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# Fear to Vote: Explosions, Salience, and Elections

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**Abstract**
Criminal groups use violence strategically to manipulate the behavior of victims and bystanders. At the same time, violence is a stimulus that causes fear, which also shapes people's reactions. Taking advantage of the randomness in the timing of antipersonnell and mine accidents in Colombia, as well as their coordinates relative to those of voting polls, we identify the effect of violence-induced fear (independent from intentions) on electoral behavior. Fortuitous landmine explosions reduce political participation. We further disentangle whether the type of fear caused

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by landmine explosions responds to an information channel (whereby people learn about the risk of future victimization) or by the salience of the explosion(which causes individuals to make impulsive decisions, driven by survival considerations), and show evidence in favor of the latter. While the turnout reduction takes place across the ideological spectrum, we document that the explosions induce a shift in the political preferences of individuals who do vote. These findings point to worrisome potential consequences for the consolidation of democracies in places affected by conflict.

# 1 Introduction

Criminal organizations recurrently resort to violence to achieve specific goals. The strategic use of violence is manifest in how criminals meticulously select targets and calibrate the timing, type, and intensity of attacks. However, irrespective of the intentions of sophisticated perpetrators, violence also generates emotions among victims and bystanders, such as fear, thus making people act in ways consistent with survival considerations. This implies that accounts of the effects of strategically-inflicted violence likely confound two mechanisms: strategic intentions and fear-driven responses. This paper aims to separate these two channels and identify the effects of fear, net from those caused by the strategic use of violence. We focus on electoral violence, a phenomenon that is pervasive in both developing and developed countries.[1]

We disentangle the electoral effects of violence-driven fear by exploiting quasi-random variation in violence, for which we leverage geo-located administrative data on all anti-personnel landmine explosions as well as novel information on the coordinates of all voting polls in Colombia.[2] We compare the voting patterns of voting polls located close to where a landmine exploded just before an election, to those of polls near where a landmine blast occurred shortly afterward. While the deployment of landmines is clearly strategic (e.g., to protect the land from rivals), the *timing* of their explosion is fortuitous: landmines cannot be activated at will. Instead, they are triggered by contact or proximity of a person, an animal, or a vehicle. In fact, landmine explosions are technically referred to as landmine 'accidents'. Thus, by comparing two areas with (endogenous) landmine presence but relying on the precise timing of the explosion relative to the (exogenous) election day, we can isolate the electoral effects of unintended exposure to violence. This teases out the fear mechanism.

We find that antipersonnel landmines that go off in the vicinity of voting polls within a month prior to the elections have a large negative impact on political participation, relative to explosions that occur close to polls within a month afterward. Specifically, they depress turnout by at least 13 percentage points, 23 percent relative to the mean.

Our Regression Discontinuity Design (RDD) stands on a number of assumptions that we explicitly state and test to the extent possible. First, we need no manipulation of the timing of landmine accidents. Specifically, we would be concerned if there were more explosions

[1] Electoral violence is the kind that political actors inflict before, during, or after elections to shape the electoral process or its outcomes. Over 100 countries are at risk of electoral violence, and about 80 witnessed substantial levels during the period 1995-2013 (Daxecker et al., 2019; Birch and Muchlinski, 2020).

[2] Anti-personnel landmines are illegal explosives buried under the surface. The circa 110 million landmines located today in 60 countries, cause about 26,000 victims per year and threat the lives of millions (see `https://rb.gy/fpyk05`). A recent example of this tragedy is the Ukraine war, where Russian troops have left behind substantial amounts of illegal underground explosives (see, e.g. `https://rb.gy/ujkcar` and `https://rb.gy/nklsel`).

before elections than afterward. This assumption is crucial for our argument about the fortuity of the timing of landmine explosions, and we demonstrate that the distribution of blasts across days leading to an election does not differ statistically from the distributions of explosions across days after it. Second, we need to ensure that explosions before elections do not occur closer to the voting poll than explosions after elections. Reassuringly, we find that the distance-to-poll distribution of landmine accidents prior to the election day is not statistically different from that observed after elections. Third, even if the timing of a landmine explosion is accidental (and thus as good as random), it may still be the case that landmines are *placed* differentially in the vicinity of an electoral poll before an election relative to thereafter. Testing this assumption is challenging as the location of buried landmines is largely unknown. However, using the recent ceasefire declared by one of the main landmine users in Colombia (the Revolutionary Armed Forces of Colombia, FARC from the Spanish acronym), we provide suggestive empirical evidence about its validity.[3] Finally, we show that a large number of poll-level and (more aggregated) municipal-level characteristics are balanced around the (election day) cut-off. Importantly, these include all the pre-explosion outcomes as well as various measures of violence (such as geo-located homicides) and territorial contestation.

Once we establish that the fear induced by explosions (above and beyond the strategic goals of perpetrators) increases the costs of voting and reduces political participation, we face a second challenge. There are two key reasons why landmine explosions may cause fear, and they manifest in different types of behavioral responses. On the one hand, the explosions may convey *information* that other landmines (and the armed groups that placed them) are likely close by, representing additional risks. In this case, such risks may translate into fear (about future victimization) and generate conscious responses to avoid it. Hence, if landmine explosions occur prior to an election and in the proximity of a voting poll, this would decrease turnout. One implication of the information channel is that if landmine explosions are recurrent, the *additional* information gathered from a new explosion is marginal, and thus behavioral responses should be smaller. A second implication is that, to the extent that the perceived risk of victimization is present, the electoral effects of an explosion should be long-lasting.

On the other hand, due to their prominence, contrast with surroundings, and often (but not necessarily) surprising nature, landmine explosions are *salient* stimuli (Bordalo et al., 2022b). Indeed, the unpredictability in the timing of landmine explosions, together with their capacity to produce damage, kill, or injuries, makes them salient. Salience, in turn, shifts people's attention 'bottom-up' (i.e., automatically and involuntarily) and distorts behavior in the

[3]In addition, in section 2, we discuss how landmines are seldom used to disrupt elections relative to other, more direct, strategies commonly utilized by criminal organizations.

short-run relative to current goals and expectations. In our context, landmine explosions, make people prioritize short-term survival considerations in decision-making, thus reducing turnout. In this sense, landmine explosions resemble terror attacks. The widespread fear produced by such salient events shapes short-run people's behavior in a range of daily activities, including voting.[4]

We separate salience from information by showing that our estimated effects are both short-lived (which is consistent with the short-term distortion of salience) and unchanged after controlling either for the history of explosions in the affected area (i.e., the bulk of prior information) or for the underlying risk of future explosions. Moreover, the baseline effects are not heterogeneous based on either of these two variables. This implies that the electoral effects of landmine explosions are largely explained by salience and not information.

Several other pieces of evidence are coherent with this interpretation. First, we leverage grid-level Facebook mobility data and show that landmine explosions trigger an immediate, large, and temporary decrease in mobility (which supports the idea that it is driven by salience rather than information). Second, we rely on survey evidence to demonstrate that individuals who report a landmine accident in their community during the previous year are four percentage points less likely to have voted in the last election, even controlling for their frequency of voting and exposure to violence in the context of Colombia's armed conflict. Further, we show that the majority of those who did not vote reported *fear* as the main reason for this. Third, consistent with the fear mechanism, we find suggestive evidence that voting polls located near areas that have benefited from humanitarian landmine clearance experience an increase in turnout. These facts suggest that the electoral reaction to the blast likely responds fear, and that in turn, such fear is presumably driven by 'bottom-up' shifts of attention.

We rule out other three alternative mechanisms, namely that landmine accidents damage the road network and reduce the access to voting polls; that they exacerbate other types of violence in the proximity of voting polls, which could reduce electoral participation to consciously avoid increasing insecurity; and that they reduce the trust that citizens have on local institutions, making them less likely to participate in the electoral process.

In addition to exploring political participation, we also examine the voting patterns of people who cast their vote despite of the blast. We document that landmine accidents generate an 18 percent reduction in the vote share of incumbent parties as well as a 22 percent reduction in the vote share of left-wing candidates. Moreover, we show that a fraction of those votes go to parties historically associated with counter-insurgent paramilitary groups. To explore the

[4]During the decade spanning from 2011 to 2020 there were 109,988 terrorist attacks in 156 countries, with a casualty toll of 258,350 people (START, 2022).

mechanisms behind this second set of results, we follow an abundant psychology literature on how emotions are interconnected to pose that blast-driven bottom-up fear likely evolved into top-down anger (Tsai and Young, 2010; Nussbaum, 2019). Indeed, anger is often the go-to reaction after experiencing fear. Moreover, while fear makes people withdraw from its source, anger drives them toward it. The implication for our context is that voters who approach the polling station after a blast are angry voters, that seek to punish the party held responsible for the explosion. This type of negative reciprocal punishment is common in many social settings (Fehr and Gächter, 2000, 2002). Indeed, it has been shown that violence is particularly prone to lead to retaliation (Zeitzoff, 2014). In the Colombian case, left-wing guerrillas (and especially FARC see section 2) are responsible for the large majority of landmines. Therefore voters are more likely to blame the left-wing guerrillas for the explosion and then punish the democratic left in the polls. In addition, relative to control polling stations, voters exposed to landmine explosions prior to election day, vote disproportionally more for the type of parties that actively promote a violent strategy against guerrillas and are historically associated with counter-insurgent paramilitary groups.

We also rule out alternative mechanisms for this second set of results. First, we preclude the possibility that the documented reduction in political participation drives the change in votes' composition. This would be the case if individuals affected by a landmine explosion chose to abstain from voting based on their political preferences or ideology, which would be conceptually inconsistent with the bottom-up salience mechanism. Second, we show that our findings are not driven by how different parties react to the landmine explosion with differential (legal and illegal) campaigning strategies. Overall, consistent with the idea that the landmine explosion is salient, the falsification of these two mechanisms suggests that the residual channel likely holds, namely that the fear induced by landmine accidents generates anger among voters, which changes their political preferences.

Our findings are robust to a battery of tests and alternative specifications, including measuring turnout relative to each poll vote's potential or using (the log of) total votes cast; weighting or not by vote potential; using only one landmine explosion per poll/year (the closest to the election day) or using only poll stations with one explosion in the days around the election to account for the potential endogeneity (after the second blast) inherent in instances with more than one explosion; controlling for the amount of rainfall around voting polls during the month leading to the election; adding poll- and municipal-level controls selected using a machine learning LASSO algorithm (Belloni et al., 2014); estimating our main model using the local randomization method suggested by Cattaneo et al. (2020); and addressing all the other known challenges of using discrete running variables in RD settings (Kolesár and Rothe, 2018; Imbens and Wager, 2019).

We contribute to research on the economics of crime and conflict, political economy, and behavioral economics. First, we contribute to the research on how organized criminal groups use violence to affect electoral outcomes. Perpetrators carefully tune-up violence to, e.g. induce an electoral demand for policy change (Montalvo, 2011), target swing voters (Robinson and Torvik, 2009), undermine the legitimacy of the government (Condra et al., 2018), discourage (or induce) turnout (Collier and Vicente, 2012; Acemoglu et al., 2013), or support incumbents when political competition is high (De Feo and De Luca, 2017).[5] We show that violence *per se* (i.e., detached from the intentions of the perpetrator) can also have large effects on electoral outcomes.[6] Another advantage of leveraging landmine explosions is that our treatment is largely homogeneous and comparable across space and time. Our findings also uphold previous evidence on how violence shapes the composition of votes, especially favoring right-wing parties (Berrebi and Klor, 2006, 2008; Getmansky and Zeitzoff, 2014; Kibris, 2011; Sabet et al., 2022).[7] Our paper suggests that support for right-wing parties could be driven by the most extreme, often pro-war, coalitions. In addition, it also documents a novel and interesting result, namely that voters are likely to blame the party that they associate with the occurrence of violence (in our case the left).

Second, our paper relates to recent political economy papers on how fear affects political participation and the support of specific political parties. Among these, Campante et al. (2020) document that the Ebola outbreak in the U.S. was instrumentalized by the Republican party to create fear, which depressed turnout and the vote share of Democrats. In a similar vein, Mansour et al. (2022) suggest that the media coverage of the HIV epidemic during the 1980s induced fear of contracting the virus and increased the electoral support of the Democratic party. Other papers show that repression (e.g., Bautista et al., 2023 and Young, 2019) and terror attacks (e.g., Vasilopoulos et al., 2019) can lead to long-lasting fear with context-specific effects regarding partisan support. While disease outbreaks, repression, and terror could also be interpreted as salient shocks, the findings of these and related papers are mostly mediated by political manipulation and media amplification. This implies

[5] Special interests with *de facto* power can influence elections through other non-violent (legal or illegal) means. These include voter manipulation through patron-client relations (Baland and Robinson, 2008; Anderson et al., 2015) as well vote-buying, fraud, and ballot stuffing (Myerson, 1993; Lizzeri and Persico, 2001; Groseclose and Snyder, 1996; Dal Bó, 2007; Robinson and Verdier, 2013; Vicente, 2014; Dekel et al., 2008).

[6] A related strand of the literature emphasizes how violence can also be inflicted *after* elections (Alesina et al., 2019). This may respond to a range of objectives, from influencing the policy choices of elected politicians (Dal Bó and Di Tella, 2003; Dal Bó et al., 2006; Daniele and Dipoppa, 2017), to punishing the electorate for voting for anti-elite newcomers (Fergusson et al., 2021) or punish newly enfranchised minorities (Naidu, 2012). The expectation of costly post-election unrest can also influence how people vote ex-ante (Ellman and Wantchekon, 2000).

[7] An exception is Garcia-Montoya et al. (2022), which shows that in the US context, school shootings lead to an increase in voting for the Democratic party.

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, a large literature on behavioral economics studies how emotions influence choices (Chichilnisky, 2009; Chanel and Chichilnisky, 2009; Nguyen and Noussair, 2014; Kassas et al., 2022). We complement these insights by presenting empirical evidence on how violence-induced fear can affect consequential behaviors such as political participation. Behavioral science also documents that individuals frequently depart from the standard model of choice under uncertainty, particularly when deciding upon risky options (e.g., Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Bordalo et al. (2022b) argue that this is consistent with the salience of some lottery payoffs, which shifts attention bottom-up and affects decision-making.[8] We also contribute to the research on the behavioral consequences of salience. In particular, we argue that because of its prominence and often surprising nature, violence is a salient stimulus that makes individuals re-calibrate their perceived risk and decide under the veil of fear.

## 2 Context

**2.1 Violence and landmines** Colombia's conflict started in the mid-1960s, when the Revolutionary Armed Forces of Colombia (FARC from the Spanish acronym) and the *National Liberation Army* (ELN) were founded. The conflict became three-sided in the 1970s when self-defense and paramilitary organizations were armed and trained by the military in counter-insurgency. These groups became illegal in 1989, and, in 1997, joined forces under an umbrella organization called *United Self-Defense of Colombia* (AUC).

Both guerrilla and paramilitary groups fight for territorial control. One key strategy to secure the strongholds and to protect illegal crops is the employment of anti-personnel landmines. In fact, Colombia is the country with the highest number of victims of improvised anti-personnel mines.[9] These types of mines were commonly manufactured and planted by the guerrillas, especially by FARC. Indeed, the main milestone in the fabrication and planting of improvised mines in Colombia came in 2008, when FARC's secretariat launched a strategy

[8] Bordalo et al. (2012, 2013, 2020) provide theoretical models of salience and demonstrate how it can explain seemingly irrational behaviors such as probability weighting, reference points, menu effects, framing, and exotic preferences.

[9] Improvised landmines are homemade explosives that detonate by contact *or even in the proximity* of a person or object. They are harder to detect and remove without risking an explosion (Landmine Monitor, 2019). Over 12,000 Colombians have been directly affected by such artifacts since 1999.

that they called *Plan Renacer Revolucionario de las Masas* (Revolutionary Rebirth of the Masses). In an internal secret memorandum, commander 'Alfonso Cano' instigated all fronts to strengthen their ongoing production and planting of landmines in order to protect their strongholds (see Appendix Figure A1 for a picture of the memo in the original Spanish). 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.

**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. Election years, however, do not coincide with those of national elections.[12] 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. The first takes place in May, and the runoff (only binding if no candidate gets at least 50 percent of the votes in the first round) in 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. We thus have four presidential and four congressional elections (in 2006, 2010, 2014, and 2018) and five local elections (in 2003, 2007, 2011, 2015, and 2019).

Colombia uses a secret ballot for all elections. In contrast to neighboring countries such as Brazil, Colombia has never implemented electronic voting, mainly because of political opposition (UNDP, 2018). 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 other to vote there (as opposed to a default location designated by the municipality). In contrast, since January 2003, new voters are automatically registered in the poll nearest their residence address. In any case, during a

[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.
[12]The exception is 1994 since, when local elections were introduced in 1988, terms lasted three years. However, since 2003 the term of locally elected bodies was extended to four years, and the election year became the year right after national elections take place.

window that ends two months prior to an election, voters can enroll in a poll of their choice (MOE, 2022b).

**2.3 The interplay between conflict and elections** Armed groups and other criminal organizations that operate under democratic regimes with sufficient *de facto* political power have incentives to employ violent means to shape the political process for their private benefit. Returns include obtaining favorable policies, receiving a share of public contracts, or directly benefiting from public procurement.[13] Additionally, some left-wing insurgencies seek to disrupt the electoral process for ideological reasons, arguing against its legitimacy and broad social representatives. 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. Indeed, the enactment of local elections at the end of the 1980s opened the political arena to previously excluded left-wing political groups. In turn, local economic and political elites allied with paramilitary militias to silence the new political challengers, and they did so by collectively targeting left-wing candidates, activists, and sympathizers (Steele, 2017; Steele and Schubiger, 2018; Fergusson et al., 2021). The infamous massacres of Segovia (1988 and 1996) and Remedios (1983 and 1997), and the assassination of two left-wing presidential candidates in 1990 as well as of the candidate of the liberal party in the same year are examples of this brutal strategy that sought to influence elections by completely eliminating the 'enemy.'

Guerrillas, on the other hand, have shown no unified stance regarding the electoral process, and their strategy varies across fronts and over time. Most fronts question the legitimacy of elections but refrain from attempting to influence them. 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. In accordance with these observations, Gallego (2018)'s empirical analysis reveals that FARC violence decreases turnout while, in contrast, paramilitary violence reduces political competition.[14]

[13]Other social groups such as lobbies, unions, or churches also exploit their *de facto* power to influence politics, albeit through non-violent means (Alesina et al., 2019).

[14]On the other hand, García (2009) argues that the relationship between armed groups' degree of territorial control and turnout is negative.

In spite of the diverse and evolving engagement of Colombia's illegal armed groups with the electoral process, there is 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.

## 3 Data

This section describes the main data sources and the measurement of both our treatment and main outcome. We also discuss the ancillary data sets used to test the validity of identification assumptions as well as some potential mechanisms.

**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.[15] 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.[16] The data include the number of votes obtained by each candidate as well as the poll's vote potential and its address, which we use for the geo-coding. The location of voting polls is determined (and published) by the National Civil Registry. Polls are usually located at parks, parking lots, or school yards.[17] The location of polls is very rarely changed.

Panel A of Figure 1 shows the spatial distribution of the 12,109 voting polls that were enabled for the 13 elections that constitute our sample. 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. For robustness, we also look at the log of the total number of votes as an alternative measure of poll-level political participation. Moreover, 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 as well as that for parties across the

[15]The official ballot scrutiny and the enactment of the official electoral results are performed by the National Elections Council. Rarely are there significant mismatches between the preliminary and the official counts, and the pre-count bulletins issued by the National Civil Registry are largely trusted by all political actors.
[16]We managed to geo-locate 98% of the voting polls using Google's Geocoding API. The remaining 2% had inaccuracies in their addresses.
[17]Under Law 1227, all (public and private) educational institutions must make their premises available for the electoral process.

ideological spectrum. We then converted these totals in rates using either the total votes cast in each poll/election or the poll's vote potential. Our results are robust to either choice.

A few clarifications are in order. First, the definition of 'incumbent' varies according to the type of election and the election year. While national congress and city-council members can be re-elected indefinitely, local executives cannot aspire to immediate re-election and presidential re-election was only in place from 2006 to 2014. Thus, in many instances, incumbency is defined at the party level. Second, for the left-to-right ideological coding of parties, we rely on the classification of Fergusson et al. (2021), who followed a four-step procedure (which often involved coding government programs and party manifestos) to classify the ideology of 178 parties and 212 party-less candidates between left-wing, right-wing, or neither. Third, we identify parties that have been shown to have strong ties with illegal paramilitary groups. To that end, and following the cited statement of Paramilitary leader Salvatore Mancuso before the Supreme Court, we identified parties for which at least one-third of their elected congress members were prosecuted because of ties with paramilitary groups.[18]

**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 all demining events. It provides geo-located data on landmine explosions in a consistent way since 2001, as well as a brief description of the accident. Based on that description, we undertake text analysis to code the alleged party responsible for placing the landmine and information about the resulting victims (including their gender, age, and whether they are civilians or a member of the public force).

Panel B of Figure 1 shows the spatial distribution of the 5,653 landmine explosions that 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

[18] Valencia (2007) lists all the legislators prosecuted by partisan membership. Appendix Table A1 summarizes the parties classified as left-wing or right-wing following Fergusson et al. (2021), as well as those classified as having ties with paramilitaries.

our inference.[19] 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. It is worth highlighting that our findings are robust to the size of the spatial buffer and that of the temporal window. We explore these and other robustness tests in section 5.

Ultimately, these refinements reduce our sample to 543 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). Figure A2 of the Appendix overlays the geo-location of voting polls and that of the landmine explosions of the reduced estimation sample.

Finally, we use a range of additional variables as controls as well as to test the RD 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

A direct comparison of the electoral outcomes of voting polls located close to a place where a landmine exploded before the elections and those of polls not exposed to an explosion would most likely yield biased results of the electoral effects of landmine blasts. This is because landmines are not deployed randomly in the territory. Rather, they are commonly used to protect strongholds, illegal crops, and the routes used for the illegal drug trade and the smuggling of weapons. In turn, the location of such strongholds, crops, or trade routes responds to strategic considerations, geographical feasibility, and historical factors, which make these areas likely very different from others. This implies that the naive comparison of voting patterns in places with and without landmines would potentially be contaminated by a range of confounders.

For this reason, we rely instead on a regression discontinuity design that uses as a running variable the day of a landmine explosion relative to the election day.[20] Therefore, our

[19]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.

[20]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

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 $i$ stands for 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. $T_i$ represents the treatment status. It is an indicator equal to one if the explosion happened before the election.

Note that the running variable takes discrete values –the number of days since the election. This is problematic when only a few values are observed because it leads to large extrapolations for the days close to the election. In our case, there are 104 different explosion days over a 60-day window around the elections, which suggests that this threat should not be a major concern in this context (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).

In our main specification, we only keep explosions that occurred within a 4Km radius of a poll station. We then test the robustness of this choice, which is necessarily arbitrary. 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. $\alpha_e$ 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, $\varepsilon_{impe}$ 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, $\beta$, 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 in polls exposed to a landmine blast that took place shortly afterward. To interpret $\beta$ as a

to the issue of serially correlated outcomes that commonly affects RDiT strategies (Hausman and Rapson, 2018).

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.[21] The latter allows us to give a similar weight to each voter, instead of giving the same weight to poll stations of different sizes. Our results are, however robust to not using this weight. 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.

## 5 Results

This section discusses our estimated results. We start by assessing the validity of the main identifying assumptions of our empirical strategy. Then we describe the main findings regarding the impact of landmine explosions on political participation and on the composition of votes. Finally, we discuss a battery of robustness tests.

**5.1 Validity of the empirical design** We start our analysis by testing the validity of the main identifying assumptions underlying our research design. First, we explore how landmines could have been manipulated to burst around the election day. Note that 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, while different actors in the Colombian conflict have tried to influence electoral outcomes, they have used instruments other than landmines. This is because antipersonnel landmines are mainly a deterrence weapon, and the timing of their explosion is hard to control.

Beyond this qualitative evidence, we follow Cattaneo et al. (2018) to perform a formal

[21]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 as to give the same weights to all the observations within the optimal bandwidth.

statistical manipulation test based on density discontinuity around the (election day) cut-off. Panel A of Figure 2 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` associated with the null hypothesis of no difference in the density of explosions before and after elections is 0.71).[22] 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, perhaps more subtle, way of manipulation in our setting could arise if organized criminal groups seeking to alter electoral outcomes could trigger landmine explosions closer to poll stations before the elections relative to after the elections. We test this alternative in Panel B of Figure 2, 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) and that after elections is depicted on the right-hand side. 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 in the densities (`p-value` of 0.38).[23]

Even if the timing of the explosion is as good as random, a third form of manipulation would occur if organized criminal groups placed landmines in the vicinity of voting polls differentially prior to the elections relative to subsequently. While this is much harder to test due to the lack of data on the location of unexploded landmines, 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.[24] Rather, it started collaborating with the government to reveal the location of minefields (Perilla et al., 2023). 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

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

[23]We find a `p-value` of 0.55 when estimating the test suggested by McCrary (2008).

[24]The ceasefire was declared on December 20th, 2014 to signal FARC's commitment to the peace process and its capacity to hold accountable all of its fronts, which were scattered throughout Colombia. The organization then started to withdraw troops to more remote areas, where military contact with government security forces and other armed groups was unlikely to take place. The ceasefire was largely met until replaced with the definitive bilateral truce and the final peace agreement in 2016.

differential effect before and after the ceasefire (see Column 2 of Table 6).[25]

In addition to the different forms of manipulation, all of which we rule out, the second main assumption is related to potential differences in poll station or municipality characteristics 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 A2, 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 characteristic for the non-treated observations. Column 2 reports the outcome of univariate regressions within the optimal bandwidth.[26] 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, including the main outcomes of our analysis. This is true both at the voting poll and at the municipality levels.[27] Importantly, we find no evidence of 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 the 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.[28]

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. We now turn to describe such results.

**5.2 The effect of landmine explosions on electoral participation** In Table 2, we report our main estimates of the effects of landmine explosions on poll-level turnout. These

[25]Table 6 explores this, as well as other potential heterogeneous effects 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. In Appendix Table A3, we present all the heterogeneous effects but for a bandwidth twice as large as the optimal one to reduce concerns about power.

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

[27]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.

[28]In Table A4, we present municipality-level characteristics for those 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 external validity issues for the sample of municipalities affected by landmines and supports the idea that the timing of the explosion was random. However, between (i) and (iii), there are major differences in terms of the incidence of conflict and other socioeconomic dimensions, which suggests that our estimates should not be extrapolated to any type of municipality in Colombia.

are obtained from estimating equation (4.2), which we do non-parametrically following Cattaneo et al. (2020). 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. Each column reports the robust p-value and 95% confidence interval, as well as two additional p-values depending on how we cluster the standard errors: The p-value labeled [1] is associated with standard errors clustered at the running variable level, as suggested by Lee and Card (2008). The one labeled [2] is based on municipal-level clusters. The results are robust to any of these decisions regarding inference.

We find that a landmine explosion that takes place in the few days prior to an election discourages political participation. Specifically, based on the even columns, it reduces turnout between 13 and 37 percentage points (22 and 62 percent of the sample mean, respectively).[29] Panels A and B of Figure 3 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 A5 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.

Similarly, Panels A and B of Figure 4 explore how the estimated effect of landmine explosions on turnout varies with the size of the bandwidth, over a range from 10 to 45 days.[30] Consistent with the idea that the explosion distorts decision-making while it is salient, we find that when a shorter window is used, and thus when the treatment is defined by an explosion very close to election day, the drop in political participation is larger. Put differently, the magnitude of the effect decreases in absolute value with the size of the bandwidth. By the same token, Panels C and D vary the radius of the estimation buffer around poll stations

[29] Alternatively, instead of computing the poll-level turnout, which divides the total votes cast by the poll's voting 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.

[30] Panel A focuses on the specification with a linear polynomial and panel B with the quadratic one. The radius of the estimation buffer is kept at 4Km throughout.

while keeping fixed the optimal bandwidth in terms of days around elections. We find similar results, albeit somewhat noisier. That is, the magnitude of the turnout reduction is larger the smaller the estimation buffer, which takes into account explosions that occur closer to voting polls. The documented gradients (in terms of days to election and distance to the voting poll) are consistent with an explosion-triggered salience. Indeed, we will describe (see section 6.1) that explosions induce fear and decrease mobility at a local level.

To better understand the magnitude of the coefficients, we first note that our estimates rely on voting poll-level variation and, thus are very 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 1.12 percentage points. Panel A of Appendix Figure A3 reports our original (poll-level) estimates, the computed municipality equivalent, and those found by selected papers. While the voting poll-level effect is well above the effect found by other papers, the municipal counterpart lies within the range of the effects reported in the literature.

Within Colombia, we can also compare our estimates to those of the effect of rainfall on turnout. This is relevant as rainfall has been shown to decrease political participation (Gomez et al., 2007). We do so in Appendix Table A7, where we estimate the impact of rainfall on turnout at the voting poll level. We find that a one standard deviation increase in rainfall leads to a decrease in turnout of 2 percentage points, equivalent to 16% of the effect found for landmine explosions.

**5.3 The effect of landmine explosions on voting outcomes** In addition to decreasing electoral participation, landmine explosions also changed the electoral behavior of citizens who did vote. These results are reported in Table 3. Focusing on the RD estimates that use a linear polynomial, we show the effect of an explosion on: i) the support for the incumbent 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 first measures the poll's potential turnout, and the second the actual one. The optimal bandwidth changes across columns, and thus, so does the number of effective observations.[31]

On the effect of explosions on votes for the incumbent party, we find suggestive evidence that it decreases. Regardless of the denominator (and hence also of the optimal bandwidth), the drop in the share of votes for the incumbent is 18 percent of the sample mean (Columns 1 and 2). In spite of the meaningful magnitude, the estimates are not statistically significant. In addition, we find strong evidence that voters punish left-wing parties. Specifically, explosions decrease the vote share of the left (as defined by Fergusson et al., 2021) in a substantial magnitude (22 to 31 percentage points depending on the denominator used to compute the share, Columns 3 and 4). This is consistent with the idea that voters blame the left-wing guerrillas for the violent event, and translate that into a vote against the democratic left. Indeed, FARC has historically been the main fabricator and user of antipersonnel landmines in Colombia. Finally, we document that a non-negligible part of these votes goes to parties that have proven alliances with illegal right-wing militias (Columns 5 and 6). Therefore, in addition to punishing the left, voters exposed to these salient violent events become more supportive of parties that back a violent –and often illegal–counterinsurgency strategy. These findings are largely unchanged if we control for the poll-level vote potential (Panel A of Table A8 in the Appendix) or if we fit a quadratic polynomial instead (Panel B).[32]

In Appendix Table A9, 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 (those for which at least a third of congress members have been prosecuted because of alliances with paramilitary groups) are coded as right-wing by Fergusson et al. (2021).[33] 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 percentage points depending on the denominator, 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 the effect is not robust to the denominator used to compute the vote share (Columns 5 and 6).

[31]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. Moreover, recall that there is a balance in terms of the number of candidates in local elections as well as regarding their party composition (see Appendix Table A2).

[32]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.

[33]The authors follow a conservative classification procedure to make sure that all parties classified as either left- or right-wing are so. This implies that the bulk of the 390 parties and party-less candidates classified are neither left- nor right-wing.

Figure 5 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, C and D on the vote share of the left, and E and F on the vote share of parties allied with paramilitaries. 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.

Finally, fixing a buffer of 4Km around the poll station, Appendix Figure A4 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. Similarly, Appendix Figure A5 shows the robustness to estimation buffers of different radii around the polls, from 2 to 6Km.

To understand the magnitude of the estimated effects, we perform two exercises. First, we perform a back-of-the-envelope calculation to explore the extent to which landmine blasts could have distorted aggregate municipal electoral results. Making similar assumptions to those made to compute the municipal-level turnout reduction (see above), 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 0.61 (0.01) percentage points. 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 25% of the close races.[34]

Second, we follow DellaVigna and Kaplan (2007) to compute the explosion-led *persuasion rate* (the share of voters that are persuaded by the explosion to change their vote).[35] We find that landmine accidents persuaded 8.6 percent of left-wing voters to vote for parties outside the left, and 3.05 percent 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 regarding the persuasion rates of different media-related treatments (see Appendix Figure A3, Panel B).

**5.4 Additional robustness** We conduct a wide set of empirical exercises to assess the robustness of the effects of landmine explosions on political participation and on electoral behavior. Appendix D motivates all the robustness tests that we perform, discusses their nature, and describes the obtained results. Here we limit the discussion to a brief summary.

[34]We define close races as elections decided by a margin of victory lower than ten percentage points. For left-wing parties, we find 63 close races in municipalities that were affected by FARC violence during the last two decades.

[35]See Appendix C for a detailed explanation.

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, 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. 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

In this section, we explore the potential mechanisms that drive the effects of landmine explosions on electoral participation and voting behavior.

### 6.1 Mechanisms of the effect of landmine explosions on turnout

*6.1.1 Fear to go to vote.* Our argument is that, due to their prominent and often surprising nature, landmine accidents are salient shocks that engender fear and make exposed individuals involuntarily distort their planned behavior in the short run (Bordalo et al., 2022b). Specifically, driven by survival considerations, frightened individuals reduce their mobility to avoid a fatal accident. This hurts political participation if an election is taking place a few days after the landmine explosion. In principle, however, there is a second channel through which landmine accidents could produce fear. Indeed, such explosions may carry information about the underlying risk of landmines in the surroundings, and potentially also on the presence of illegal armed groups. People, therefore would reduce mobility to consciously avoid unpleasant and likely fatal encounters. In this case, while also mediated by fear, the behavioral response is 'top-down'.

To partially distinguish between these two mechanisms, we perform two tests. In the first, we add as covariates in our main specification the recent history of landmine explosions, as well as a proxy of the underlying risk of a landmine explosion around the voting poll. For the latter, we use the number of explosions that took place around the voting poll during the two years after the election. In the second, instead of adding these variables as covariates, we interact them with the treatment variable to explore potential heterogeneous effects. The intuition behind both these tests is that individuals previously more exposed to explosions may react less to a new blast if they are already well informed about the embedded potential risks.

Panels A and B of Table 5 report the results of the first and second tests, respectively. Covariates/interaction terms are included both in the extensive (Columns 1, 3, and 5) and the intensive (Columns 2, 4, and 6) margins. Past landmine explosions are computed within the same estimation buffer over periods of 3 to 9 (Columns 1 and 2), 3 to 12 (Columns 3 and 4), and 3 to 15 (Columns 5 and 6) months from the date of the election. The control/interaction of the risk proxy is included in Column 7). As for the results of the first test (Panel A), in all cases, the coefficient of interest is unchanged by the inclusion of the described covariates. Regarding the second test (Panel B), we find no statistically significant heterogeneity based on the measures of past exposure and the one of risk. If anything, most of the interaction terms are negative, which suggests that people who have been more exposed to landmine explosions in the past, may recall (traumatic) memories associated with them. This may couple the current exposition to re-victimization and hence to more fear and a larger behavioral reaction to the explosion (Enke et al., 2020; Marsh, 2022; Bordalo et al., 2022a,b).

Moreover, recall that for a given buffer around the poll, 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 days 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., 2022b; Dessaint and Matray, 2017; Kunreuther et al., 1978). Overall, this evidence supports that the observed reaction is consistent with the salience of the shock involuntarily distorting voters' behavior, rather than the change driven by the information content of the shock.

We provide four additional pieces of evidence about the empirical relevance of the fear mechanism (some of which also support its salience nature). First, at the core of the argument is the idea that individuals exposed to a landmine blast update the risk of being a victim of a similar explosion if they move around. To test this hypothesis, we computed people's mobility using raster data from Facebook that measures, daily, the number of people moving between tiles of 350m $\times$ 350m (about 1,150 square feet).[36] Using this high-frequency

[36]The data is available daily from June 2021 to March 2022, a period with no elections (and outside our sample dates). 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

information, we explore the extent to which mobility changes after a landmine explosion.[37]

To this end, and given the random timing of landmine explosions and the fact that they take place at different points in time, 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.[38] We estimate this model using both two-way fixed effects (TWFE) and the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020) –which is not affected by contaminated comparisons that may bias TWFE estimates. We plot the coefficients of the dynamic specification in Appendix Figure A6 and the overall average treatment effects on the treated in Appendix Table A11. 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). The short-lasting effect is consistent with a fear mechanism driven by salience.

Second, we leverage on the nationally representative Political Culture Survey, from Colombia's National Statistics Department. In the 2017 and 2021 waves, the survey instrument included a question on the extent to which landmine explosions were a threat to the respondent's community during the last 12 months. We correlate the answer to this question with an indicator about whether the respondent voted in the last elections, as well as with an indicator about whether the main reason for not voting was a feeling of fear.[39] We control for a large set of individual characteristics, as well as for the propensity of the respondent to vote in elections (available only for the 2017 wave).

The results are reported in Table 4. Column 1 shows the correlation between identifying landmine explosions as a threat to the community and having voted in the last elections controlling for how frequently the respondent states that she goes to vote. The coefficient is negative and significant. Reporting that landmine explosions are a threat to the community is correlated with a 4.3 percentage points lower likelihood of having voted in the last elections. This is equivalent to a 7.3 percent reduction in the probability of voting. The magnitude of the correlation remains similar when controlling for gender, age, household access to utilities, and the respondent's level of education (see Column 2).

Columns 3 and 4 explore whether the voting abstention is due to fear. To that end, we

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. The resulting sample includes 41 explosions.

[37] Bailey et al. (2018) use similar data to construct an index of social connectedness.

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

[39] In the survey, the question on voting in the last election comes before the question on landmine accidents, which alleviates concerns about the recalling of the violent event driving the voting response.

leverage on the survey question addressed to the sub-sample of subjects who declared not having voted in the last election and that elicit the reasons for that choice. We find that reporting that landmine explosions were a threat to the community over the last 12 months is correlated with a 16 percentage points higher likelihood of reporting that the main reason for not voting in the last elections is fear. When compared with the sample mean, this is equivalent to a 479 percent increase in the probability of arguing that fear is the main obstacle to voting.

One concern is that these correlations just reflect the difference in responses by people affected or not from conflict. To partially address this, in Columns 5 to 8, we repeat the same exercise but focus on the sub-sample of individuals that stated to have been victimized by conflict.[40] We find qualitatively similar results, with the fear result being still relevant but about half of the size.

The third piece of evidence that supports the *fear* mechanism exploits one of the main post-conflict investments to reduce landmine victimization, i.e., humanitarian demining. These demining activities, launched at the beginning of peace negotiations between FARC and the government, 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., 2023). We use these data to construct grids of 5 square Km as well as 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.

We find that a grid that moves from zero demining to three demining episodes (the median cumulative humanitarian demining conditional on at least one episode) witnesses a turnout surge from one to two percentage points (see Panel A of Appendix Table A12). This result is consistent with demining increasing the perceived safety of moving around, therefore increasing political participation.[41]

Fourth and last, Table 6 provides additional (albeit more suggestive) evidence consistent with how the salience of landmine explosions produces fear. It does so by exploring heterogeneities parametrized by the type of victim of the landmine accident (whether civilian or combatant) and by the type of election at stake (whether local or national). In Column 3, we show that the interaction of the indicator of whether there was an explosion before

[40]In particular, the sub-sample of conflict-affected respondents includes responses from victims of displacement, forced recruitment, dispossession, stigmatization, and killings.

[41]In Appendix Table A13, we find that there is an increase in voting for the government party after demining, consistent with voters rewarding the incumbent for increasing safety in the area. We also document an increase in the vote share of the left.

the election and a dummy of whether the associated victim was a civilian is very small and not significant. The same happens with the coefficient of the interaction of a pre-election explosion and a dummy of whether the election is local, i.e., for municipal mayors (Column 4).

We interpret the absence of these heterogeneous effects as consistent with the fear mechanism. Indeed, the fact 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 related to the identity of the victim or the importance of the election. If people are frightened by an explosion that occurs close in time to the election day and close in space to the voting poll, then it does not matter if the landmine hurts a civilian or if the ballot is presidential.

*6.1.2 Explosion-driven violence surge.* An alternative mechanism of the explosion-led reduction in political participation may arise if the landmine blast causes a violence spiral at the local level, and this in turn, reduces the willingness to go to vote. Such an increase in violence could be triggered, for instance, by the military arriving in the affected area to engage in confrontation with the group held responsible for placing landmines. Regarding this alternative, the first thing to note is that Table 1 provides *prima facie* evidence against any differential surge in guerrilla attacks between treated and control municipalities, neither two weeks before nor during the day of the election. Unfortunately, the nature of the conflict data in Colombia only allows us to conduct this analysis at the municipality level.

Nonetheless, to explore the empirical validity of this hypothesis at the level at which we undertake our main analysis, we gathered geo-coded data on the universe of homicides in Colombia from 2014 on-wards (as recorded by the SIJIN unit of the National Police).[42] We then constructed a balanced panel of the voting polls from our main sample during the two months before the election and estimated a staggered difference-in-differences model at the weekly level to identify the effect of landmine explosions on homicides. An outcome, in this case, is the occurrence of a homicide in week $t$ within 4km from a voting poll. In turn, the treatment is the occurrence of an explosion before the election.[43] Note that, in this case, voting polls that were affected by an explosion after an election serve as never-treated units. We implement the TWFE model as well as De Chaisemartin and d'Haultfoeuille (2020) estimator. For both models, we find no change in the occurrence of homicides after the explosion (see Appendix Table A14 and Figures A7 and A8). We conclude that this alternative channel is implausible.

[42] This is the best proxy of violence that is available at our level of analysis.

[43] 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.

*6.1.3 Access to vote.* Another alternative mechanism would occur if landmine explosions damaged the road network and therefore increased the costs of voting. For a context other than landmines, this is the case of Afghanistan, as documented by Condra et al. (2018). To formally explore this idea, we leverage the geo-location of the road networks of Colombia (as compiled by Prem et al., 2023) and compute the demeaned distance of all the spots where a landmine exploded to the nearest road. We interact such continuous measures with the indicator of an explosion happening before the election. Column 5 of Table 6 shows that the interaction term is small in magnitude and not statistically significant. Additionally, we find similar (null) results when using different types of roads, depending on their quality and size (results reported in Columns 6 to 8).

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. In the first, 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 is 'key' to arrive to the poll.[44] Second, we identify the explosions that occurred within 50 (or 100) meters from a 'primary' road leading to a voting poll.[45] In Table A15 of the Appendix, 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. This is true both in terms of magnitude and significance.

Overall, we conclude that poll station access is not likely a relevant mechanism of the effect of landmine blasts on political participation.

*6.1.4 Trust in institutions.* One final alternative to our proposed mechanism could arise if explosions decreased trust in democratic institutions among the exposed, thereby decreasing political participation for reasons other than fear. Landmine explosions, in fact, could generate disappointment in the government's handling of territorial disputes. We test this idea indirectly in two different ways. First, we look at the share of blank votes a recognized proxy of protest voting (Alvarez et al., 2018). In Columns 9 and 10 of Appendix Table A9, we find no change in the proportion of voters choosing to vote blank after a landmine blast. Second, we explore a set of questions about 'trust in institutions' from the political culture survey discussed earlier. In Appendix Table A16, 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. Overall, we find no evidence of a change in

[44]Here, 'key' means that the road belongs to the shortest path distance between the spot of the explosion and the voting poll (over all the different roads that need to be taken to access the station) that is above the median of the empirical distribution.

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

institutional trust following a landmine explosion in the past 12 months. This is suggestive of the lack of validity of this potential mechanism to explain our results regarding political participation.

**6.2 Effects on voting** Recall that, regarding the effect of landmine explosions on voting decisions, we find that they lead to a drop in the vote share of left-wing parties and to an increase in the vote share of parties associated with paramilitary groups. We posit that this effect could be driven by at least three channels. The first such channel has to do with the composition effect of the documented reduction in turnout: after a landmine blast, voters self-select to cast their vote based on their political ideology. Specifically, left-wing supporters may be differentially less likely to vote after an explosion than pro-paramilitary supporters. The second channel is related to the reaction of local politicians to the explosion. For instance, paramilitary-supporting candidates may campaign after the landmine accident to obtain political returns from it, by blaming the left. Finally, angry voters may change their political preferences after the explosion, punishing the party that is to blame for the shock.

*6.2.1 Change in the composition of voters.* We perform three different exercises to partially test whether the effect of landmine explosions on voting behavior is driven by a change in the ideology composition of voters. We start by estimating a version of Table 4 that tests for heterogeneous effects using individual information from the political culture survey respondents. Specifically, we interact the dummy that identifies exposure to landmine explosions with the stated political ideology of the respondent. If the effects of landmine accidents on voting behavior were coming from a composition effect, we should then expect that left-wing voters should be more affected by landmine explosions in their political participation choice. Columns 1 to 4 of Appendix Table A17 suggest that this is not the case: the reduction in political participation is not differential for left-wing voters.

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 again study potential heterogeneous effects. Specifically, we study whether the blast-driven voting behavior 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.

Second, we follow DellaVigna and Kaplan (2007) and include turnout as a "bad control" in the voting regressions. We find that the point estimates change very little when adding this control (see Appendix Figure A9). 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.[46] We find no major change in the effect of the landmine explosion on voting once we account for the indirect effect through turnout. 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.

*6.2.2 Change in campaigning strategy.* An alternative mechanism of the effect of landmine explosions on the electoral outcomes of affected polling stations 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, 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.[47] Upon completion, we only found *three* tweets related to a landmine explosion. By and large, this suggests that, at least in our sample, online campaigning seems rather unresponsive to such explosions.

The flip side of legal campaigning is illegal practices also aimed at electoral success, such as vote buying and electoral fraud. These phenomena are not alien to Colombian politics, especially in rural areas (Rueda, 2017; Tule, 2020; Holland and Freeman, 2021; MOE, 2022a; Fajury, 2022). This implies that, even if legal (online) campaigning did not seem to react to landmine explosions, it may well be the case that explosions changed the incentive to buy votes in certain areas. This is because the cost of voting increased for affected individuals, and hence 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 A2, 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 across them, which is consistent with the idea that the incentives to obtain votes illegally did not change because of the explosion.

[46]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.

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

*6.2.3 Change in voters' preferences.* A large psychology literature argues that emotions often come in bundles, with specific emotions being closely connected in a sequential manner to other previously experienced emotions. This is the case of anger, which is often the byproduct of fear (Tsai and Young, 2010; Nussbaum, 2019). Individuals that are shocked with fear portray a first reaction, which is involuntary and short-lived: they withdraw from the source of the emotion. A second and subsequent emotion is anger, which is however shaped by cognition. Angry individuals return to the source of the shock and seek retaliation. We pose that this is the main mechanism explaining our findings regarding voting behavior, especially given our falsification of the mechanisms pertaining to a change in the composition of voters and to a change in the campaign strategies of candidates in affected areas.

In particular, albeit not directly testable, we argue that the documented explosion-led changes in voting patterns are consistent this. Because left-wing guerrillas (and especially FARC) have traditionally been responsible for the placement of landmines in Colombia, landmines-affected voters attempt through their vote to punish the democratic left for the wrongdoings of the insurgency. 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).

## 7 Conclusions

Violence is rarely randomly allocated but rather its deployment mostly responds to strategic and tactic considerations. This makes it hard to disentangle the effect of the perpetrator's objective from the fear generated by the violent stimulus. This paper overcomes these challenges by studying the electoral effects of quasi-random (accidental) explosions in rural Colombia, which are not intended to affect electoral outcomes to begin with.

To identify the effect of fear and separate it from that the the strategic intention of the perpetrator, we leverage these accidental explosions to compare electoral outcomes in voting polls located close to an explosion that occurred shortly before the election to those of posts close to explosions that took place shortly afterward. We find that landmine accidents decrease political participation. Moreover, we document that this fear-driven reaction is triggered by the salience of violence rather than a conscious reaction to the information conveyed by the blast about the potential of future victimization. We rule out several alternative mechanisms, such as reduced access to polling stations or retaliatory violence.

We also find large effects on electoral outcomes, specifically a reduction in the vote share of left-wing parties and an increase in that of parties associated with counter-insurgent illegal groups. This is consistent fear-driven anger, which in turn changes political preferences and makes voters seek to punish the democratic left for violence that they accrue to left-wing guerrillas. We rule out that these effects are driven by changes in voters' composition associated with the reduction in turnout or by differential (legal or illegal) campaigning strategies.

These results point to worrisome potential consequences for the consolidation of democracies in places affected by conflict. This is true even after peace, as antipersonnel landmines are hard to detect and costly to remove, and may remain active for decades.

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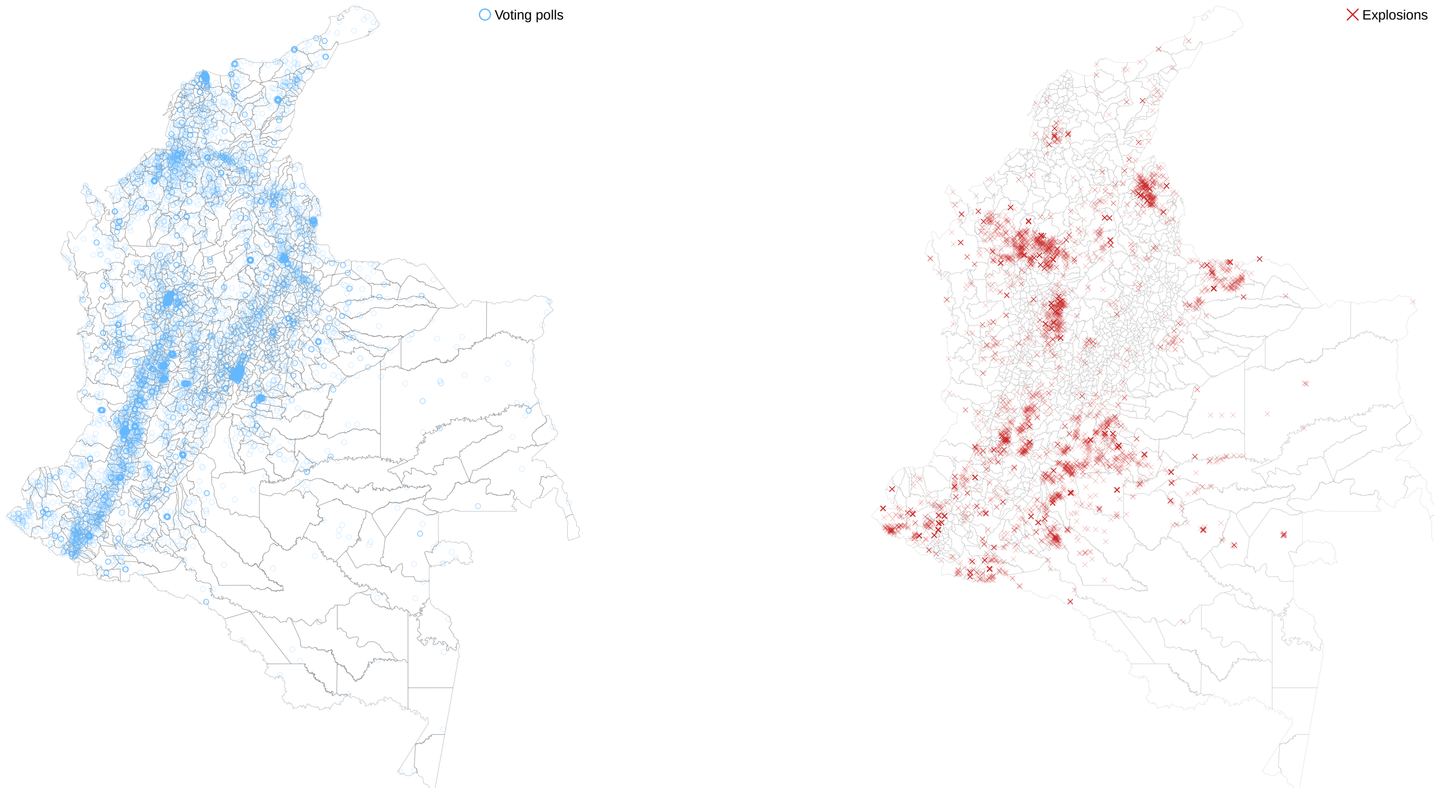
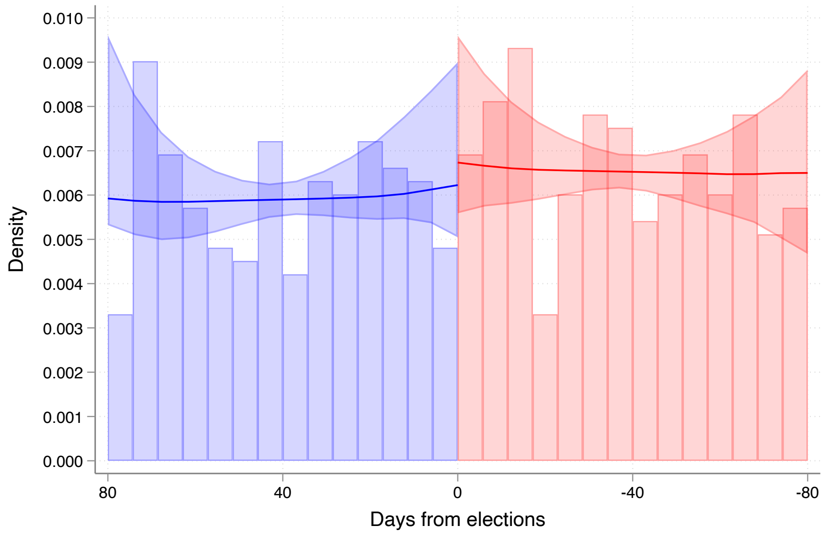
Figure 1. Voting Polls and Landmine Explosions



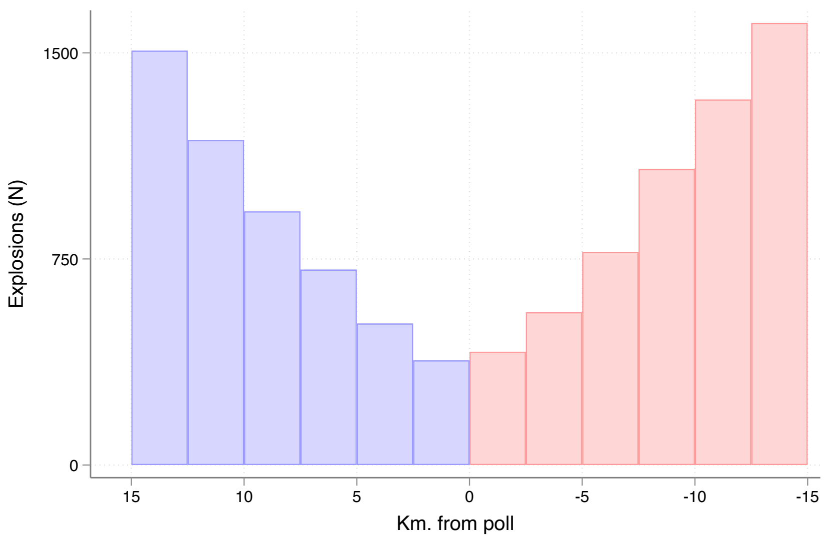

**A.** Voting Polls **B.** Landmine Explosions

**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 2. Explosions Distribution



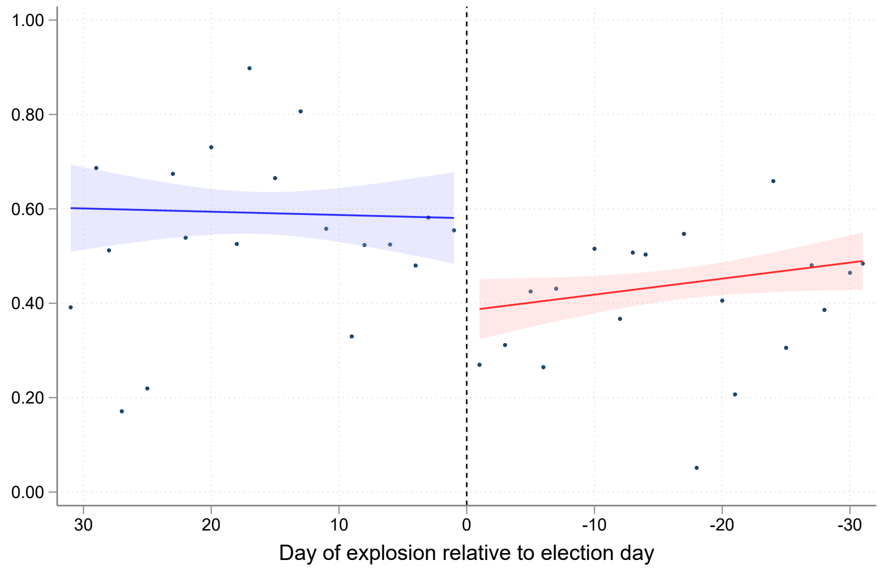

**A.** Across Days



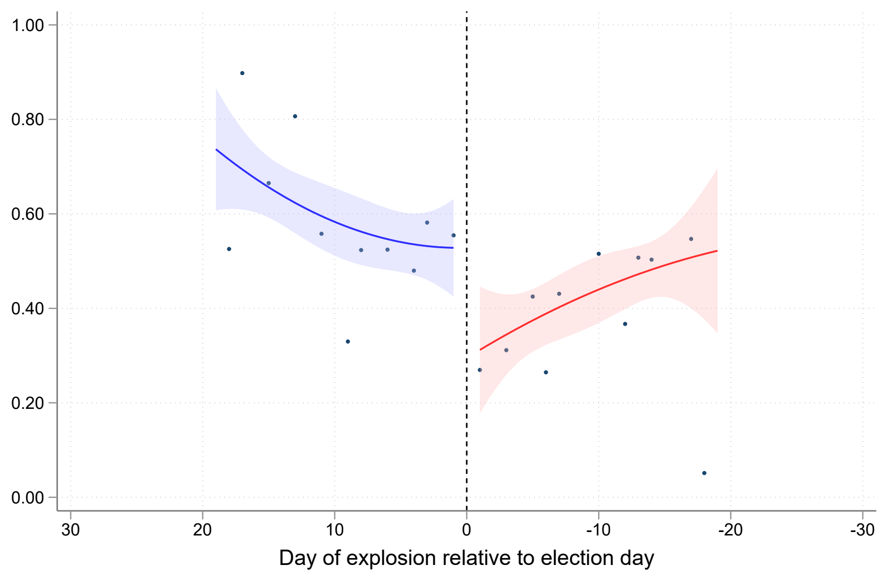

**B.** Over Distance

**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 3. RDD Estimates for Turnout



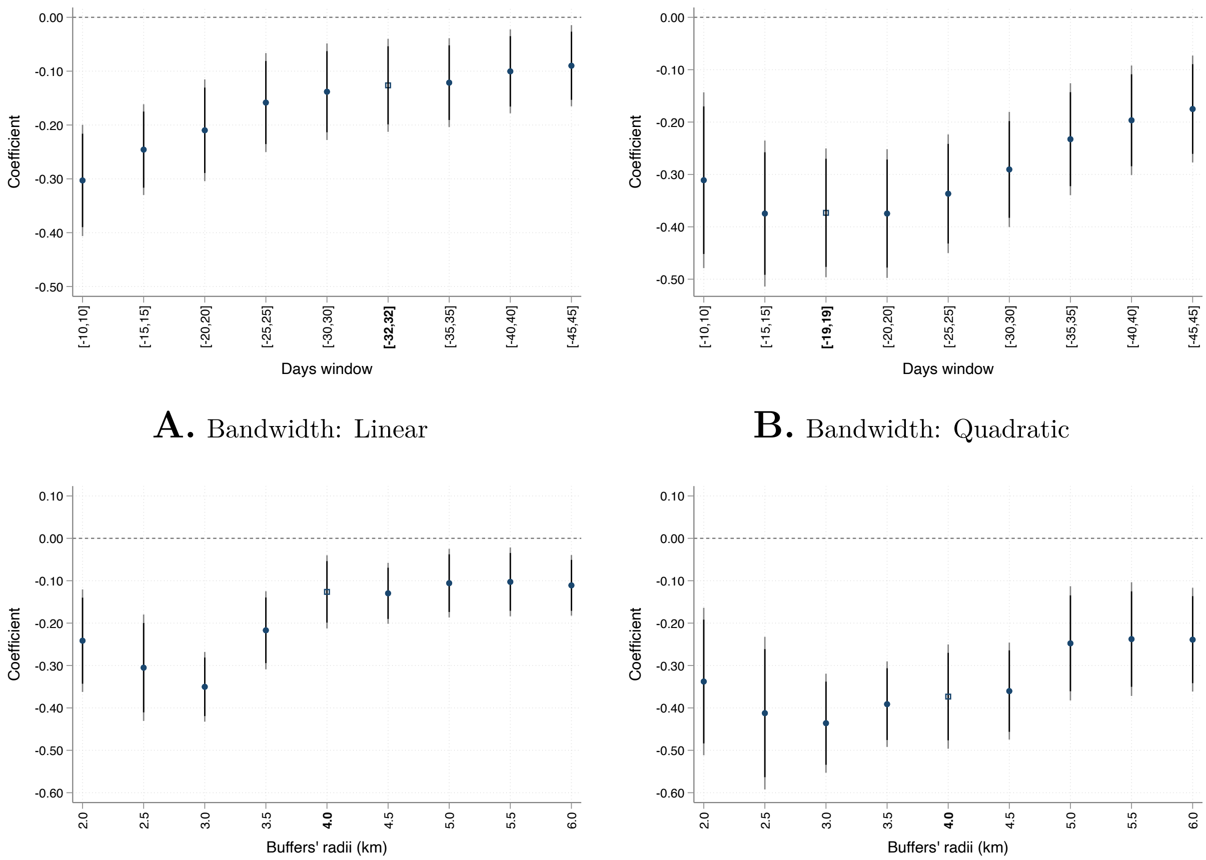

**A.** Linear




**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 4. Turnout and Explosions Over Different Bandwidths and Buffers' Radii




**A.** Bandwidth: Linear

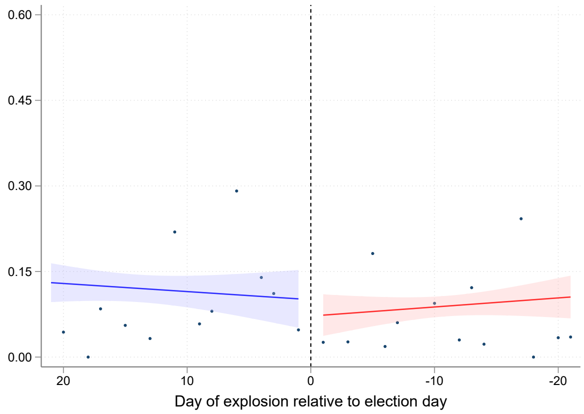
**B.** Bandwidth: Quadratic

**C.** Buffer's Radio: Linear

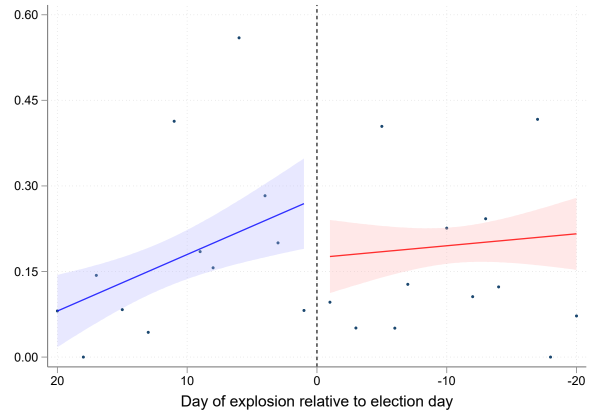
**D.** Buffer's Radio: Quadratic

**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.

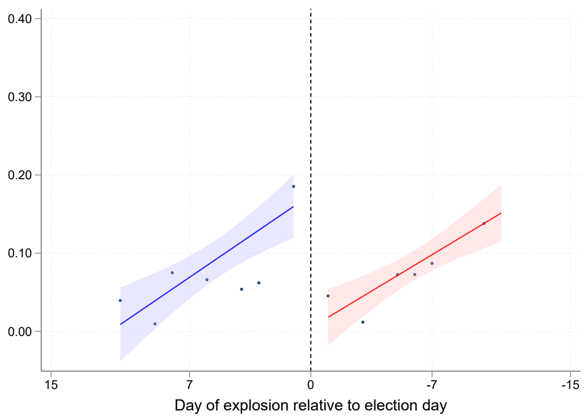
Figure 5. The Effect of Explosions on Voting Behavior



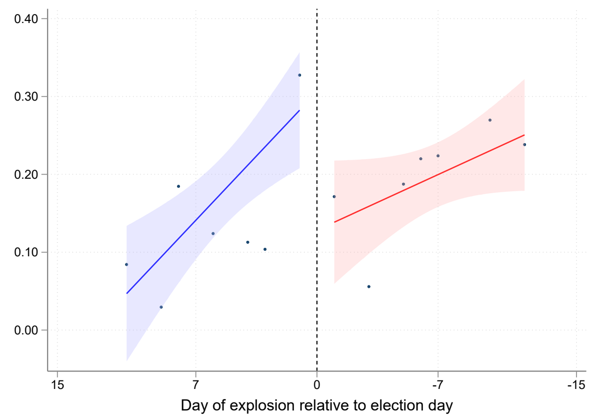

**A.** Incumbent Over Potential



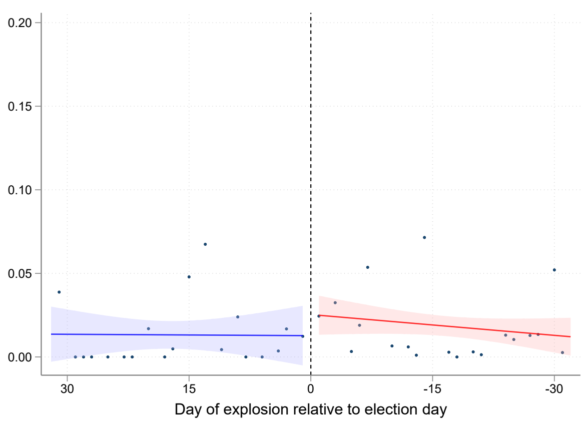

**B.** Incumbent Over Votes



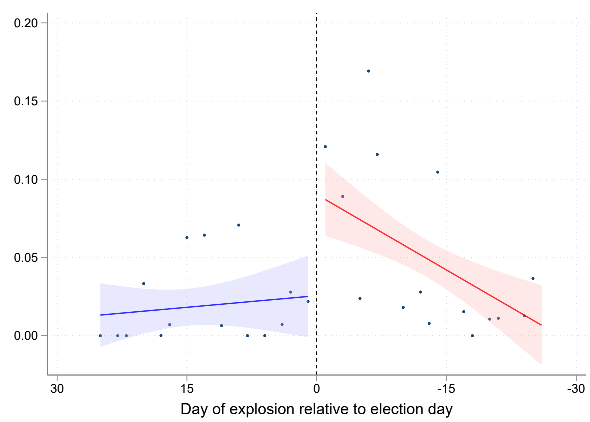

**C.** Left-wing Over Potential




**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 in Poll and Municipality Characteristics by Treatment Status

| | Mean Control | Difference in Mean | RDD Estimate |
|---|---|---|---|
| | (1) | (2) | (3) |
| **A. Poll Station Level** | | | |
| Ln Potential Voters | 5.74 | 0.12 | 0.31 |
| | (0.96) | (0.10) | [-0.38,0.91] |
| Turnout | 0.48 | 0.00 | 0.15 |
| | (0.27) | (0.04) | [-0.13,0.49] |
| Political Competition | 0.48 | 0.01 | 0.04 |
| | (0.26) | (0.03) | [-0.25,0.29] |
| Incumbent Vote Share | 0.15 | -0.01 | -0.01 |
| | (0.21) | (0.02) | [-0.20,0.15] |
| Left Vote Share | 0.25 | 0.01 | -0.10 |
| | (0.29) | (0.04) | [-0.36,0.17] |
| Right Vote Share | 0.07 | -0.02 | 0.00 |
| | (0.14) | (0.03) | [-0.09,0.11] |
| Paramilitaries Vote Share | 0.07 | -0.04* | 0.04 |
| | (0.14) | (0.02) | [-0.03,0.16] |
| Nighttime Lights | 11.31 | -2.87 | 2.41 |
| | (14.88) | (3.59) | [-3.65,6.99] |
| Homicides | 1.32 | -0.25 | -5.00 |
| | (0.87) | (0.41) | [-14.29,1.53] |
| Latent Explosion Risk (1 year) | 0.29 | -0.06 | 0.08 |
| | (0.45) | (0.08) | [-0.15, 0.30] |
| Rainfall (30 days pre-election) | 1.95 | 0.52 | 1.43 |
| | ( 2.74) | ( 0.56) | [-0.64, 3.83] |
| **B. Municipality Level** | | | |
| Any Attack | 0.36 | 0.09 | -0.16 |
| | (0.48) | (0.07) | [-0.38,0.19] |
| Any Attack (election day) | 0.01 | 0.01 | -0.06 |
| | (0.08) | (0.01) | [-0.15,0.02] |
| Any Attack (2 weeks pre-election) | 0.08 | 0.01 | -0.07 |
| | (0.27) | (0.04) | [-0.07,0.23] |
| Any Demobilized | 0.50 | 0.07 | 0.28 |
| | (0.50) | (0.08) | [-0.16,0.53] |
| Ln Potential Voters | 9.92 | -0.13 | 0.04 |
| | (1.09) | (0.24) | [-0.60,0.70] |
| Mayor Aff. Government | 0.22 | -0.05 | 0.18 |
| | (0.41) | (0.06) | [-0.30,0.49] |
| Mayor Aff. Opposition | 0.23 | -0.04 | 0.13 |
| | (0.42) | (0.08) | [-0.08,0.51] |
| Mayor Aff. Left-wing Party | 0.18 | -0.02 | -0.19 |
| | (0.38) | (0.05) | [-0.12,0.22] |
| Mayor Aff. Right-wing Party | 0.02 | 0.06 | 0.04 |
| | (0.15) | (0.04) | [-0.10,0.03] |
| Number of Candidates | 27.14 | -3.40 | -7.80 |
| | (16.83) | (5.12) | [-16.31, 35.37] |
| Any Right-wing Candidate | 0.67 | -0.19 | 0.53 |
| | (0.47) | (0.18) | [-1.68, 1.79] |
| Any Paramilitary Candidate | 0.37 | -0.07 | -0.18 |
| | (0.49) | (0.12) | [-1.76, 0.87] |
| Any Left-wing Candidate | 0.60 | -0.02 | 0.16 |
| | (0.49) | (0.18) | [-0.42, 1.59] |
| Any UP Candidate (1997-2000) | 0.06 | 0.03 | 0.02 |
| | (0.24) | (0.04) | [-0.09, 0.18] |

**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 quadratic estimates of the average treatment effects around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth. 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. | 409 | 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 sample includes 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 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 | -0.125*** | -0.117*** | -0.112** | -0.111*** | -0.111** | -0.104** | -0.133*** |
| Robust p-value | 0.004 | 0.006 | 0.015 | 0.007 | 0.016 | 0.012 | 0.002 |
| CI 95% | [-0.25, -0.05] | [-0.24, -0.04] | [-0.23, -0.02] | [-0.23, -0.04] | [-0.22, -0.02] | [-0.22, -0.03] | [-0.26, -0.06] |
| Election Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1136 | 1136 | 1136 | 1136 | 1136 | 1136 | 1136 |
| Bandwidth Obs. | 323 | 375 | 323 | 366 | 323 | 375 | 340 |
| Mean | 0.584 | 0.601 | 0.584 | 0.601 | 0.584 | 0.601 | 0.577 |
| Bandwidth | 26.2 | 30.2 | 26.2 | 29.4 | 26.8 | 30.3 | 28.2 |
| **B. Heterogenous Effect** | | | | | | | |
| Explosion Before × Z | -0.121* | -0.005 | -0.087 | 0.005 | -0.078 | 0.001 | 0.013 |
| | (0.064) | (0.009) | (0.067) | (0.012) | (0.064) | (0.008) | (0.011) |
| Explosion Before | -0.193*** | -0.241*** | -0.198*** | -0.226*** | -0.198*** | -0.222*** | -0.306*** |
| | (0.063) | (0.078) | (0.064) | (0.077) | (0.063) | (0.077) | (0.075) |
| Z | -0.038 | -0.009 | -0.061 | -0.018 | -0.068 | -0.013 | -0.012 |
| | (0.042) | (0.009) | (0.045) | (0.012) | (0.041) | (0.008) | (0.010) |
| Observations | 204 | 204 | 204 | 204 | 204 | 204 | 204 |
| Mean Dep. Variable | 0.580 | 0.580 | 0.580 | 0.580 | 0.580 | 0.580 | 0.580 |

**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.

Table 6. Heterogeneous Effects

| Dep. Variable: | Turnout | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Z: | Baseline | Post Ceasefire | Civilian Victim | Local Election | 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) | (7) | (8) |
| Explosion Before × Z | | -0.049 | -0.017 | -0.088 | -0.004 | -0.039 | -0.058 | -0.023 |
| | | (0.210) | (0.100) | (0.181) | (0.056) | (0.030) | (0.046) | (0.033) |
| Explosion Before | -0.295*** | -0.295*** | -0.282** | -0.301*** | -0.304*** | -0.273*** | -0.238*** | -0.259*** |
| | (0.088) | (0.088) | (0.114) | (0.089) | (0.088) | (0.090) | (0.090) | (0.089) |
| Z | | | 0.038 | | 0.030 | 0.019 | -0.019 | -0.012 |
| | | | (0.087) | | (0.050) | (0.026) | (0.034) | (0.030) |
| Observations | 204 | 204 | 204 | 204 | 204 | 204 | 204 | 204 |
| Mean Dep. Variable | 0.580 | 0.580 | 0.580 | 0.580 | 0.580 | 0.580 | 0.580 | 0.580 |

**Note:** 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 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). Civilian victim is a dummy that takes the value one if in the explosion there was a civilian victim involved (column 3). Local election is a dummy that takes the value one if the election is for mayors (column 4). Distance to a road is the demeaned distance from the explosion to closest road (column 5-8). Robust standard errors are presented in parentheses. *** 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.[48]

## 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.[49] 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.

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

[49] 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 2014 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.[50] 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.

[50]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 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 $\alpha_j$ 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:

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

Here, $\alpha_C$ and $\alpha_T$ 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:

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

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

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.

## D 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 A18.[51] 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 A18, 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 A18, 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 A18, 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 A18 Columns 5 and 6 show that the effects are similar if anything larger when excluding these "contaminated" controls.[52]

Fourth, in Appendix Table A19, 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.[53] 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).

[51]In the Appendix, we present the robustness when using the voting over the actual voters (Table A20) as well as for a quadratic polynomial (Table A21).

[52]In Figure A14, we present the coefficients for excluding contaminated controls using a distance for up to 20 km.

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

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 A18, 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 measure is reported in Column 8 of Table A18. 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.[54]

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.[55] Column 9 of Table A18 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.[56]

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

[54]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.

[55]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 A10, 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.

[56]In Appendix Figure A11, we present the robustness of the results of this method to different radii.

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 A18. 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.[57]

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[57]In Appendix Figures A12 and A13, 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, así como se le presento a su jefe, a su asesor y amigo CHACIN. Igual de importante reforzar en los encuentros con los ELENOS propiciados por el gobierno, la necesidad de crear la fusión en algunas regiones de domino primordial de las FARC EP y buscar el apoyo de los asistentes a estas reuniones. A la senadora PIEDAD, hablarle sobre la necesidad de crear un partido del pueblo y buscar su alianza al movimiento Bolivariano.

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

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

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

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

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

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

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

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

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

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

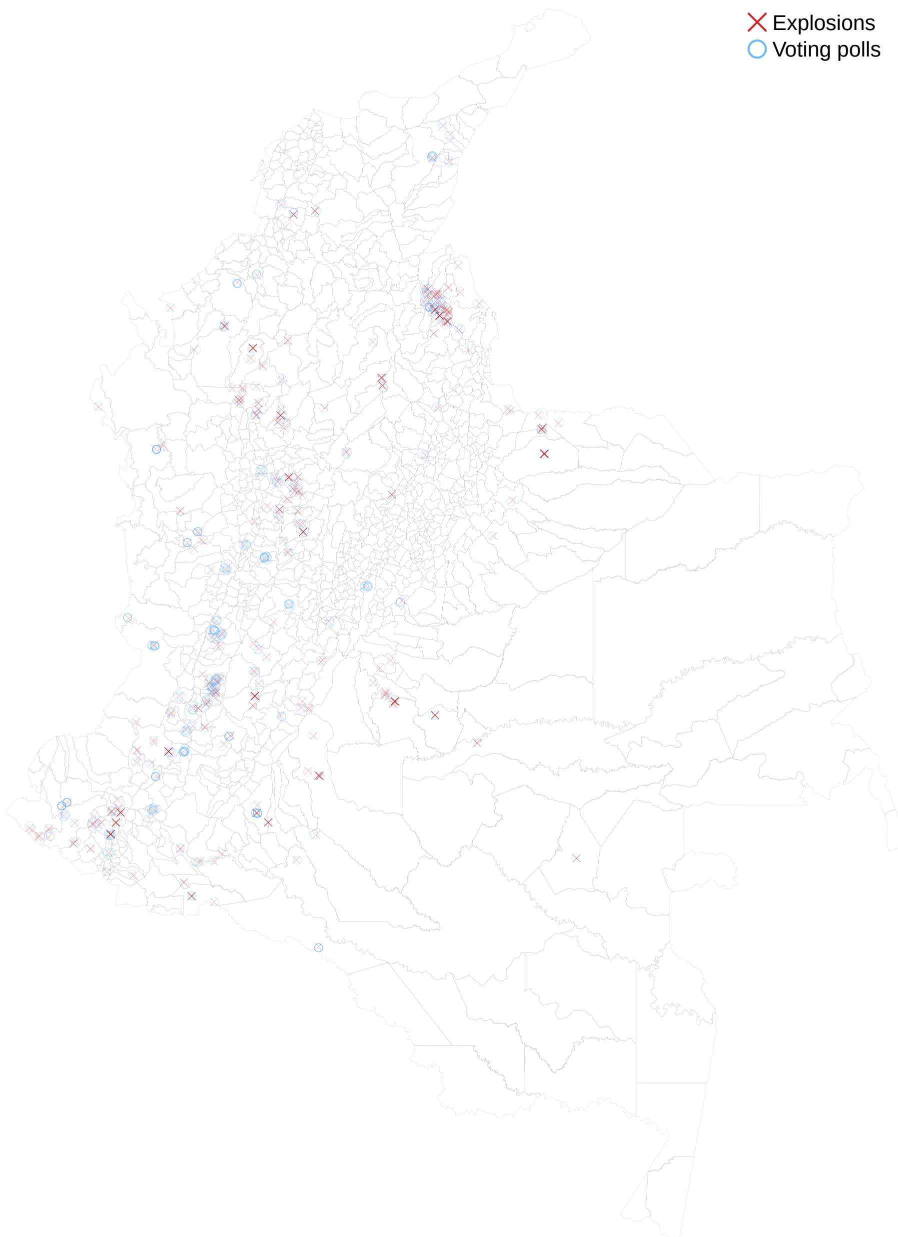
12. Los grupos encargados de la tarea telefónica se debe incrementar en todas las áreas de operaciones enemigas, está comprobado que estando lo bastando cerca de ellos arroja buenos resultados para IC.

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

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

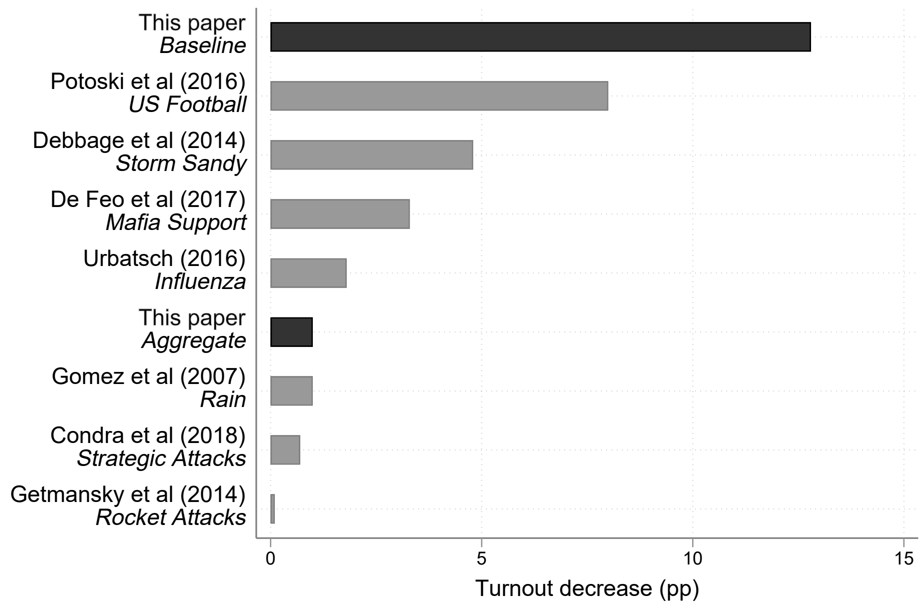
Es todo y espero sus opiniones. Alfonso

Figure A2. Landmine Explosions and Voting Polls Inside Donuts' Distance and Time Windows

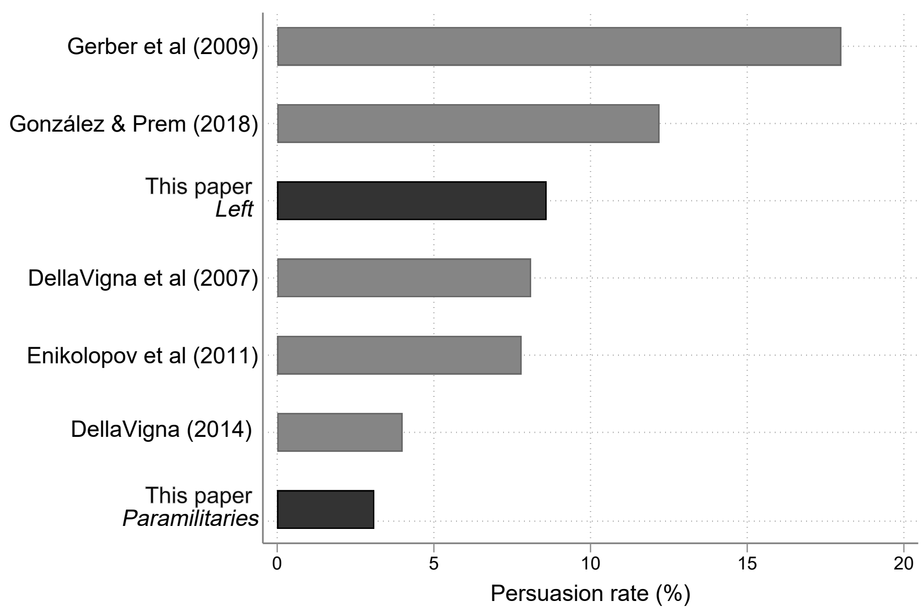



**Notes**: This figure shows the spatial distribution of the landmine explosions and voting polls inside donuts of 4km and 60 days around the election, between 2003 and 2019, with red dots and blue circle hollows, respectively.

Figure A3. Our Estimates in the Literature



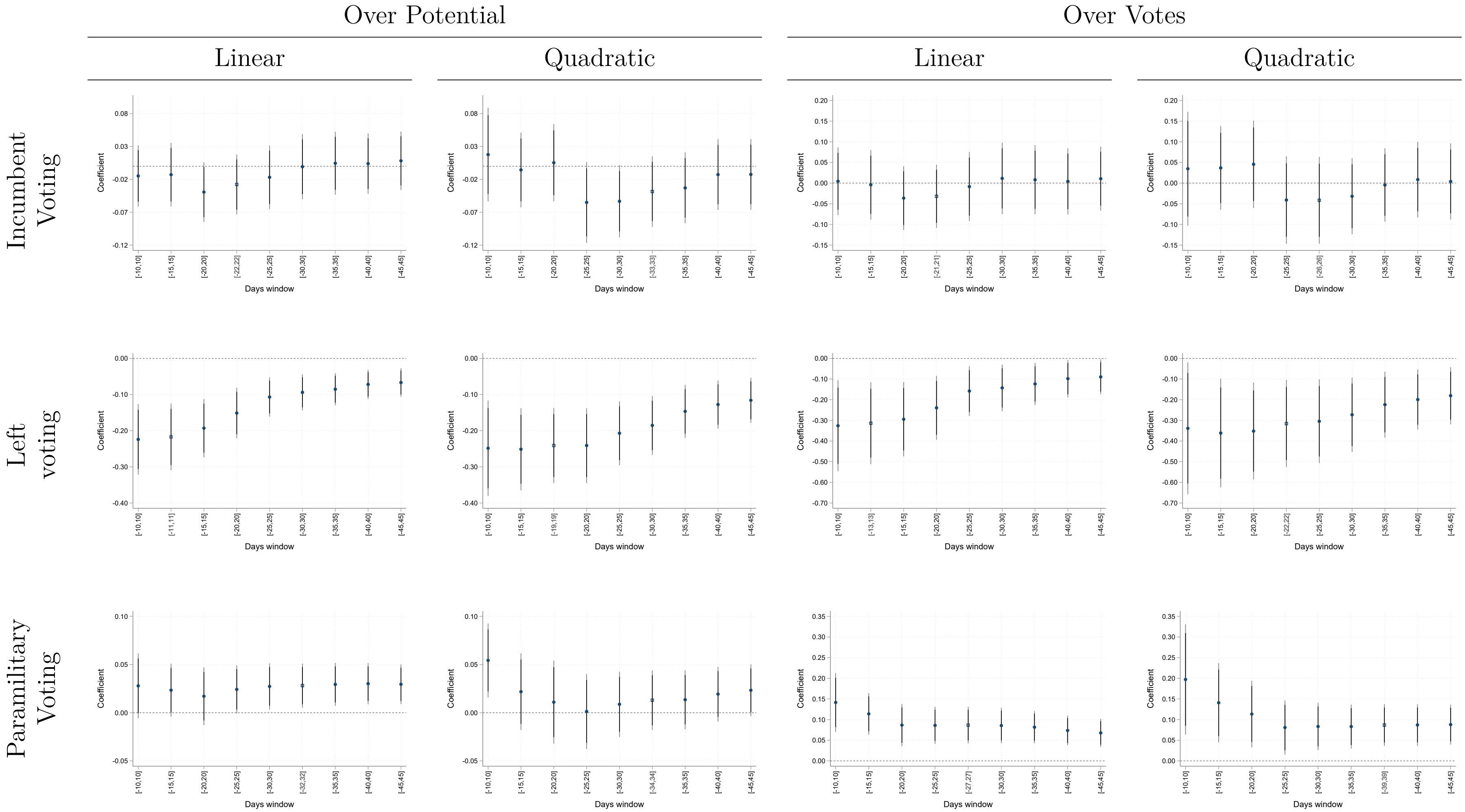

**A.** Turnout




**B.** Persuasion Rate

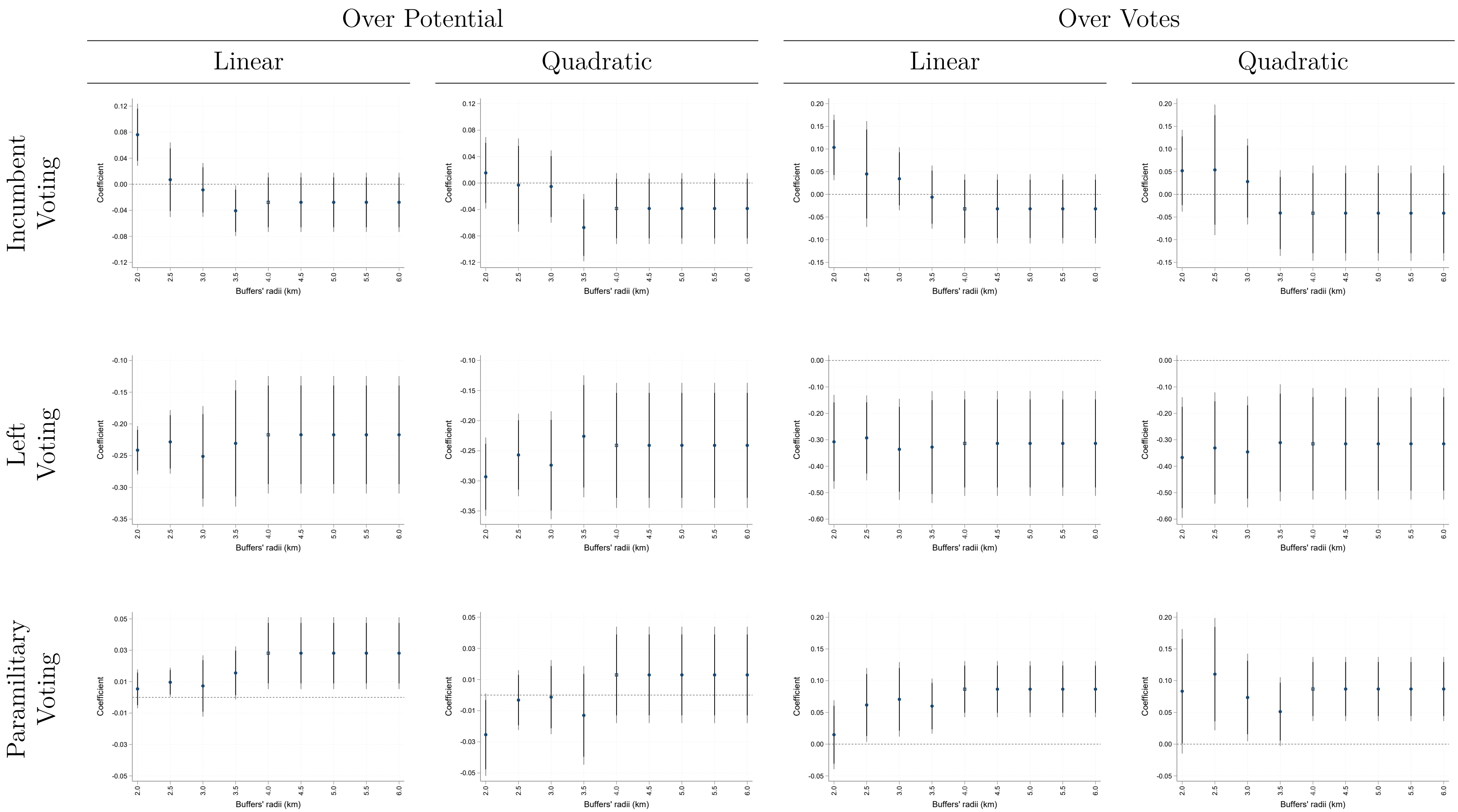
**Notes**: This figures plots how our estimates compare to the existing literature. In panel A, the figure presents the size of our estimates compared to other studies that relate turnout and other kind of events. De Feo and De Luca (2017); Getmansky and Zeitzoff (2014) indicate a decrease on turnout 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 A4. Voting and Landmine Explosions Over Different Days Windows



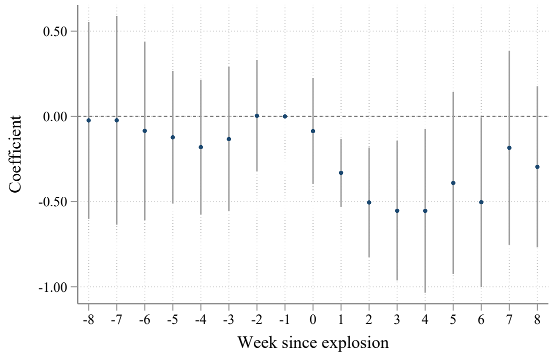

**Notes:** This figure plots local linear and quadratic estimates of the average treatment effects on voting behavior around the cut-off, using triangular kernel weights and optimal MSE bandwidth over different days windows. We report the estimates divided by potential voters (first two columns) and 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 A5. Voting and Landmine Explosions Over Different Buffers' Radii

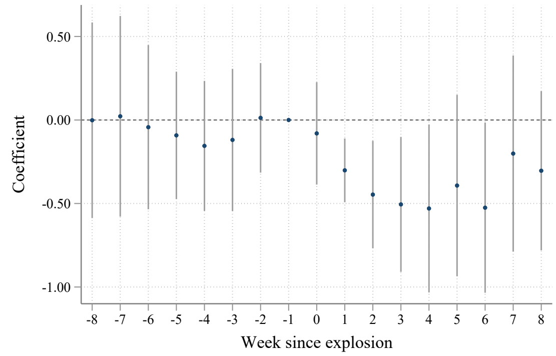



**Notes:** This figure plots local linear and quadratic estimates of the average treatment effects on voting behavior around the cut-off, using triangular kernel weights and optimal MSE bandwidth over different buffers' radii. We report the estimates divided by potential voters (first two columns) and 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.

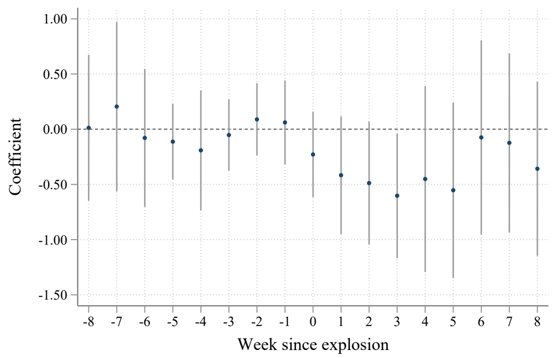
Figure A6. Mobility and Landmine Explosions



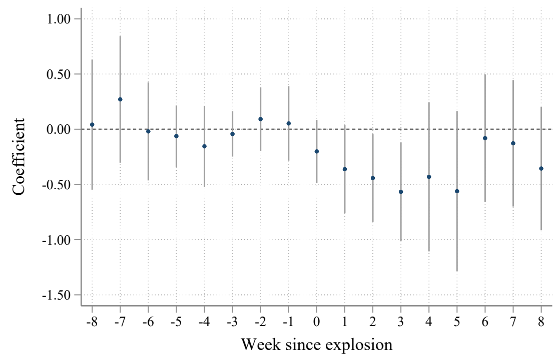

**A.** All Tiles




**B.** Conflict-affected Tiles



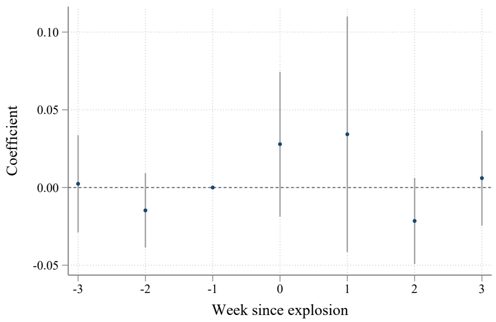

**C.** All Tiles



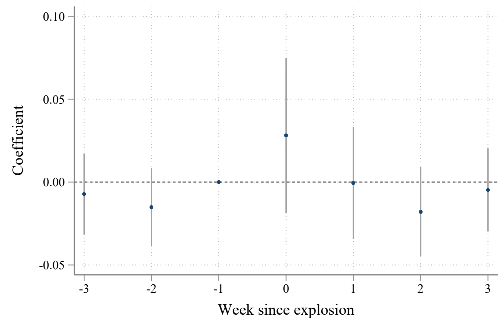

**D.** Conflict-affected Tiles

**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. In Panel A, we present the estimates using a Two-way Fixed Effects model, and in Panel B, 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%.

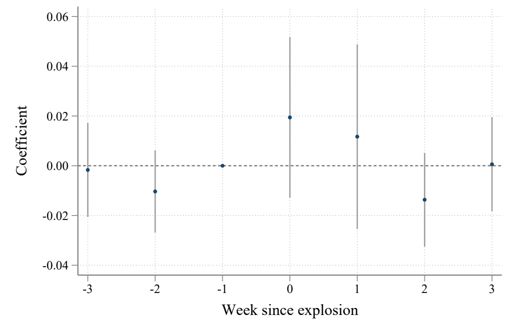
## Figure A7. Homicides and Landmine Explosions: TWFE



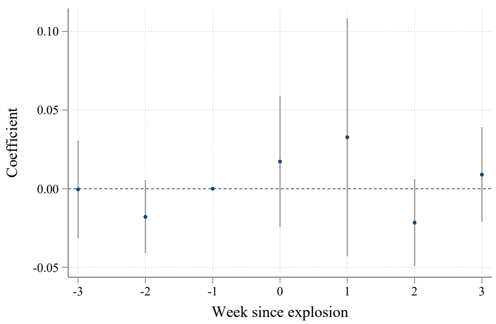

**A.** N. Homicides



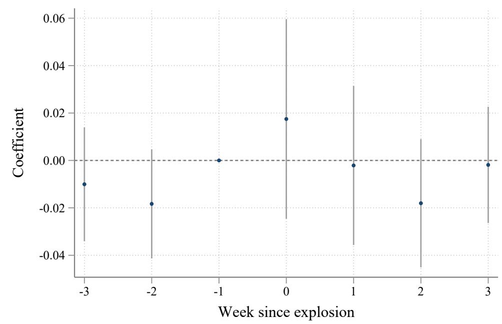

**B.** Any Homicide



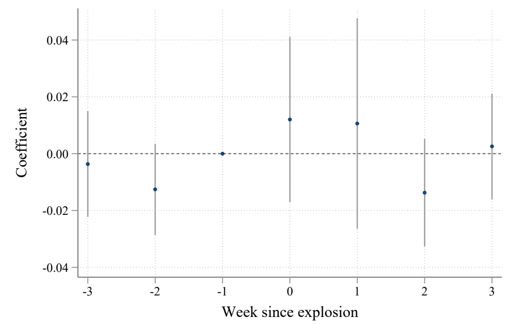

**C.** Ln Homicides




**D.** N. Homicides - BW



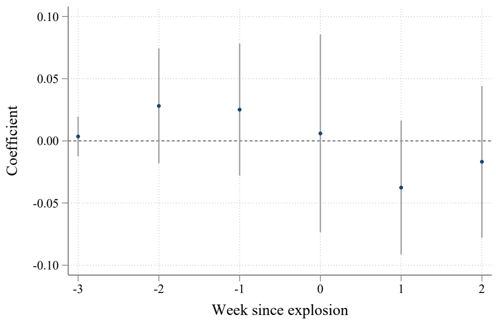

**E.** Any Homicide - BW



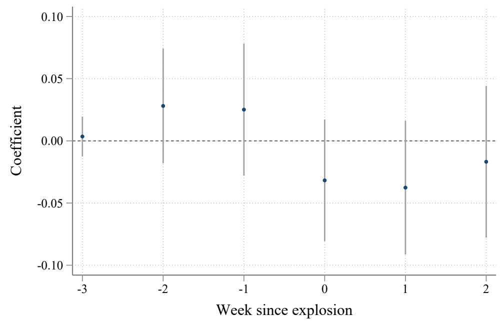

**F.** Ln Homicides - BW

**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.

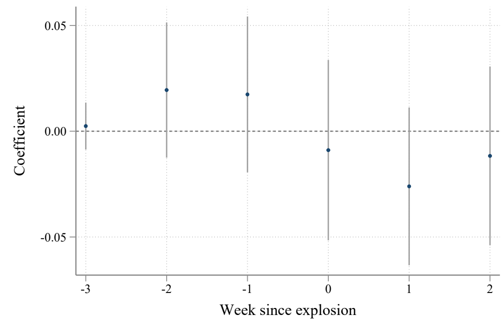
Figure A8. Homicides and Landmine Explosions: De Chaisemartin and d'Haultfoeuille (2020)



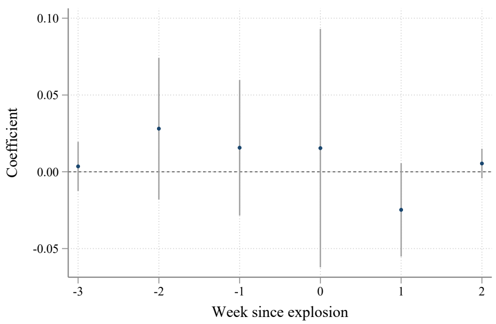

**A.** N. Homicides



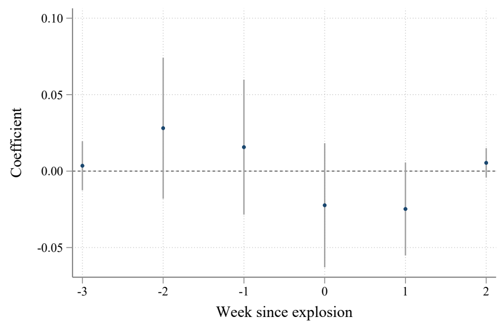

**B.** Any Homicide



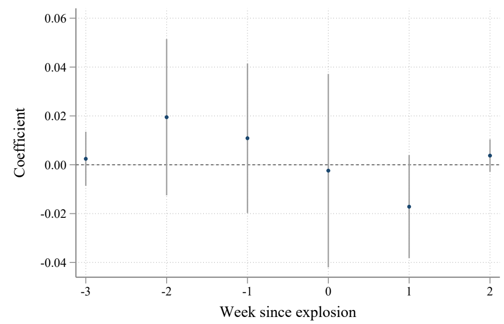

**C.** Ln Homicides




**D.** N. Homicides - BW



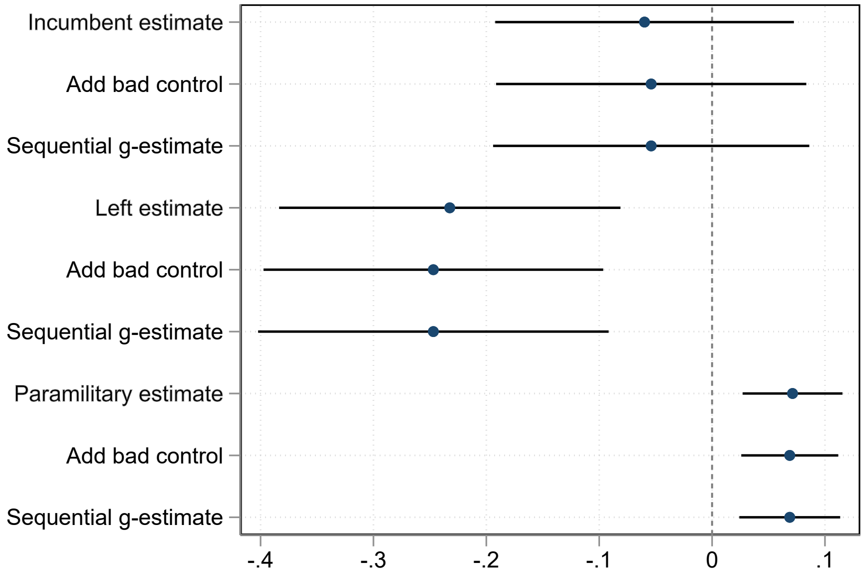

**E.** Any Homicide - BW



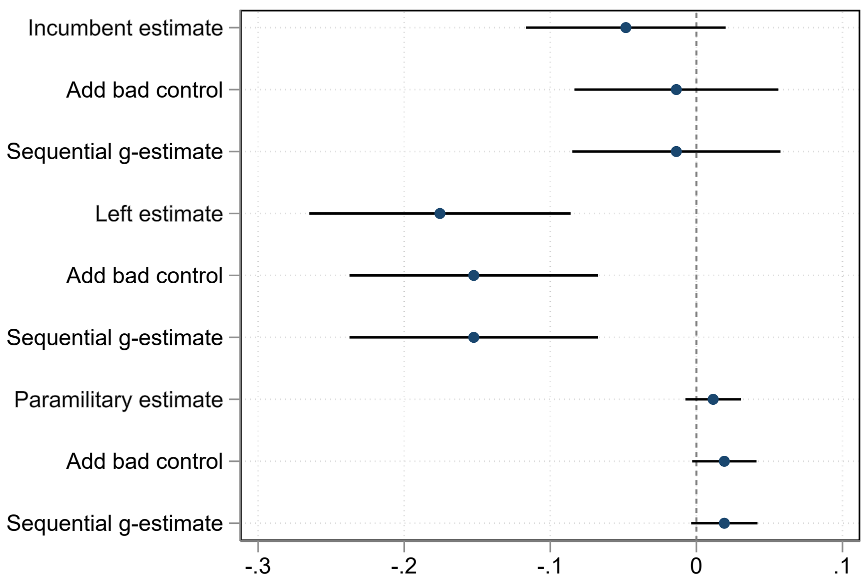

**F.** Ln Homicides - BW

**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 A9. Mediation Analysis



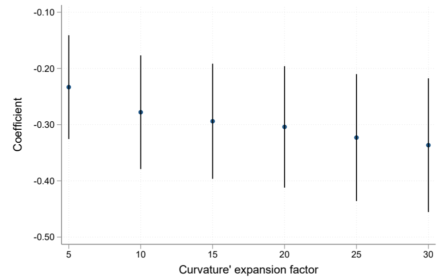

**A.** Over Potential Voters



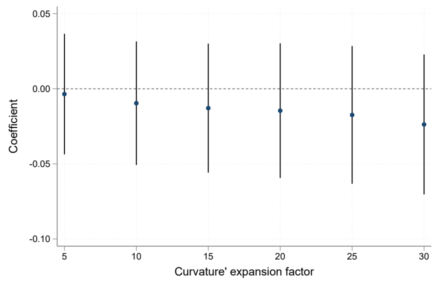

**B.** Over Actual Voters

**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.

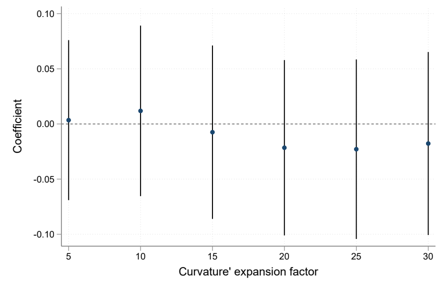
Figure A10. Curvature' Expansion Factor



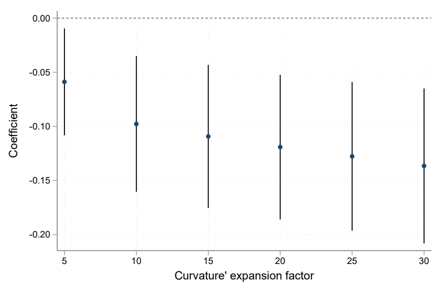

**A.** Turnout



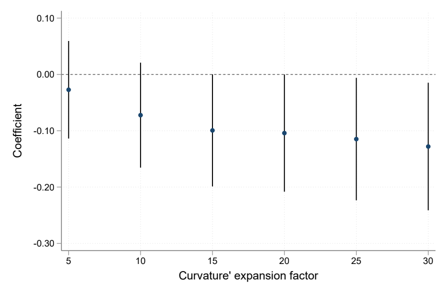

**B.** Incumbent Over Potential



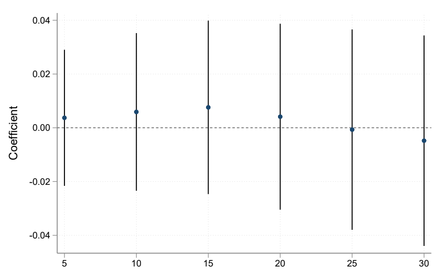

**C.** Incumbent Over Votes



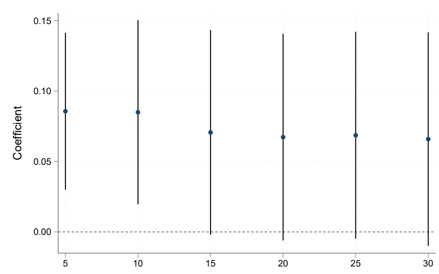

**D.** Left-wing Over Potential




**E.** Left-wing Over Votes



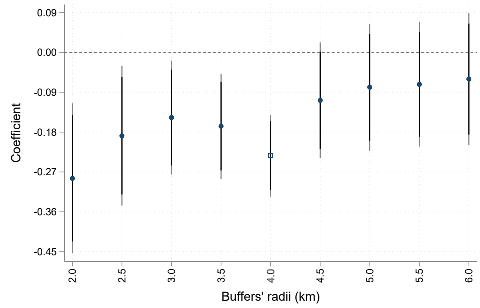

**F.** Paramilitary Over Potential



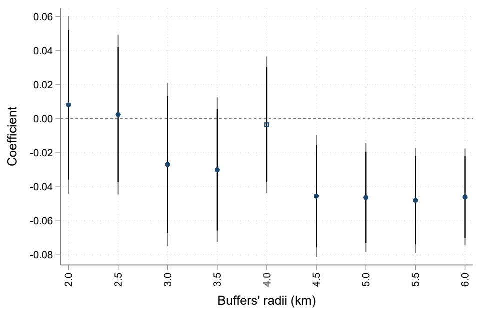

**G.** Paramilitary Over Votes

**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.

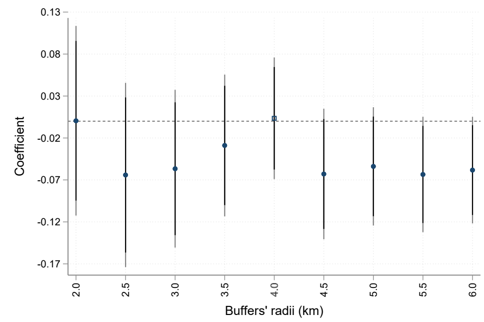
Figure A11. Imbens and Wager (2019) Method: Voting Behavior Over Different Buffers' Radii



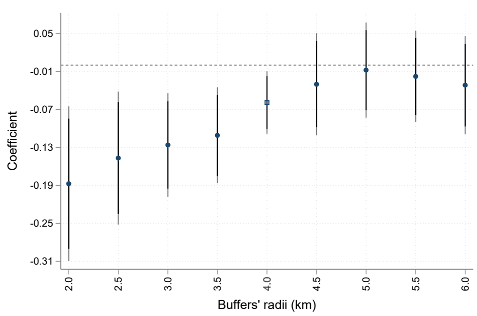

**A.** Turnout



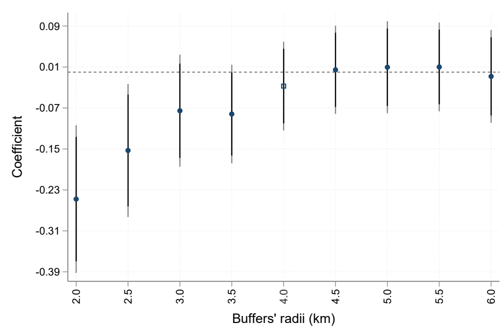

**B.** Incumbent Over Potential



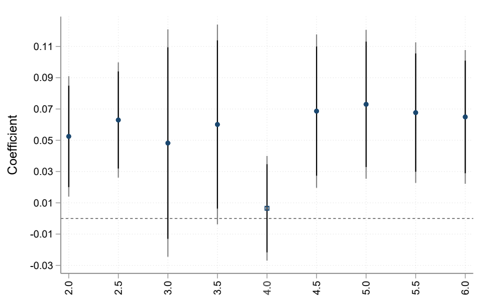

**C.** Incumbent Over Votes



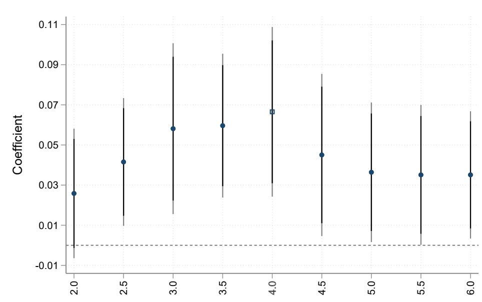

**D.** Left Over Potential




**E.** Left Over Votes



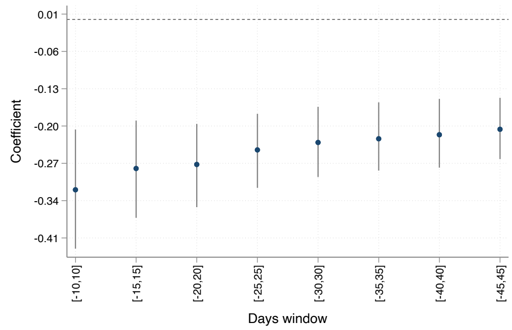

**F.** Paramilitary Over Potential



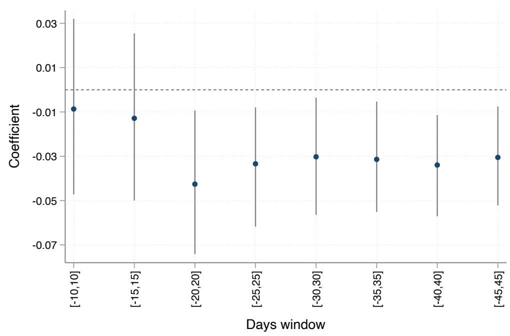

**G.** Paramilitary Over Votes

**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.

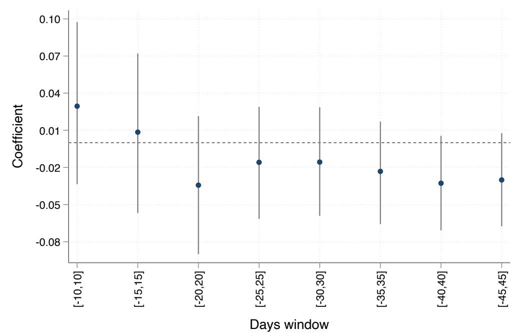
Figure A12. Local Randomization: Voting Behavior Over Different Bandwidths



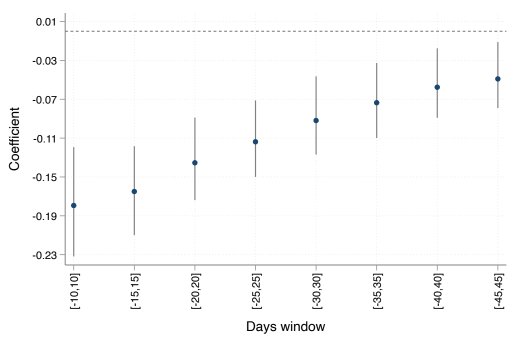

**A.** Turnout



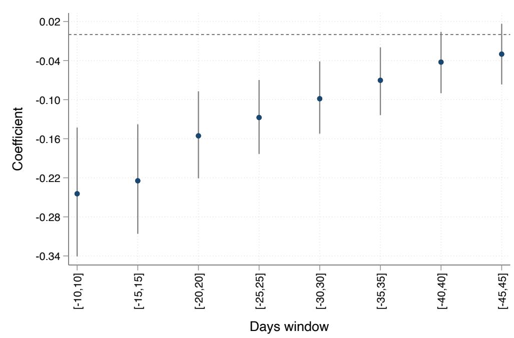

**B.** Incumbent Over Potential



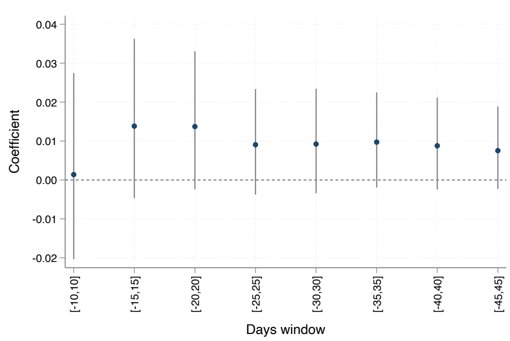

**C.** Incumbent Over Votes



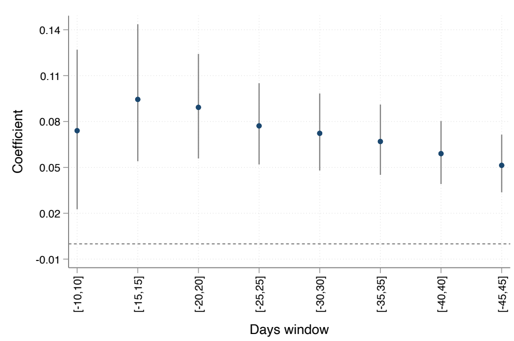

**D.** Left Over Potential




**E.** Left Over Votes



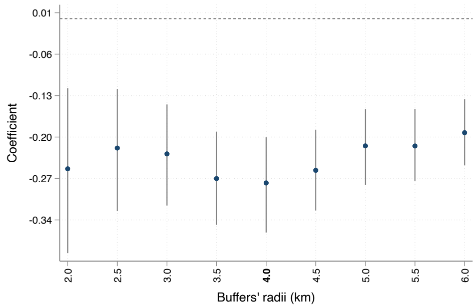

**F.** Paramilitary Over Potential



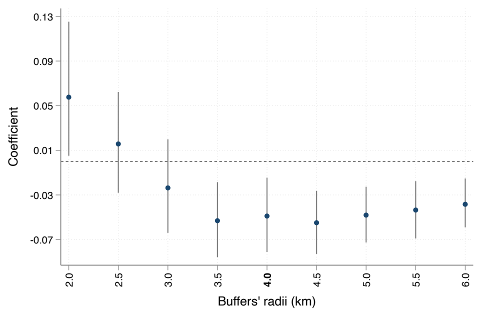

**G.** Paramilitary Over Votes

**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.

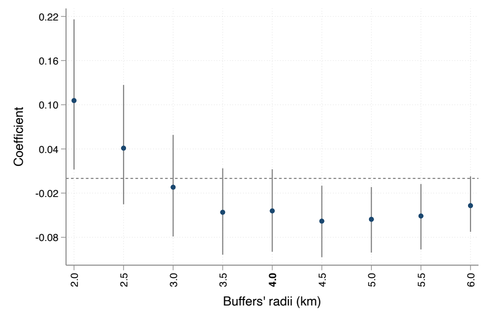
Figure A13. Local Randomization: Voting Behavior Over Different Buffers' Radii



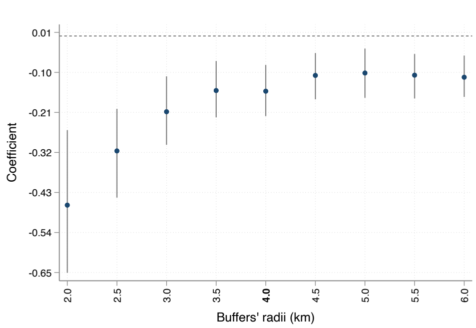

**A.** Turnout



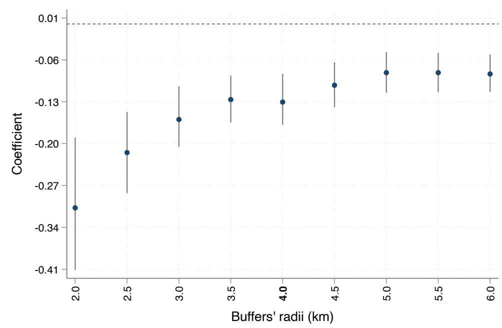

**B.** Incumbent Over Potential



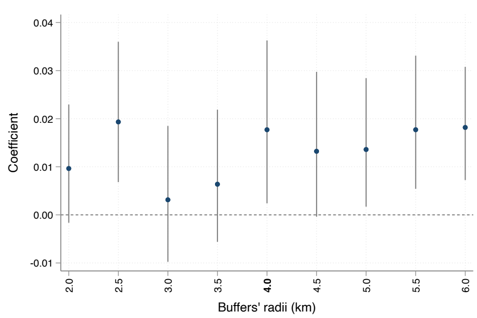

**C.** Incumbent Over Votes



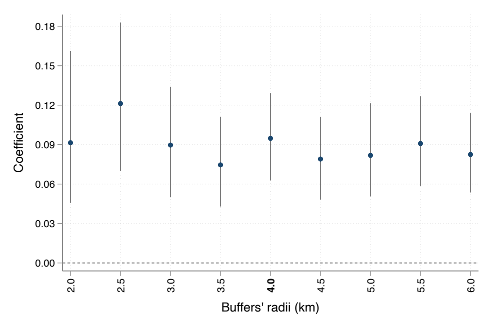

**D.** Left Over Potential




**E.** Left Over Votes



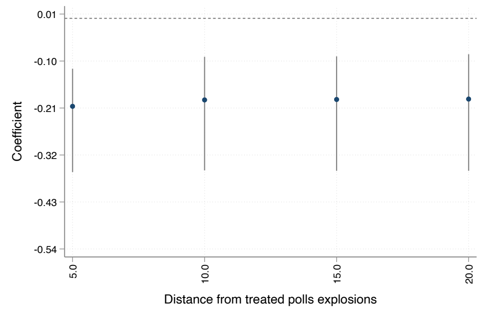

**F.** Paramilitary Over Potential



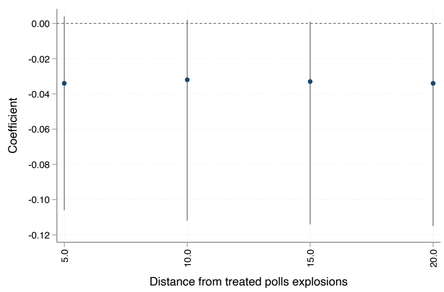

**G.** Paramilitary Over Votes

**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.

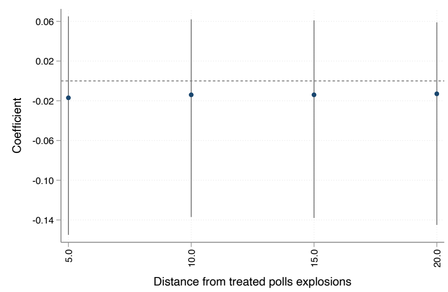
Figure A14. Excluding "contaminated" controls



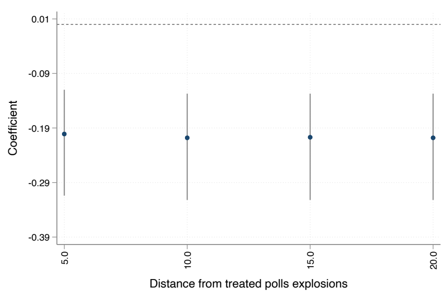

**A.** Turnout



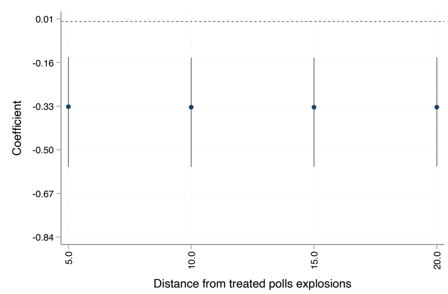

**B.** Incumbent Over Potential



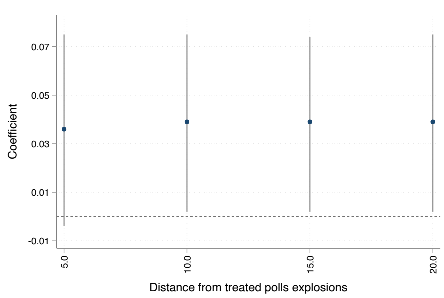

**C.** Incumbent Over Votes



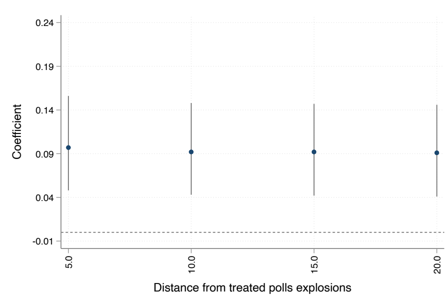

**D.** Left Over Potential




**E.** Left Over Votes



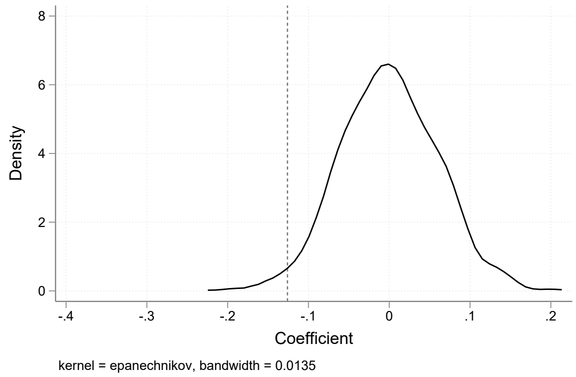

**F.** Paramilitary Over Potential



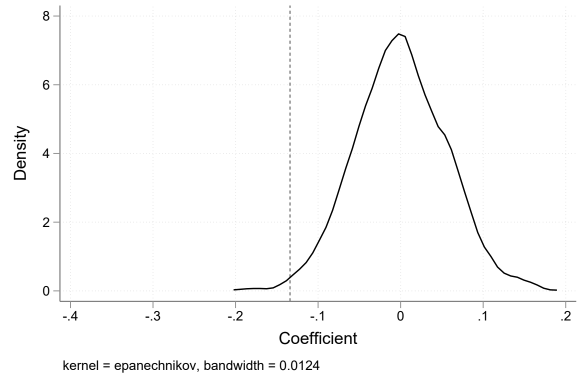

**G.** Paramilitary Over Votes

**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.

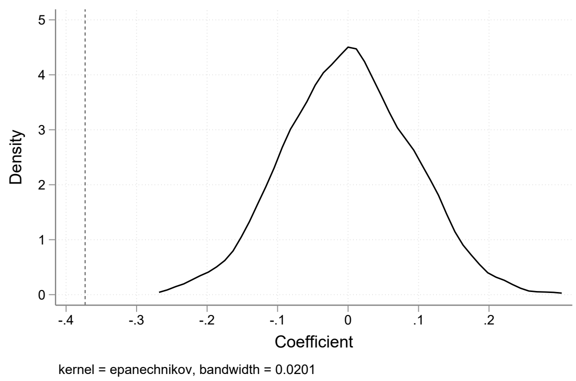
Figure A15. Distribution of Placebo Treatments on Turnout



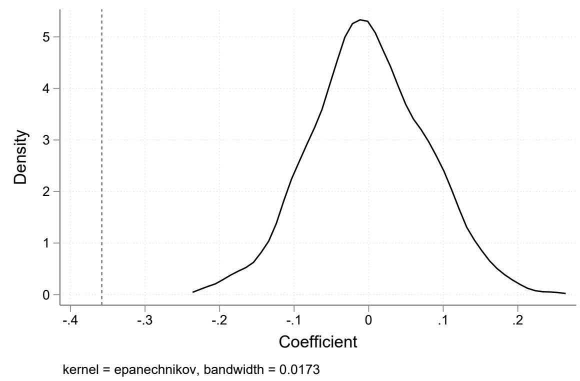

**A.** Linear: No Controls




**B.** Linear: Controls Potential




**C.** Quadratic: No Controls




**D.** Quadratic: Controls Potential

**Notes**: This figure plots the distribution of placebo treatments where we randomize the assignment of a municipality to have explosions before the elections. We run the regressions using the main specification from Table 2 and, in the red line, we present the coefficient. In all cases, the p-value, i.e., the number of cases where the placebo effect shows a larger effect after the landmine explosion, is smaller than 0.01 in all graphs.

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. Difference in Characteristics by Treatment Status II

| | Mean Control | Difference in Mean | RDD Estimate |
|---|---|---|---|
| | (1) | (2) | (3) |
| **A. Poll Station Level - Geographic** | | | |
| Dist. to School | 0.67 | -0.07 | -0.16 |
| | (0.64) | (0.08) | [-0.65,0.22] |
| Dist. to Roads | -1.05 | 0.04 | -0.03 |
| | (1.65) | (0.25) | [-1.16,1.07] |
| Dist. to Mun. Capital | 1.34 | 0.05 | 0.23 |
| | (1.30) | (0.21) | [-1.07,1.27] |
| Dist. to Closest Village | 0.72 | -0.06 | 0.18 |
| | (1.48) | (0.23) | [-0.67,1.05] |
| Dist. to Police Station | 0.67 | -0.07 | -0.16 |
| | (0.64) | (0.08) | [-0.65,0.22] |
| **B. Municipality Level - Socio-demographic** | | | |
| Ln Population | 11.19 | -0.18 | -0.07 |
| | (1.08) | (0.23) | [-0.59,0.66] |
| Ln Value Added | 5.94 | 0.01 | 0.35 |
| | (1.38) | (0.28) | [-0.77,0.69] |
| Rurality Index | 0.59 | 0.00 | -0.11 |
| | (0.26) | (0.05) | [-0.28,0.11] |
| Poverty Index | 69.90 | -0.06 | 4.60* |
| | (15.73) | (2.98) | [-0.08,17.88] |
| Police Stations | 0.09 | 0.01 | 0.01 |
| | (0.06) | (0.01) | [-0.06,0.03] |
| Number of Schools | 87.84 | -6.19 | 24.22 |
| | (86.30) | (17.81) | [-34.30,28.38] |
| Road Density | 22.43 | 4.37 | 20.84 |
| | (22.16) | (3.09) | [-11.02,19.25] |
| Deforestation | 0.03 | 0.00 | 0.02 |
| | (0.05) | (0.01) | [-0.08,0.06] |
| Gold Suitability | 1.26 | 0.02 | 0.10 |
| | (7.75) | (0.61) | [-11.38,3.72] |
| Coffee Production | 1.19 | 0.10 | 0.03 |
| | (1.73) | (0.25) | [-0.59,2.06] |
| Coca Production | 0.14 | -0.01 | -0.03 |
| | (0.20) | (0.03) | [-0.04,0.21] |
| **C. Municipality Level - Electoral Offenses** | | | |
| Any Moving Votes | 0.24 | 0.11 | 0.19 |
| | (0.43) | (0.12) | [-0.16,0.68] |
| Any Vote Buying | 0.32 | -0.00 | 0.19 |
| | (0.47) | (0.12) | [-0.66,0.15] |
| Any Electoral Offense | 0.93 | -0.09 | 0.07 |
| | (0.26) | (0.07) | [-0.48,0.91] |

**Note:** This table reports the differences in 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 quadratic estimates of the average treatment effects around the cut-off, calculated using triangular kernel weights and the optimal MSE bandwidth. In square brackets 95% robust confidence intervals, following Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Heterogeneous Effects Increased Bandwidth

| Dep. Variable: | Turnout | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Z: | Baseline | Post Ceasefire | Civilian Victim | Local Election | 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) | (7) | (8) |
| Explosion Before × Z | | 0.019 | 0.098 | -0.130 | 0.001 | -0.014 | -0.073 | -0.029 |
| | | (0.064) | (0.064) | (0.096) | (0.037) | (0.023) | (0.065) | (0.025) |
| Explosion Before | -0.225*** | -0.226*** | -0.294*** | -0.229*** | -0.230*** | -0.221*** | -0.194*** | -0.210*** |
| | (0.051) | (0.052) | (0.077) | (0.051) | (0.049) | (0.053) | (0.058) | (0.055) |
| Z | | | -0.059 | | 0.019 | -0.003 | -0.004 | -0.009 |
| | | | (0.048) | | (0.021) | (0.016) | (0.013) | (0.015) |
| Observations | 409 | 409 | 409 | 409 | 409 | 409 | 409 | 409 |
| Mean Dep. Variable | 0.582 | 0.582 | 0.582 | 0.582 | 0.582 | 0.582 | 0.582 | 0.582 |

**Note:** 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 bandwidth was constructed doubling the baseline from RDD and using triangular kernel weights. Post ceasefire is a dummy that takes the value one after 2014 (column 2). Civilian victim is a dummy that takes the value one if in the explosion there was a civilian victim involved (column 3). Local election is a dummy that takes the value one if the election is for mayors (column 4). Distance to a road is the demeaned distance from the explosion to closest road (column 5-8). Robust standard errors are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4. Differences in Municipality Characteristics for in and out of Sample

| | Mean RD Sample | Mean at Least One Explosion | Mean All Municipalities | Difference (1) and (2) | Difference (1) and (3) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| 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) | 1776.73 | 1556.46 | 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 municipalities. Column 1 presents the mean of a variable for municipalities in our main sample. Column 2 presents the mean for municipalities out of our sample that had at least one landmine explosion between 2013 and 2019. Column 3 presents the mean for all 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 A5. 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 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. 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, and we present the standardized version. 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 A8. 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 A9. 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 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. 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 A12. 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 A13. 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 A14. Homicides After Landmine Explosions

| Dep. Variable: | Homicides | | | | | |
|---|---|---|---|---|---|---|
| Sample: | Full sample | | | Bandwidth sample | | |
| | Total | Dummy | Log | Total | Dummy | Log |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **A. Two-way Fixed Effect** | | | | | | |
| Post Explosion | 0.002 | -0.019 | -0.006 | 0.007 | -0.014 | -0.002 |
| | (0.025) | (0.014) | (0.013) | (0.024) | (0.013) | (0.012) |
| **B. De Chaisemartin and d'Haultfoeuille (2020)** | | | | | | |
| Post Explosion | -0.013 | -0.030 | -0.015 | -0.000 | -0.017 | -0.006 |
| | (0.025) | (0.023) | (0.016) | (0.018) | (0.012) | (0.010) |
| Observations | 2961 | 2961 | 2961 | 2961 | 2961 | 2961 |
| Mean Dep. Var. | 0.025 | 0.022 | 0.016 | 0.025 | 0.021 | 0.016 |
| Treated | 110 | 110 | 110 | 110 | 110 | 110 |
| Never Treated | 434 | 434 | 434 | 434 | 434 | 434 |

**Notes**: This table presents the overall ATT using two staggered difference-in-differences models for the effect of landmine explosions on pre-election homicides. The dependent variable is an standardize measure of mobility at the 350x350m measured by Facebook. The number of homicides were computed 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 A15. 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 A16. 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 A17. 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 A18. 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 A19. 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 |
| [1] 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.

Table A20. 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 A21. Robustness Estimates for Main Outcomes: Quadratic Polynomial

| | Unweighted | Uniform Kernel | Polls with Only One Explosion | One Explosion per Poll | Excluding Controls | | LASSO | Topographic Distance | Local Randomization |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | 5km | 10km | | | |
| | (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.