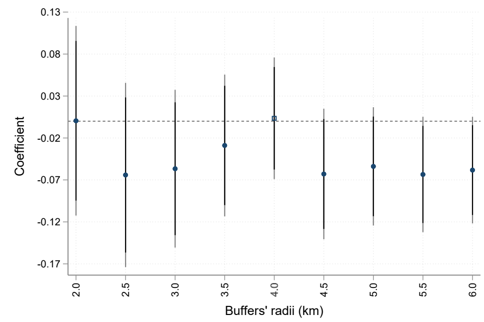
Figure A14. Imbens and Wager (2019) Method: Voting Behavior Over Different Buffers' Radii



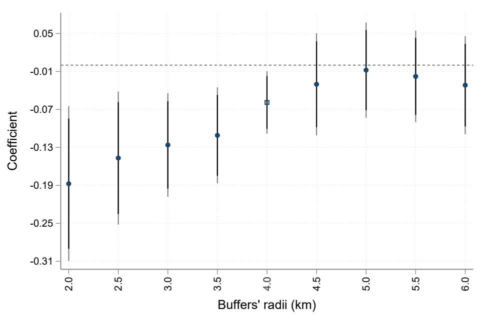
A. Turnout



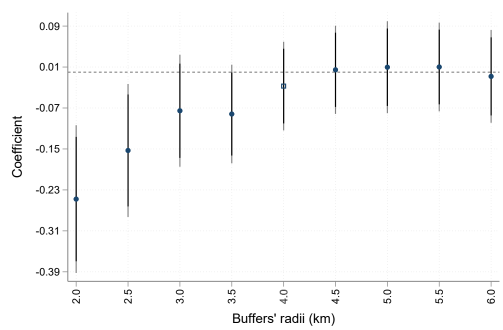
B. Incumbent Over Potential



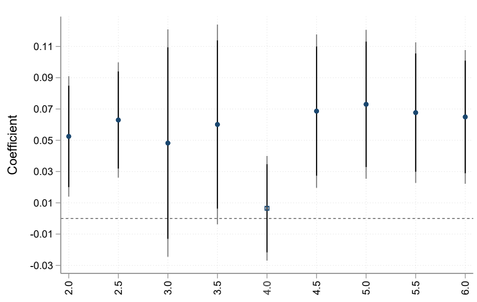
C. Incumbent Over Votes



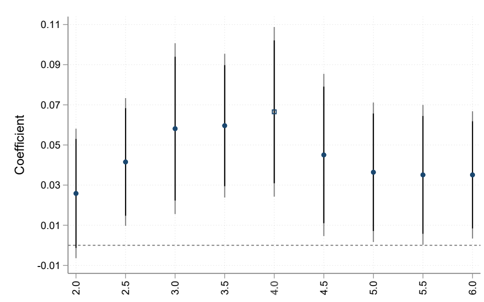
D. Left Over Potential



E. Left Over Votes



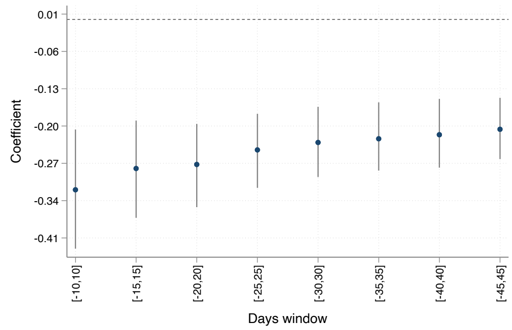
F. Paramilitary Over Potential



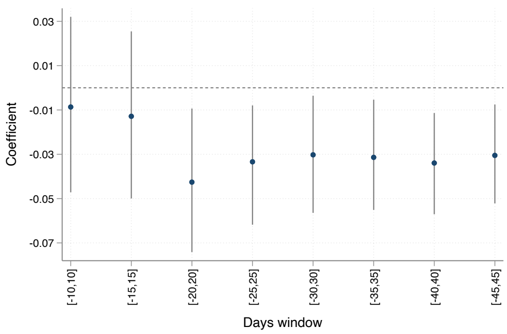
G. Paramilitary Over Votes

Notes: This figure presents the RD estimator suggested by Imbens and Wager (2019) across different buffers' radii (x−axis). The outcomes is specify in the name of the panels. We use the second derivative bound of the response function as the curvature. We first estimate a quadratic polynomial between the outcome of interest and the running variable and use that coefficient multiplied by an expansion factor of 5.

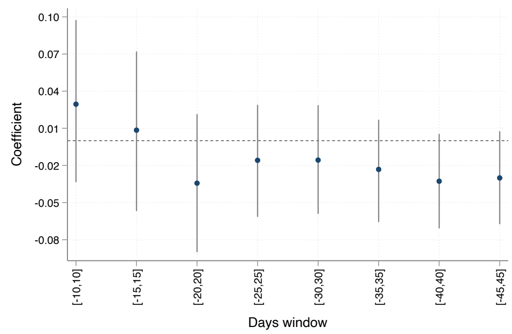
Figure A15. Local Randomization: Voting Behavior Over Different Bandwidths



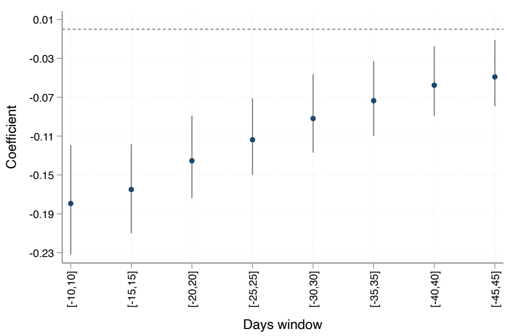
A. Turnout



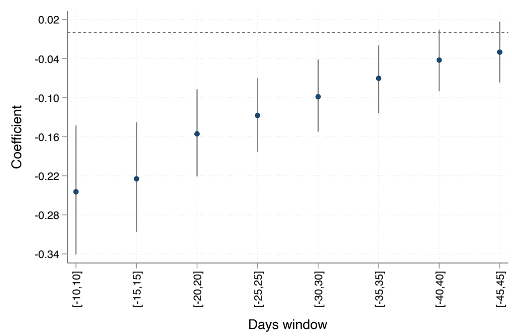
B. Incumbent Over Potential



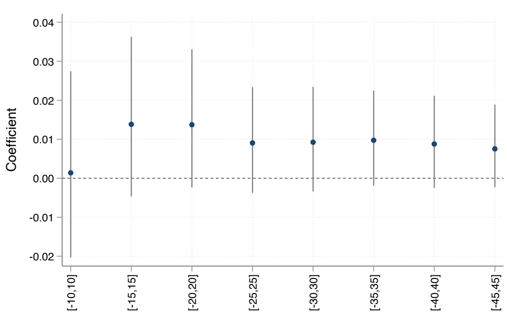
C. Incumbent Over Votes



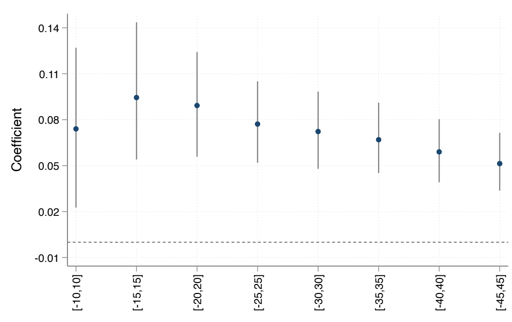
D. Left Over Potential



E. Left Over Votes



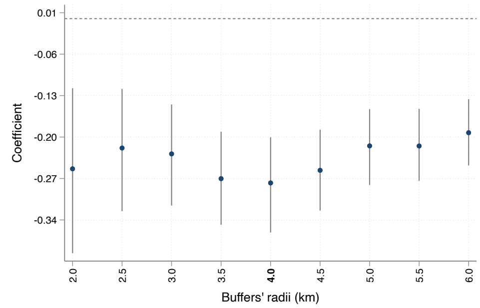
F. Paramilitary Over Potential



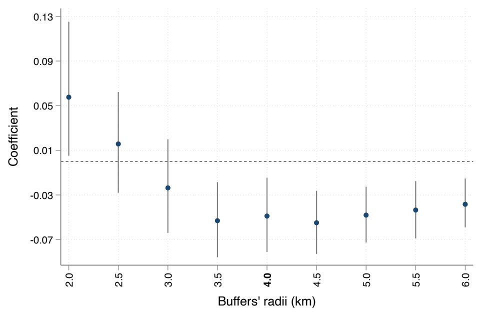
G. Paramilitary Over Votes

Notes: This figure presents the local randomization approach as suggested by Cattaneo et al. (2020), using buffers of 4 kilometers from the voting polls and different time windows since the election day (x−axis). We calculate the estimates using a triangular kernel and a polynomial degree of order one. All columns include election fixed effects.

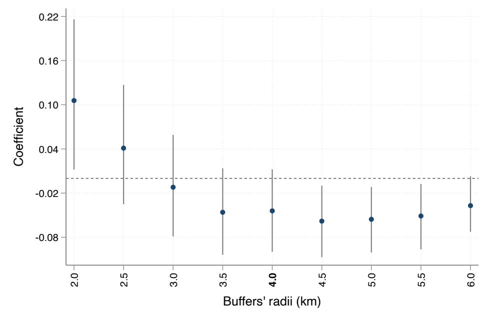
Figure A16. Local Randomization: Voting Behavior Over Different Buffers' Radii



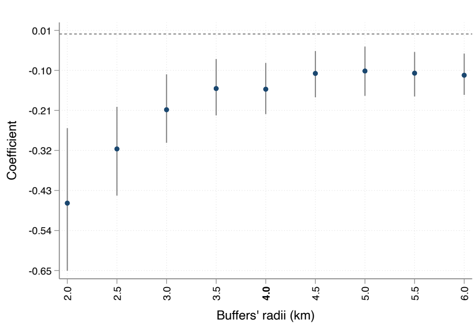
A. Turnout



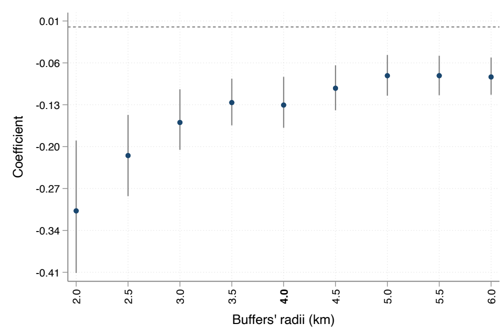
B. Incumbent Over Potential



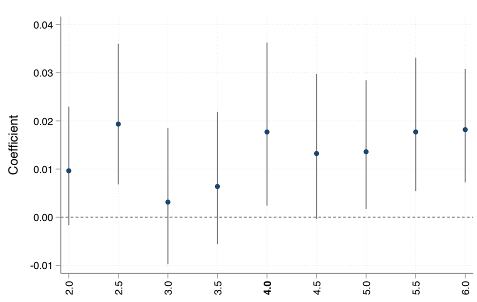
C. Incumbent Over Votes



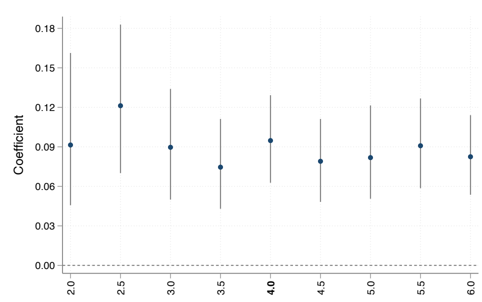
D. Left Over Potential



E. Left Over Votes



F. Paramilitary Over Potential



G. Paramilitary Over Votes

Notes: This figure presents the local randomization approach as suggested by Cattaneo et al. (2020), using a bandwidth of $+/-20$ days since the elections and explosions occurring within a buffer of different ratios from the voting poll (x−axis). We calculate the estimates using a triangular kernel and a polynomial degree of order one. All columns include election fixed effects.

TABLE A1. Party Classifications and Sample Appearance

Type	Party Name	Election Year
Left	Alianza Social Indígena	2003, 2006, 2010
	Alianza Nacional Popular	2003
	Asociación Nacional Indígena	2014
	Asociación de Autoridades Tradicionales Indígenas	2015
	Autoridades Indígenas de Colombia	2006, 2010, 2011, 2014, 2015, 2018, 2019
	Colombia Humana	2019
	Fuerza Revolucionaria del Común	2018
	Lista de la decencia	2018
	Movimiento Alianza Indígena y Social	2015, 2018, 2019
	Movimiento Frente Social y Político	2003
	Movimiento Independiente Obrero	2007
	Polo Democrático Alternativo	2003, 2006, 2007, 2010, 2011, 2014, 2015, 2018, 2019
	Partido del Trabajo de Clombia	2003
	Unión Patriotica	2015, 2019
Paramilitaries	Alas Equipo Colombia	2006, 2007
	Colombia Democrática	2003, 2006
	Colombia Viva	2003, 2006, 2007
	Convergencia Ciudadana	2003, 2006
	Partido de Integración Nacional	2007, 2010, 2011
Right	Partido Conservador	2003, 2006, 2007, 2010, 2011, 2014, 2015, 2018, 2019
	Partido de la U	2006, 2007, 2010, 2011, 2014, 2015, 2018, 2019
	Cambio Radical	2006, 2007, 2010, 2011, 2014, 2015, 2018, 2019
	Partido Liberal	2003, 2006, 2007, 2010, 2011, 2014, 2015, 2018, 2019
	Centro Democratico	2014, 2015, 2018, 2019
	Partido Opcion Ciudadana	2010, 2011, 2014, 2015, 2018, 2019
	MIRA	2003, 2006, 2007, 2010, 2011, 2014, 2015, 2018, 2019
	Colombia Justa y Libres	2018, 2019

Note: This table presents the left-wing, paramilitaries-related, and right-wing parties. The left-wing and right-wing classification used the parties selected by Fergusson et al. (2021) and updated for elections after 2011 following a similar method. The paramilitaries-related parties were defined as those with at least one-third of their congress members prosecuted by alliances with paramilitaries, Valencia (2007) lists all the legislators prosecuted by partisan membership.

TABLE A2. RDD estimates without excluding explosions at the municipality centroide

Dep. Variable:	Turnout	Incumbent Votes Over		Left-wing Votes Over		Paramilitary Votes Over	
		Potential	Votes	Potential	Votes	Potential	Votes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Explosion before	-0.155***	-0.030	-0.042	-0.158***	-0.218***	0.005	0.041**
Robust p-value	0.000	0.147	0.216	0.000	0.003	0.950	0.024
CI 95%	[-0.28, -0.09]	[-0.08, 0.01]	[-0.12, 0.03]	[-0.25, -0.09]	[-0.39, -0.08]	[-0.03, 0.02]	[0.01, 0.08]
[1] p-value	0.024	0.232	0.468	0.122	0.061	0.824	0.188
[2] p-value	0.037	0.171	0.519	0.075	0.050	0.922	0.166
Election fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,210	2,210	2,210	2,210	2,210	2,210	2,210
Bandwidth obs.	431	406	454	244	244	454	635
Mean	0.520	0.093	0.183	0.066	0.139	0.014	0.018
Bandwidth	16.1	15.2	17.6	10.6	10.6	18.0	27.6
(Local) polynomial order	1	1	1	1	1	1	1

Note: This table presents the local linear estimates of the average treatment effects around the cut-off estimated with triangular kernel weights and optimal MSE bandwidth. All columns include explosions that are 1km or less from a voting poll. Robust p-values are presented, and computed following Calonico et al. (2014). Standard errors are clustered at the municipality level. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. All columns use linear polynomials to estimate the average treatment effects, and include election fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Heterogeneous Effects

Dep. Variable:	Turnout					
Z:	Baseline	Post Ceasefire	Distance to a Road	Distance to a Road Primary	Distance to a Road Secondary	Distance to a Road Tertiary
	(1)	(2)	(3)	(4)	(5)	(6)
Explosion before × Z		0.011	-0.001	-0.013	-0.073**	-0.027
		(0.106)	(0.042)	(0.020)	(0.034)	(0.020)
Explosion before	-0.224***	-0.224***	-0.229***	-0.221***	-0.201***	-0.211***
	(0.061)	(0.061)	(0.064)	(0.061)	(0.062)	(0.060)
Z			0.019	-0.004	-0.005	-0.011
			(0.037)	(0.017)	(0.027)	(0.018)
Observations	396	396	396	367	396	396
Mean dep. variable	0.592	0.592	0.592	0.579	0.592	0.592

Note: This table presents the OLS regression around the cut-off estimated with triangular kernel weights and election fixed effects, and within the optimal MSE bandwidth the baseline model in column 1. The optimal bandwidth comes from column 1 of Table 2. In columns 2 to 10, we interact our treatment variable with the pre-treatment characteristic Z specified in the heading of the columns. Post ceasefire is a dummy that takes the value one after 2014 (column 2). Distance to a road is the demeaned distance from the explosion to closest road (columns 3-6). Robust standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4. Difference in Characteristics by Treatment Status II

	Mean Control	Difference in Mean	RDD Estimate
	(1)	(2)	(3)
Panel A: Poll Station Level - Geographic			
Dist. to school	0.69	-0.08	-0.12
	(0.60)	(0.08)	[-0.54, 0.20]
Dist. to roads	-1.07	0.06	0.00
	(1.67)	(0.25)	[-1.20, 1.08]
Dist. to mun. capital	1.38	-0.05	0.71
	(1.25)	(0.21)	[-0.27, 1.20]
Dist. to closest village	0.80	-0.24	0.25
	(1.28)	(0.19)	[-0.60, 1.00]
Dist. to police station	0.69	-0.08	-0.12
	(0.60)	(0.08)	[-0.54, 0.20]
Ln population	11.29	-0.28	0.35
	(1.08)	(0.21)	[-0.58, 0.33]
Ln value added	6.08	-0.11	0.60
	(1.36)	(0.27)	[-0.26, 0.77]
Rurality index	0.57	0.03	-0.11
	(0.26)	(0.05)	[-0.23, 0.02]
Poverty index	69.66	1.64	0.96*
	(16.36)	(2.64)	[-0.93, 12.14]
Number of schools	89.82	-13.18	43.34
	(90.08)	(17.80)	[-6.69, 46.68]
Deforestation	0.03	0.00	0.01
	(0.06)	(0.01)	[-0.03, 0.08]
Gold suitability	1.41	-0.31	0.39
	(8.18)	(0.57)	[-5.95, 5.76]
Coffee production	1.30	0.08	-0.46
	(1.80)	(0.28)	[-1.06, 1.21]
Coca production	0.15	-0.01	0.04
	(0.21)	(0.03)	[-0.13, 0.09]
Panel C: Municipality Level - Electoral offences			
Any moving votes	0.25	-0.06	0.13
	(0.44)	(0.06)	[-0.17, 0.65]
Any vote buying	0.18	-0.01	0.14
	(0.38)	(0.12)	[-0.19, 0.49]
Any electoral offense	0.90	-0.11	-0.01
	(0.31)	(0.09)	[-0.42, 0.53]

Note: This table reports the differences in pre-election voting poll-level characteristics (Panel A) and municipality-level characteristics (Panel B) for explosions within 4 km from the voting poll and within the optimal MSE bandwidth between treatment and control groups. Column 1 presents the mean and standard deviation for the control group. Column 2 shows the estimated coefficient and standard error from an OLS regression of the poll or municipality characteristic and the treatment status, controlling for election fixed effects and with clustered standard errors at the municipality level. Finally, Column 3 presents the local linear estimates of the average treatment effects around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth, and adding election fixed effects. In square brackets 95% robust confidence intervals, following Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Differences in Poll/Municipality Characteristics for in and out of Sample

	Mean RD Sample	Mean at Least One Explosion	Mean All Polls/Municipalities	Difference (1) and (2)	Difference (1) and (3)
	(1)	(2)	(3)	(4)	(5)
Panel A: Poll station Level					
Ln potential voters	6.02	5.96	7.02	0.05	-1.00***
	(1.18)	(1.27)	(1.64)	[0.45]	[0.00]
Turnout	0.52	0.57	0.60	-0.05***	-0.08***
	(0.16)	(0.19)	(0.22)	[0.00]	[0.00]
Political competition	0.61	0.64	0.67	-0.03***	-0.05***
	(0.11)	(0.10)	(0.09)	[0.00]	[0.00]
Left vote share	0.06	0.05	0.05	0.01**	0.02***
	(0.07)	(0.06)	(0.06)	[0.02]	[0.00]
Paramilitaries vote share	0.01	0.01	0.02	-0.00	-0.00***
	(0.02)	(0.02)	(0.03)	[0.85]	[0.01]
Incumbent vote share	0.08	0.08	0.09	-0.00	-0.02***
	(0.06)	(0.07)	(0.06)	[0.26]	[0.00]
Homicides	2.73	3.11	2.63	-0.38***	0.10
	(1.79)	(2.11)	(2.37)	[0.00]	[0.31]
Dist to school	2.12	2.02	1.99	0.10**	0.14***
	(0.70)	(0.72)	(0.76)	[0.02]	[0.00]
Dist. to roads	2.13	2.01	2.10	0.12**	0.02
	(0.74)	(0.81)	(0.68)	[0.02]	[0.45]
Dist. to mun. capital	62.42	56.36	59.29	6.06**	3.13
	(42.16)	(43.89)	(241.15)	[0.02]	[0.76]
Dist. to closest village	4.16	4.36	13.55	-0.21	-9.40
	(4.42)	(5.12)	(235.24)	[0.46]	[0.35]
Dist. to police station	1.82	1.63	1.65	0.19**	0.18***
	(1.14)	(1.11)	(1.07)	[0.02]	[0.00]
Observations	543	615	11,452		
Panel B: Municipality Level					
Any FARC Attack	0.56	0.51	0.32	0.04	0.24***
	(0.50)	(0.50)	(0.46)	[0.38]	[0.00]
Any OAG Attack	0.47	0.38	0.20	0.09*	0.27***
	(0.50)	(0.49)	(0.40)	[0.07]	[0.00]
Ln Population	9.92	9.53	9.34	0.40***	0.59***
	(0.85)	(0.88)	(0.93)	[0.00]	[0.00]
Area (Km2)	1,776.73	1,556.46	877.68	220.26	899.05***
	(4130.44)	(4781.93)	(3034.23)	[0.63]	[0.00]
Poverty Index	80.38	79.45	76.02	0.93	4.36***
	(15.74)	(14.35)	(16.21)	[0.53]	[0.00]
Rurality Index	0.62	0.61	0.61	0.01	0.01
	(0.22)	(0.21)	(0.23)	[0.75]	[0.72]
Number of Schools	33.65	31.45	27.61	2.20	6.04***
	(15.61)	(16.24)	(15.42)	[0.17]	[0.00]
Coca Suitability	0.28	0.18	-0.07	0.10	0.35***
	(0.93)	(0.89)	(0.97)	[0.25]	[0.00]
Palm Suitability	0.03	0.03	0.02	-0.00	0.01
	(0.08)	(0.09)	(0.08)	[0.96]	[0.42]
Gold Suitability	2.31	0.87	0.51	1.44**	1.79***
	(9.28)	(4.42)	(3.44)	[0.03]	[0.00]
Coffee Production	1.13	0.85	0.68	0.28*	0.45***
	(1.81)	(1.59)	(1.40)	[0.09]	[0.00]
Deforestation	0.36	0.34	0.40	0.02	-0.04
	(0.36)	(0.38)	(0.54)	[0.59]	[0.35]
Observations	161	268	935		

Note: This table presents the differences between the municipalities in our sample against other polls/municipalities. Column 1 presents the mean of a variable for polls/municipalities in our main sample. Column 2 presents the mean for polls/municipalities out of our sample that had at least one landmine explosion between 2013 and 2019. Column 3 presents the mean for all polls/municipalities out of our sample, whether they had a landmine explosion or not. Finally, columns 4 and 5 show the differences between columns 1-2 and 1-3, respectively. *** p<0.01, ** p<0.05, * p<0.1.

Table A6. Robustness Main Result: Logarithm Transformation

Dep. Variable:	Ln(Votes)			
	(1)	(2)	(3)	(4)
Explosion Before	-0.821**	-1.058***	-1.088**	-1.299***
Robust p-value	0.018	0.000	0.014	0.000
CI 95%	[-1.867, -0.174]	[-1.532, -0.776]	[-2.345, -0.263]	[-1.863, -0.926]
Election Fixed Effects	Yes	Yes	Yes	Yes
Control for Log Potential	No	Yes	No	Yes
Observations	1136	1136	1136	1136
Bandwidth Obs.	214	184	302	315
Mean	6.14	6.11	6.33	6.33
Bandwidth	17.2	16.0	23.8	24.3
(Local) Polynomial Order	1	1	2	2

Note: This table reports local linear estimates of the average treatment effects on the logarithm of votes around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth. Columns 1-2 show the estimates using linear polynomials, while columns 3-4 use quadratic polynomials. We provide 95% robust confidence intervals and robust p-values, following Calonico et al. (2014). Bandwidth obs. indicates the number of observations in the optimal MSE bandwidth. Columns 2 and 4 include the logarithm of the number of potential voters in the poll as a covariate. *** p¡0.01, ** p¡0.05, * p¡0.1.

Table A7. RDD Estimates for Turnout: Fixed Bandwidth

Dep. Variable:	Turnout							
Bandwidth:	From Polynomial Order 1				From Polynomial Order 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explosion Before	-0.126***	-0.131***	-0.268***	-0.253***	-0.213***	-0.200***	-0.373***	-0.357**
Robust p-value	0.004	0.002	0.000	0.000	0.000	0.001	0.000	0.010
CI 95%	[-0.252, -0.048]	[-0.384, -0.083]	[-0.524, -0.244]	[-0.543, -0.159]	[-0.461, -0.209]	[-0.501, -0.138]	[-0.540, -0.267]	[-0.538, -0.073]
[1] p-value	0.023	0.000	0.000	0.000	0.000	0.000	0.000	0.000
[2] p-value	0.047	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Election Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for Log Potential	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1136	1136	1136	1136	1136	1136	1136	1136
Bandwidth Obs.	396	396	396	396	223	223	223	223
Mean	0.592	0.592	0.592	0.592	0.590	0.590	0.590	0.590
Bandwidth	32.0	32.0	32.0	32.0	19.6	19.6	19.6	19.6
(Local) Polynomial Order	1	1	2	2	1	1	2	2

Note: This table presents local linear estimates of the average treatment effects on turnout around the cut-off in a fixed bandwidth defined by the polynomial order, using triangular kernel weights. Estimates in columns 1 and 3 are from Table 2. Columns 1-2 and 5-6 use linear, and columns 3-4 and 7-8 use quadratic polynomials to estimate the average treatment effects. We provide 95% robust confidence intervals and robust p-values, following Calonico et al. (2014). The p-value in [1] is based on robust standard errors clustered at the running variable level, as suggested by Lee and Card (2008), while [2] uses standard errors clustered at the municipality level. Bandwidth obs. denotes number of observations in the fixed bandwidth. Even columns include the logarithm of the number of potential voters in the poll as a covariate. All estimations are weighted by the number of potential voters registered in the poll. *** p<0.01, ** p<0.05, * p<0.1.

Table A8. Turnout and Rainfall

Dep. Variable:	Turnout					
Sample:	All			Rural		
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall	-0.005***	-0.012***	-0.018***	-0.005***	-0.013***	-0.020***
	(0.002)	(0.002)	(0.005)	(0.002)	(0.003)	(0.006)
Observations	95,092	95,032	94,608	66,611	66,554	65,861
R-squared	0.351	0.420	0.495	0.351	0.417	0.489
Election FE	Yes	Yes	Yes	Yes	Yes	Yes
Department-Year FE	No	Yes	No	No	Yes	No
Municipality-Year FE	No	No	Yes	No	No	Yes
Mean dep variable	0.574	0.575	0.574	0.581	0.581	0.580

Note: This table presents estimates of election day rainfall on turnout at the rural polls. The rural polls are those polls more than 1 km away from an urban settlement (city, town, etc.). Rainfall measures the total precipitation on election day on a radius of 4km around the voting poll, and we present the standardized version by the mean and standard deviation. All columns are weighted by the size of the poll. Standard errors are clustered at the municipality level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A9. The Effect of Explosions on Voting Behavior: Control for Potential Voters and Second-degree Polynomial

Dep. Variable:	Incumbent Votes Over		Left-wing Votes Over		Paramilitary Votes Over	
	Potential	Votes	Potential	Votes	Potential	Votes
	(1)	(2)	(3)	(4)	(5)	(6)
A. Control for Potential Logarithm						
Explosion Before	-0.012	-0.018	-0.214***	-0.316***	0.027*	0.086***
Robust p-value	0.693	0.784	0.000	0.004	0.065	0.000
CI 95%	[-0.10, 0.07]	[-0.14, 0.10]	[-0.29, -0.14]	[-0.54, -0.10]	[-0.00, 0.05]	[0.05, 0.14]
[1] p-value	0.430	0.480	0.000	0.000	0.082	0.000
[2] p-value	0.475	0.676	0.000	0.000	0.132	0.001
Bandwidth Obs.	323	295	107	121	396	323
Mean	0.135	0.288	0.100	0.173	0.009	0.013
Bandwidth	26.9	22.3	10.6	11.6	31.2	26.1
(Local) Polynomial Order	1	1	1	1	1	1
B. Second-degree Polynomial						
Explosion Before	-0.039	-0.042	-0.241***	-0.315***	0.013	0.087***
Robust p-value	0.165	0.380	0.000	0.005	0.736	0.002
CI 95%	[-0.11, 0.02]	[-0.18, 0.07]	[-0.37, -0.14]	[-0.58, -0.10]	[-0.03, 0.04]	[0.03, 0.15]
[1] p-value	0.116	0.288	0.000	0.000	0.573	0.002
[2] p-value	0.161	0.319	0.000	0.000	0.812	0.007
Election Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1136	1136	1136	1136	1136	1136
Bandwidth Obs.	409	319	223	295	435	519
Mean	0.140	0.280	0.085	0.130	0.008	0.016
Bandwidth	32.6	25.5	19.8	22.4	34.0	39.1
(Local) Polynomial Order	2	2	2	2	2	2

Note: This table reports local linear estimates of the average treatment effects on voting behavior around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth. Panel A presents the main results on voting behavior using linear polynomials and controlling for the logarithm of potential voters registered at the poll. Panel B presents the estimates of the main results on voting behavior using quadratic polynomials. Columns 1 and 2 show the estimates using the vote share for the incumbent over the registered and actual voters, respectively. Columns 3 and 4 use the share of left-wing party voters over registered and actual voters, while columns 5 and 6 use the share of voters for paramilitary-related parties over registered and actual voters. We provide 95% robust confidence intervals and robust p-values, following Calonico et al. (2014). The p-value in [1] is based on robust standard errors clustered at the running variable level, as suggested by Lee and Card (2008), while [2] uses standard errors clustered at the municipality level. Bandwidth obs. indicates the number of observations in the optimal MSE bandwidth. All estimations are weighted by the number of potential voters in the poll and include election fixed effects. *** p¡0.01, ** p¡0.05, * p¡0.1.

Table A10. The effect of Explosions on Voting Behavior: Sub-sample of Candidates Running

Dep. Variable:	Incumbent Votes Over		Left-wing Votes Over		Paramilitary Votes Over	
	Potential	Votes	Potential	Votes	Potential	Votes
	(1)	(2)	(3)	(4)	(5)	(6)
A. No Controlling for Potential of Voters						
Explosion Before	-0.028	-0.032	-0.205***	-0.291***	0.041	0.146***
Robust p-value	0.121	0.400	0.000	0.005	0.176	0.008
CI 95%	[-0.09, 0.01]	[-0.13, 0.05]	[-0.30, -0.11]	[-0.52, -0.09]	[-0.02, 0.09]	[0.04, 0.26]
[1] p-value	0.191	0.406	0.000	0.000	0.189	0.002
[2] p-value	0.263	0.431	0.000	0.000	0.165	0.012
Bandwidth Obs.	278	253	109	142	129	106
Mean	0.148	0.180	0.090	0.160	0.022	0.036
Bandwidth	21.8	20.9	12.0	13.4	23.2	18.4
B. Controlling for Potential of Voters						
Explosion Before	-0.012	-0.018	-0.203***	-0.298**	0.041	0.139***
Robust p-value	0.693	0.784	0.000	0.013	0.163	0.009
CI 95%	[-0.10, 0.07]	[-0.14, 0.10]	[-0.28, -0.13]	[-0.52, -0.06]	[-0.02, 0.09]	[0.04, 0.25]
[1] p-value	0.430	0.480	0.000	0.000	0.173	0.002
[2] p-value	0.475	0.676	0.000	0.000	0.162	0.013
Observations	1136	1136	1010	1010	441	441
Bandwidth Obs.	323	295	109	125	129	106
Mean	0.135	0.288	0.090	0.174	0.022	0.036
Bandwidth	26.9	22.3	11.0	12.2	23.6	18.3
(Local) Polynomial Order	1	1	1	1	1	1

Note: This table reports local linear estimates of the average treatment effects on voting behavior around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth. Panel A presents the main results on voting behavior using linear polynomials without controlling for potential voters registered at the poll. Panel B presents the estimates of the main results on voting behavior using linear polynomials controlling for the potential of voters registered at the poll. Columns 1 and 2 show the estimates using the vote share for the incumbent over the registered and actual voters, respectively. Columns 3 and 4 use the share of left-wing party voters over registered and actual voters, while columns 5 and 6 use the share of voters for paramilitary-related parties over registered and actual voters. We provide 95% robust confidence intervals and robust p-values, following Calonico et al. (2014). The p-value in [1] is based on robust standard errors clustered at the running variable level, as suggested by Lee and Card (2008), while [2] uses standard errors clustered at the municipality level. Bandwidth obs. indicates the number of observations in the optimal MSE bandwidth. All estimations include election fixed effects. *** p¡0.01, ** p¡0.05, * p¡0.1.

Table A11. The Effect of Explosions on Voting Behavior: Additional Party Breakdowns

Dep. Variable:	Right-wing Votes Over		Non-paras Right Votes Over		Center Votes Over		Non-paras Center Votes Over		Blank Votes Over	
	Potential	Votes	Potential	Votes	Potential	Votes	Potential	Votes	Potential	Votes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Explosion Before	0.022***	0.086***	0.003	0.009	0.025	0.038**	-0.000	0.231***	-0.001	-0.002
Robust p-value	0.001	0.000	0.812	0.621	0.100	0.047	0.981	0.001	0.974	0.717
CI 95%	[0.01, 0.05]	[0.05, 0.15]	[-0.01, 0.01]	[-0.02, 0.04]	[-0.00, 0.05]	[0.00, 0.07]	[-0.09, 0.09]	[0.11, 0.45]	[-0.01, 0.01]	[-0.02, 0.02]
[1] p-value	0.020	0.000	0.782	0.488	0.125	0.092	0.306	0.000	0.904	0.543
[1] p-value	0.021	0.000	0.518	0.314	0.188	0.112	0.435	0.000	0.988	0.489
Election Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1136	1136	1136	1136	1136	1136	1136	1136	1136	1136
Bandwidth Obs.	278	253	214	184	409	375	184	138	302	339
Mean	0.025	0.057	0.015	0.029	0.008	0.010	0.191	0.358	0.024	0.037
Bandwidth	21.1	20.5	17.4	15.9	32.8	30.9	15.8	12.5	23.7	28.7
(Local) Polynomial Order	1	1	1	1	1	1	1	1	1	1

Note: This table presents the local linear estimates of the average treatment effects around the cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico et al. (2014). [1] p-value is the robust p-value based on standard errors clustered at the running variable level as suggested by Lee and Card (2008), while [2] p-value is based on standard errors clustered at the municipality level. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. All estimations are weighted by the potential voters of the poll and include election fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table A12. Explosions, electoral participation, and other conflict exposure measures

Dep. Variable:	Voted last election			
Sample:	Full		Conflict affected	
	(1)	(2)	(3)	(4)
Panel A				
Forced Recruitment	0.023	0.023	0.020	0.017
	(0.014)	(0.014)	(0.017)	(0.017)
Panel B				
Land Dispossession	0.010	0.011	0.004	-0.003
	(0.013)	(0.013)	(0.016)	(0.016)
Panel C				
Stigmatization	0.000	0.000	-0.010	-0.005
	(0.016)	(0.016)	(0.018)	(0.019)
Panel D				
Forced Displacement	0.011	0.014	0.009	0.008
	(0.009)	(0.009)	(0.017)	(0.000)
Observations	16,379	16,379	1,273	1,273
Controls	No	Yes	No	Yes
Mean dep variable	0.772	0.772	0.788	0.788

Note: This table presents the correlation between respondents who reported being exposed to different forms of victimization before and their voting behavior in the previous election, utilizing data from the ECP-DANE 2017 and 2021 waves. The even columns adjust for individual characteristics, such as gender, age, household utilities, and education level indicators. The sub-sample of conflict-affected respondents includes responses from victims of displacement, forced recruitment, dispossession, stigmatization, and killings. All columns are controlled for region fixed effects, and robust standard errors are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A13. Cumulative Humanitarian Demining and Turnout

Dep. Variable:	Turnout					
Sample:	All Grids		Exposed to Landmines		With In-land Landmines	
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Demining Events	0.007***	0.004***	0.003**	0.005***	0.004**	0.005***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	380,880	379,500	8,260	7,940	7,210	6,980
R-squared (Panel A)	0.590	0.713	0.622	0.716	0.622	0.717
Grid Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-year Fixed Effect	No	Yes	No	Yes	No	Yes
Mean Dep. Variable	0.608	0.607	0.566	0.563	0.566	0.561

Note: This table presents the correlation between humanitarian demining events and turnout. All coefficients in odd columns come from the equation $Turnout_{gmt} = \alpha_g + \gamma_t + \beta \times CumulativeDemining_{gmt} + \epsilon_{gmt}$, where g is a grid of 5x5Km, in the municipality m, and t is the electoral year taking value from 2010 to 2019. $Turnout_{gmt}$ is the total votes over potential voters, averaged for all polling stations in the tile g in electoral year t. $CumulativeDemining_{gmt}$ is the total number of humanitarian demining events in the tile g in the electoral year t. All coefficients in even columns come from the same equation including municipality-year fixed effects. Columns 1 and 2 include the tiles for the whole country, columns 3 and 4 include only the tiles that have been exposed to at least one event of humanitarian demine between 2010 and 2019, and columns 5 and 6 include only the tiles with the presence of landmines. Clustered standard errors at the tile level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A14. Cumulative Humanitarian Demining and Voting

Dep. Variable:	Incumbent Votes			Left-wing Votes			Paramilitary Votes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cumulative Demining Events	0.181**	0.210**	0.194**	0.082**	0.100**	0.099**	-0.002	0.001	0.001
	(0.077)	(0.088)	(0.088)	(0.032)	(0.040)	(0.040)	(0.003)	(0.005)	(0.005)
Observations	379,500	7,940	7,000	379,500	7,940	7,000	379,500	7,940	7,000
R-squared	0.548	0.560	0.555	0.493	0.560	0.570	0.403	0.382	0.393
Grid fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Variable	18.07	15.64	15.81	7.163	8.448	8.647	1.407	0.804	0.829

Note: This table presents the correlation between humanitarian demining events and voting. Outcomes averaged for all polling stations in the tile-year. Cumulative demining is the total number of humanitarian demining events in the tile-year. All coefficients in even columns come from the same equation including municipality-year fixed effects. Columns 1, 4, and 7 include the tiles for the whole country, columns 2, 4, and 8 include only the tiles that have been exposed exposed to at least one event of humanitarian demine between 2010 and 2019, and columns 3, 6, 9 include only the tiles with the presence of landmines. Clustered standard errors at the tile level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A15. Homicides After Landmine Explosions

Dep. Variable:	Homicides											
Sample:	Full sample			Bandwidth sample			Full sample			Bandwidth sample		
	Total	Dummy	Log	Total	Dummy	Log	Total	Dummy	Log	Total	Dummy	Log
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Two-way Fixed Effect												
Post Explosion	0.002	-0.019	-0.006	0.007	-0.014	-0.002	0.010	0.000	0.004	0.008	0.000	0.003
	(0.025)	(0.014)	(0.013)	(0.024)	(0.013)	(0.012)	(0.011)	(0.006)	(0.006)	(0.010)	(0.006)	(0.005)
B. De Chaisemartin and d'Haultfoeuille (2020)												
Post Explosion	-0.013	-0.030	-0.015	-0.000	-0.017	-0.006	0.005	-0.003	0.001	0.007	-0.000	0.002
	(0.025)	(0.023)	(0.016)	(0.018)	(0.012)	(0.010)	(0.013)	(0.008)	(0.007)	(0.011)	(0.008)	(0.007)
Observations	2961	2961	2961	2961	2961	2961	7967	7967	7967	7967	7967	7967
Mean Dep. Var.	0.025	0.022	0.016	0.025	0.021	0.016	0.012	0.011	0.008	0.012	0.010	0.008
Treated	110	110	110	110	110	110	318	318	318	318	318	318
Never Treated	434	434	434	434	434	434	1148	1148	1148	1148	1148	1148

Notes: This table presents the overall ATT using two staggered difference-in-differences models for the effect of landmine explosions on pre-election homicides. In columns 1 to 6, the number of homicides were computed 4km around the voting polls in our sample, while in columns 7 to 12, they were computed 8km around the voting polls in our sample. In Panel A, we present the two-way fixed effect model. In Panel B, we present the model suggested by De Chaisemartin and d'Haultfoeuille (2020) computing the ATT 2 weeks after the treatment. Following De Chaisemartin and d'Haultfoeuille (2020), we find that the share of ATTs that enter in the weighted sum as negative is 0%. Standard errors are clustered at the voting poll level. *** p<0.01, ** p<0.05, * p<0.1.

Table A16. Explosions, Voting Behavior, and Access to Voting Polls

Dep. Variable:	Turnout	Incumbent Votes Over		Left-wing Votes Over		Paramilitary Votes Over	
		Potential	Votes	Potential	Votes	Potential	Votes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Excludes directly connected explosions up to 50 meters from the road							
Explosion Before	-0.282***	-0.038*	-0.004	-0.219***	-0.315***	0.028**	0.089***
Robust p-value	0.000	0.057	0.632	0.000	0.002	0.037	0.000
CI 95%	[-0.415, -0.191]	[-0.104, 0.002]	[-0.128, 0.078]	[-0.327, -0.126]	[-0.560, -0.120]	[0.002, 0.056]	[0.049, 0.150]
Observations	1128	1128	1128	1128	1128	1128	1128
Bandwidth Obs.	213	222	183	121	138	406	325
Mean	0.60	0.099	0.211	0.089	0.173	0.010	0.014
Bandwidth	17.8	19.3	15.0	11.2	12.4	32.2	27.0
B. Excludes directly connected explosions up to 100 meters from the road							
Explosion Before	-0.282***	-0.038*	-0.005	-0.218***	-0.313***	0.028**	0.089***
Robust p-value	0.000	0.057	0.625	0.000	0.002	0.038	0.000
CI 95%	[-0.416, -0.192]	[-0.104, 0.002]	[-0.128, 0.077]	[-0.327, -0.126]	[-0.557, -0.119]	[0.002, 0.056]	[0.049, 0.150]
Observations	1106	1106	1106	1106	1106	1106	1106
Bandwidth Obs.	212	221	182	120	137	403	322
Mean	0.60	0.099	0.211	0.089	0.173	0.010	0.014
Bandwidth	17.5	19.3	15.1	11.2	12.5	32.2	27.2
C. Excludes all explosions up to 50 meters from the road							
Explosion Before	-0.278***	-0.042**	-0.044	-0.217***	-0.309***	0.037***	0.120***
Robust p-value	0.000	0.038	0.314	0.000	0.002	0.002	0.000
CI 95%	[-0.414, -0.184]	[-0.111, -0.003]	[-0.136, 0.044]	[-0.334, -0.136]	[-0.562, -0.121]	[0.014, 0.066]	[0.078, 0.177]
Observations	1046	1046	1046	1046	1046	1046	1046
Bandwidth Obs.	193	273	256	115	126	348	256
Mean	0.60	0.156	0.323	0.089	0.173	0.007	0.015
Bandwidth	17.5	22.3	21.8	11.7	12.4	30.8	21.2
D. Excludes all explosions up to 100 meters from the road							
Explosion Before	-0.264***	-0.046**	-0.039	-0.215***	-0.286***	0.042***	0.126***
Robust p-value	0.000	0.025	0.401	0.000	0.005	0.001	0.000
CI 95%	[-0.406, -0.169]	[-0.118, -0.008]	[-0.132, 0.053]	[-0.332, -0.133]	[-0.536, -0.094]	[0.018, 0.073]	[0.082, 0.188]
Election Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1028	1028	1028	1028	1028	1028	1028
Bandwidth Obs.	178	247	264	112	120	339	222
Mean	0.56	0.156	0.323	0.089	0.173	0.007	0.020
Bandwidth	16.4	21.2	22.0	11.8	12.5	30.0	20.9

Note: This table presents the local linear estimates of the average treatment effects around the cut-off estimated with triangular kernel weights and optimal MSE bandwidth. All columns exclude the explosions that are directly related to a voting poll through a road in our sample. Panels A and B exclude blasts directly connected to the voting polling by a road. Panels C and D exclude all explosions near a major road. Robust p-values are presented, and computed following Calonico et al. (2014). Standard errors are clustered at the municipality level. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. All columns use linear polynomials to estimate the average treatment effects, and include election fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A17. Explosions and Trust

Dep. Variable:	Trust in					
	Mayor		Governor		Mayor and Governor	
	Total	Dummy	Total	Dummy	Total	Dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Explosions Before	0.003	0.008	0.042*	0.007	0.024	0.001
	(0.022)	(0.011)	(0.023)	(0.011)	(0.021)	(0.012)
Observations	11,631	11,335	11,631	11,631	11,631	11,631
Mean dep variable	-0.0550	0.245	-0.0478	0.258	-0.0545	0.299
R-squared	0.017	0.013	0.016	0.016	0.019	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the correlation between respondents who reported being exposed to at least one landmine explosion before and trust in elected local government entities, utilizing data from the ECP-DANE 2017 and 2021 waves. The odd-numbered columns represent the standardized values of the continuous trust variable. Even-numbered columns indicate if the corresponding trust variable value is above the median of the empirical distribution. All columns adjust for individual characteristics, such as gender, age, household utilities, and education level indicators. The sample includes only responses from conflict-affected individuals, including victims of displacement, forced recruitment, dispossession, stigmatization, and killings. All columns are controlled for region fixed effects, and robust standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A18. Mobility After Landmine Explosions

Dep. Variable:	Mobility Index				
Sample:	Two-way Fixed Effect			De Chaisenmartin and d'Haultfoeuille (2020)	
	0-8 Weeks	0-4 Weeks	5-8 Weeks	0-8 Weeks	0-4 Weeks
	(1)	(2)	(3)	(4)	(5)
A. All Tiles					
Post Explosion	-0.351**	-0.486***	-0.344	-0.370	-0.433*
	(0.176)	(0.150)	(0.222)	(0.287)	(0.241)
B. Conflict-affected Tiles					
Post Explosion	-0.355**	-0.446***	-0.356	-0.348	-0.374*
	(0.177)	(0.150)	(0.229)	(0.214)	(0.206)
Observations (Panel A)	2220696	2220696	2220696	2220696	2220696
Observations (Panel B)	39569	39569	39569	39569	39569
Mean Dep. Var. (Panel A)	0.139	0.139	0.139	0.139	0.139
Mean Dep. Var. (Panel B)	0.151	0.151	0.151	0.151	0.151
Treated	41	41	41	41	41
Never Treated (Panel A)	55206	55206	55206	55206	55206
Never Treated (Panel B)	879	879	879	879	879

Notes: This table presents the overall ATT using different staggered difference-in-differences models for the effect of landmine explosions on mobility. The mobility was computed using Facebook population density maps at the tile level. In columns 1 to 3, we present the two-way fixed effect model, while in columns 4 and 5, we present the model suggested by De Chaisemartin and d'Haultfoeuille (2020) computing the ATT for the number of weeks after the treatment. Panel A presents the results for all tiles with mobility measure in the country, while panel B restricts the sample to those that were in the surrounding of previously demined areas or areas that are still in danger of explosion. Standard errors are clustered at the tile level. *** p<0.01, ** p<0.05, * p<0.1.

Table A19. Heterogeneous Effects by Victim's Characteristics and Type of Election

Dep. Variable:	Turnout				
Z:	Female	Civilian	Dead	Under 18	Local Election
	(1)	(2)	(3)	(4)	(5)
Explosion before × Z	-0.088	0.076	-0.151	-0.005	-0.133
	(0.090)	(0.067)	(0.095)	(0.163)	(0.085)
Explosion before	-0.216***	-0.277***	-0.217***	-0.211***	-0.227***
	(0.067)	(0.077)	(0.062)	(0.061)	(0.061)
Z	-0.007	-0.058	0.138	-0.094	
	(0.064)	(0.056)	(0.087)	(0.151)	
Observations	396	396	396	396	396
Mean dep. variable	0.592	0.592	0.592	0.592	0.592

Note: This table presents the OLS regression around the cut-off estimated with triangular kernel weights and election fixed effects, and within the optimal MSE bandwidth. The optimal bandwidth comes from column 1 of Table 2. In columns 1 to 5, we interact our treatment variable with the pre-treatment characteristic Z specified in the heading of the columns. Female is a dummy that takes the value one if at least one victim of the explosion was a female (column 1). Civilian is a dummy that takes the value one if at least one victim of the explosion was a civilian (column 2). Dead is a dummy that takes the value one if at least one victim of the explosion was a killed (column 3). Under 18 is a dummy that takes the value one if at least one victim of the explosion was under 18 (column 4). Local election is a dummy that takes the value one if the election is for mayors (column 3). Robust standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A20. Explosions and Electoral Participation by Voter's Ideology

	Survey: Full Voted last election		Survey: Conflict-affected Voted last election		RDD Turnout
	(1)	(2)	(3)	(4)	(5)
Explosions Before × Left Wing	0.005	0.005	0.006	-0.001	0.018
	(0.018)	(0.018)	(0.021)	(0.021)	(0.086)
Explosions Before	-0.055***	-0.051***	-0.047*	-0.052**	-0.283***
	(0.020)	(0.020)	(0.024)	(0.024)	(0.056)
Left Wing	-0.034***	-0.029***	-0.034***	-0.022*	-0.037
	(0.003)	(0.003)	(0.011)	(0.011)	(0.075)
Observations	13,178	13,155	1,480	1,478	204
Mean Dep. Variable	0.804	0.804	0.787	0.787	0.580
R-squared	0.008	0.045	0.010	0.070	
Controls	No	Yes	No	Yes	

Note: This table presents estimates of explosions during last year on voting report interacted with left-wing ideology. The outcome coded as dummy variable. Even columns control for individual characteristics, such as gender, age, and indicators for education level. The sample of conflict-affected people includes responses from victims of displacement, forced recruitment, dispossession, stigmatization and killings. All columns control for region fixed effects. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A21. Robustness Estimates of The Effects on Turnout and Voting Behavior

	Unweighted	Uniform Kernel	Polls with Only One Explosion	One Explosion per Poll	Excluding 5km	Controls 10km	LASSO	Topographic Distance	Optimized RD	Local Randomization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Dep. Variable - Turnout										
Explosion Before	-0.282***	-0.125***	-0.272***	-0.149***	-0.206***	-0.191***	-0.147***	-0.179***	-0.233***	-0.224***
Robust p-value	0.000	0.010	0.000	0.000	0.000	0.001	0.001	0.000	[-0.186, -0.280]	0.000
B. Dep. Variable - Incumbent										
Explosion Before	-0.036*	-0.053	-0.050**	-0.020	-0.034*	-0.032*	-0.038**	-0.044**	-0.004	-0.040***
Robust p-value	0.063	0.108	0.012	0.323	0.069	0.058	0.044	0.027	[0.016, -0.024]	0.008
C. Dep. Variable - Left										
Explosion Before	-0.090***	-0.215***	-0.176***	-0.219***	-0.201***	-0.208***	-0.206***	-0.225***	-0.059**	-0.182***
Robust p-value	0.002	0.000	0.001	0.000	0.000	0.000	0.000	0.000	[-0.034, -0.084]	0.000
D. Dep. Variable - Paramilitaries										
Explosion Before	0.014	0.028*	0.010	0.024	0.036*	0.039**	0.027*	0.012	0.007	0.009
Robust p-value	0.385	0.074	0.963	0.138	0.081	0.037	0.074	0.408	[0.024, -0.010]	0.152
Bandwidth (Panel A)	16.8	23.6	20.0	30.8	16.4	19.6	27.2	30.4		32.0
Bandwidth Obs. (Panel A)	204	302	153	338	161	166	327	332		396
Bandwidth (Panel B)	33.3	18.7	20.0	26.3	20.2	17.5	20.7	20.5		21.8
Bandwidth Obs. (Panel B)	426	221	134	295	192	157	253	220		278
Bandwidth (Panel C)	28.0	9.7	12.7	11.7	12.6	12.9	11.3	11.4		11.4
Bandwidth Obs. (Panel C)	327	105	68	110	110	103	121	107		121
Bandwidth (Panel D)	20.3	22.4	29.3	31.3	20.9	23.0	31.3	32.2		32.4
Bandwidth Obs. (Panel D)	253	295	222	359	192	225	396	365		409
Observations (Panel A)	1136	1136	654	870	957	919	1136	983	366	1136

Note: This table presents different robustness exercises for turnout (Panel A) and the total votes for the incumbents, left, and paramilitaries-related parties over the number of potential voters (Panels B, C, and D, respectively). Column 1 presents the unweighted local estimates of the average treatment effects. Column 2 presents the estimates around the cut-off estimated with uniform kernel weights. Column 3 presents the estimates of the average treatment effects using polls with only one explosion in a 60-days window. Column 4 takes only the closest explosion to the poll to estimate the average treatment effect. Column 5 and 6 exclude from the control polls those that were inside a buffer of 5 and 10 kilometers of an explosion that affected a treated poll in the year t and election j. Column 7 includes the number of OAG demobilized combatants in $t-1$ as a lasso selected control following Belloni et al. (2014). In column 8, we computed the results weighting the distance criteria with terrain elevation. Column 9 presents the results of the average treatment effect and the 95% confidence intervals following the optimized RD estimator suggested by Imbens and Wager (2019), using a curvature of 0.0004 and explosions in a window of 30 days. Finally, column 10 presents the local randomization approach as suggested by Cattaneo et al. (2020), within a bandwidth of 20 days, and present the p-values based on randomization inference. In columns 1 to 8, 95% robust confidence intervals and robust p-values are computed following Calonico et al. (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Columns 1 to 10, excluding column 2 and 9, use triangular kernel. All columns include election fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table A22. Robustness Estimates for Main Outcomes: Over Votes

	Unweighted	Uniform Kernel	Polls with Only One Explosion	One Explosion per Poll	Excluding 5km	Controls 10km	LASSO	Topographic Distance	Optimized RD	Local Randomization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Dep. Variable - Incumbent										
Explosion Before	-0.031	-0.066	-0.005	-0.022	-0.017	-0.014	-0.046	-0.031	0.003	-0.035
Robust p-value	0.685	0.276	0.820	0.582	0.420	0.461	0.208	0.222	[0.040, -0.034]	0.190
B. Dep. Variable - Left										
Explosion Before	-0.220***	-0.329***	-0.196	-0.317***	-0.332***	-0.334***	-0.292***	-0.325***	-0.027	-0.253***
Robust p-value	0.002	0.002	0.164	0.002	0.001	0.001	0.002	0.002	[0.017, -0.071]	0.000
C. Dep. Variable - Paramilitaries										
Explosion Before	0.093***	0.073***	0.047	0.077***	0.097***	0.092***	0.084***	0.067***	0.067	0.076***
Robust p-value	0.000	0.006	0.178	0.000	0.000	0.000	0.000	0.005	[0.089, 0.045]	0.000
Bandwidth (Panel A)	22.7	19.1	20.9	23.7	15.4	18.7	20.2	18.1		20.9
Bandwidth Obs. (Panel A)	295	223	153	275	145	164	253	194		253
Bandwidth (Panel B)	13.7	10.9	13.5	13.0	13.1	13.6	12.6	13.4		12.7
Bandwidth Obs. (Panel B)	157	107	86	137	128	121	138	137		138
Bandwidth (Panel C)	26.3	19.9	25.2	24.6	19.4	20.5	28.1	26.7		26.9
Bandwidth Obs. (Panel C)	323	223	184	288	178	180	340	285		323
Observations (Panel A)	1136	1136	654	870	957	919	1136	983	366	1136

Note: This table presents different robustness exercises for the vote share of incumbents, left and paramilitaries-related parties *over* the number of actual voters (Panels A, B and C, respectively). Column 1 presents the unweighted local estimates of the average treatment effects. Column 2 present the estimates around the cut-off estimated with uniform kernel weights. Column 3 the estimates of the average treatment effects using polls with only one explosion. Column 4 take only the closest explosion to the poll to estimate the average treatment effect. Column 5 and 6 exclude from the control polls those that were inside a buffer of 5 and 10 kilometers of an explosion that affected a treated poll in the year t and election j. Column 7 includes the number of OAG demobilized combatants in $t-1$ as a lasso selected control following Belloni et al. (2014). In column 8, we computed the results weighting the distance criteria with terrain elevation. Column 9 presents the results of the average treatment effect and the 95% confidence intervals following the optimized RD estimator suggested by Imbens and Wager (2019), using a curvature of 0.0004 and explosions in a window of 30 days. Finally, column 10 presents the local randomization approach as suggested by Cattaneo et al. (2020), within a bandwidth of 20 days, and present the p-values based on randomization inference. In columns 1 to 8, 95% robust confidence intervals and robust p-values are computed following Calonico et al. (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Columns 1 to 10, excluding column 2 and 9, use triangular kernel. All columns include election fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table A23. Robustness Estimates for Main Outcomes: Quadratic Polynomial

	Unweighted	Uniform Kernel	Polls with Only One Explosion	One Explosion per Poll	Excluding 5km	Controls 10km	LASSO	Topographic Distance	Local Randomization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Dep. Variable - Turnout									
Explosion Before	-0.339***	-0.322***	-0.376***	-0.352***	-0.289***	-0.312***	-0.377***	-0.409***	-0.310***
Robust p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B. Dep. Variable - Incumbent									
Explosion Before	-0.049**	-0.076**	-0.054**	-0.058**	-0.032	-0.056*	-0.057**	-0.069***	-0.032**
Robust p-value	0.028	0.042	0.035	0.047	0.246	0.070	0.042	0.008	0.012
C. Dep. Variable - Left									
Explosion Before	-0.178***	-0.257***	-0.183***	-0.233***	-0.210***	-0.201***	-0.226***	-0.229***	-0.197***
Robust p-value	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000
D. Dep. Variable - Paramilitaries									
Explosion Before	0.008	0.021	-0.008	0.008	0.030	0.022	0.009	-0.017	0.012*
Robust p-value	0.613	0.337	0.446	0.964	0.327	0.537	0.933	0.221	0.052
Bandwidth (Panel A)	28.2	24.2	21.6	20.5	27.6	23.3	19.1	19.4	19.6
Bandwidth Obs. (Panel A)	340	315	160	226	257	225	223	196	223
Bandwidth (Panel B)	25.0	25.7	31.2	26.7	36.1	21.7	30.9	24.9	32.6
Bandwidth Obs. (Panel B)	315	319	244	295	377	201	375	279	409
Bandwidth (Panel C)	21.4	17.6	20.9	20.3	20.5	21.0	19.8	20.6	19.8
Bandwidth Obs. (Panel C)	278	214	153	226	192	180	223	220	223
Bandwidth (Panel D)	36.0	30.3	28.1	30.8	28.3	28.0	30.4	24.8	34.0
Bandwidth Obs. (Panel D)	469	375	200	338	270	245	375	279	435
Observations (Panel A)	1136	1136	654	870	957	919	1136	983	1136

Note: This table presents different robustness exercises for turnout the vote share of incumbents, left and paramilitaries-related parties *over* the number of potential voters (Panels B, C and D, respectively) using a quadratic polynomial. Column 1 presents the unweighted local estimates of the average treatment effects. Column 2 present the estimates around the cut-off estimated with uniform kernel weights. Column 3 the estimates of the average treatment effects using polls with only one explosion. Column 4 take only the closest explosion to the poll to estimate the average treatment effect. Column 5 and 6 exclude from the control polls those that were inside a buffer of 5 and 10 kilometers of an explosion that affected a treated poll in the year t and election j. Column 7 includes the number of OAG demobilized combatants in $t-1$ as a lasso selected control following Belloni et al. (2014). In column 8, we computed the results weighting the distance criteria with terrain elevation. Finally, column 9 presents the local randomization approach as suggested by Cattaneo et al. (2020), within a bandwidth of 20 days, and present the p-values based on randomization inference. In columns 1 to 8, 95% robust confidence intervals and robust p-values are computed following Calonico et al. (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Columns 1 to 10, excluding column 2 and 9, use triangular kernel. All columns include election fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table A24. Explosions, Voting Behavior, and Rainfall

Dep. Variable:	Turnout	Incumbent Votes Over		Left-wing Votes Over		Paramilitary Votes Over	
		Potential	Votes	Potential	Votes	Potential	Votes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Explosion before	-0.207***	-0.039*	-0.038	-0.220***	-0.309***	0.033**	0.094***
Robust p-value	0.000	0.066	0.340	0.000	0.003	0.042	0.000
CI 95%	[-0.359, -0.130]	[-0.111, 0.004]	[-0.142, 0.049]	[-0.339, -0.135]	[-0.563, -0.116]	[0.001, 0.061]	[0.046, 0.155]
[1] p-value	0.000	0.087	0.258	0.000	0.000	0.086	0.002
[2] p-value	0.001	0.117	0.292	0.000	0.000	0.136	0.003
Election fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	993	993	993	993	993	993	993
Bandwidth obs.	251	262	262	107	124	341	287
Mean	0.57	0.135	0.279	0.089	0.173	0.009	0.012
Bandwidth	21.1	24.0	23.1	11.4	12.9	31.3	27.2

Note: This table presents the local linear estimates of the average treatment effects around the cut-off estimated with triangular kernel weights and optimal MSE bandwidth. Robust p-values are presented, and computed following Calonico et al. (2014). Standard errors are clustered at the municipality level. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. All columns control for mean rainfall inside bandwidth, use linear polynomials to estimate the average treatment effects, and include election fixed effects. *** p<0.01, ** p<0.05, * p<0.1.