AN ANALYSIS OF PRE-ELECTION VIOLENCE THROUGH DECISION THEORY, EXPERIMENTAL DESIGN AND SPATIAL ECONOMETRICS

BY

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DISSERTATION

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Abstract

This dissertation explores the multifaceted dynamics of pre-election violence across three interconnected chapters. In the first chapter, I focus on the conflicting perspectives in the literature surrounding the geography of pre-election violence. The proposed decision-theoretic model suggests that the location of violence is largely determined by the perpetrating party's ability to distinguish its own supporters from those of its rivals, a capability I define as "discrimination capacity." The findings posit that violence can occur both in competitive districts and party strongholds in settings where perpetrating parties have high discrimination capacity. In contrast, the absence or low levels of this capacity create a stricter geographical divide, with violence concentrated in opposition-dominated districts.

The second chapter delves into the impact of pre-election violence on voter behavior. This chapter utilizes a causal identification strategy by leveraging an unexpected inter-party violent event that divided a public opinion survey into two comparable (pre- and post-violence) samples in Zimbabwe. Through a Difference-in-Differences analysis, the chapter reveals differential effects of violence on opposition and government supporters' mobilization.

The third chapter uncovers divergent effects across geographic contexts, emphasizing the role of spatial dynamics in shaping the relationship between heightened levels of fear and political participation within different religious groups in Nigeria. Findings from the geographically weighted regression analysis show that extreme fear leads to political mobilization for Christians and Muslims in areas where they form the majority and demobilization when they are a minority within their surrounding communities.

In conclusion, the dissertation findings underscore the importance of governing parties' discrimination capacity, contextual factors, and spatial heterogeneity in understanding the complex interplay between pre-election violence, extreme fear and voter turnout. The insights presented hold implications for scholars, policymakers, and electoral practitioners navigating the challenges posed by pre-election violence in diverse socio-political contexts.

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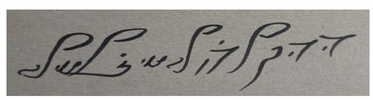

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Chapter 1

A Formal Model of Pre-Election Violence

1.1 Introduction

Election violence is increasingly becoming a global concern. Until recently, violence surrounding elections was widely regarded as a phenomenon particular to developing nations or new democracies. In turn, studies of election violence have tended to focus on new democracies in Africa[1] and Asia[2] or historical cases from comparatively early periods of democracy in what are now "mature" democracies.[3] Of late, however, the general concern over the possibility of election-related violence in advanced democracies has been rising, particularly in the aftermath of the post-election riots following the 2020 US presidential election (Kleinfeld, 2021; Kalmoe & Mason, 2022). Considering the election-related violence that took place on January 6, 2021 in the United States as a unique, isolated event would be a mistake. In fact, there have been multiple events of both pre- and post-election violence in the context of advanced democracies in Western Europe

[1] e.g., Straus & Taylor (2013); D. Bekoe (2013)

[2] e.g., Wilkinson & Haid (2009)

[3] For the historical instances of election-related violence in the United States see Stohl (1975), Rable (2007), Cantrell (1990), Granade (1968), Chin (2003) and Egerton (2014), for Germany, see Retallack (2017) and Charnysh & Ziblatt (2022), for France, see (Merriman, 2009, p.737), and for Switzerland, see Villiger (2013).

and the US.[4] Hence, electoral violence is not a merely research area for scholars focusing on a geographical region like sub-Saharan Africa. It is a concerning phenomenon all around the world, and scholars should strive to understand when, why, and how violence is utilized by political parties, supporters, militants and/or terrorist groups to influence elections.

This chapter will focus on one type of electoral violence: pre-election violence organized by political elites, particularly those in the governing party. We know from influential studies that ruling elites can use and have often used violence as an instrumental tool to stay in office and consolidate their power through suppressing dissent and intimidating rivals (North et al., 2009; Fearon & Laitin, 2000). Scholars of electoral violence narrowed this larger argument to the specific use of violence prior to elections as a strategic tool by political elites to manipulate the results of an upcoming election in their favor (Hafner-Burton et al., 2014; Fjelde & Höglund, 2016). The consensus in this smaller branch of the vast political violence literature is that pre-election violence is more likely to occur when there is uncertainty surrounding the likely winner of an electoral contest (Höglund, 2009; Lehoucq, 2003; Dunning, 2011) and/or when national elections are competitive (Brass, 1997; Laakso, 2007; D. Bekoe, 2013; Austin, 1994).

Until recently, electoral violence scholars have based their subnational theories on the notion that this established link between competitiveness of elections and occurrence of violence should follow through at the district level. Stated differently, the theoretical expectation has been that parties will commit violence in the most competitive districts and/or districts that matter the most to them. Several researchers find evidence in line with this theoretical expectation in India (Wilkinson, 2006; Wilkinson & Haid, 2009; Dhattiwala

[4]Several elections in Spain have been disrupted by violence, instances of which include the murder of Basque socialist councilman Isaías Carrasco by suspected ETA gunman two days ahead of general elections in 2008, the train bombings by al-Qaeda before the national elections in 2004. In the US, the murder of Arkansas Democratic Party Chairman Bill Gwatney, an elected superdelegate before he was able to vote at the 2008 National Democratic Convention. In France, far-right National Front supporters killed two immigrants during their election campaign in 1995 (von Borzyskowski, 2019). In the Netherlands, the murder of far-right Dutch politician Pim Fortuyn during his campaign activities only nine days before general elections in 2002.

& Biggs, 2012), Kenya (Kasara, 2014), Zimbabwe (Robinson & Torvik, 2009) and/or several sub-Saharan African countries (Choi & Raleigh, 2021).[5] In sum, conventional wisdom has stated that competitive districts are more vulnerable to pre-election violence.

Nonetheless, recent scholarship has challenged this idea by arguing that it can be strategically more beneficial for political parties to commit violence in their rivals' strongholds than in competitive districts. These scholars find evidence supporting their theory in several countries such as Burkina Faso, Ghana, Kenya, Liberia, Tanzania, Zimbabwe (Rauschenbach & Paula, 2019), and Zambia (Wahman & Goldring, 2020; Rauschenbach & Paula, 2019). Besides the contradictory findings in cases like Zimbabwe, empirical evidence supporting two diametrically opposed theories in individual country cases suggests that there remains variation to be explained across countries in terms of how political parties maximize their electoral gains through political violence at the subnational level.

I resolve this empirical contradiction by revisiting theory. I define a concept called "discrimination capacity" as political parties' capability of distinguishing their own supporters from those of their rivals.[6] I argue when political parties can *detect* or *collect* information on the party affiliation and/or voting behavior of individual voters, they gain the capacity to commit selective violence against members of rival parties in *any* district.[7] In such cases, they acquire the ability to target individuals or small groups of voters in *any* district including competitive districts that matter the most in legislative and/or concurrent elections. When political parties lack the capacity *discriminate* among

[5] Although Choi & Raleigh (2021) focus on political violence in general, their argument about the locational patterns of violence can be extended to pre-election violence.

[6] In earlier iterations of my work, I referred to this concept as "discrimination technology." As justification for my use of the term "technology," it is not very hard to imagine surveillance technology enabling the state or powerful political parties to collect information discriminating among voters. Since this is a capacity that can be advanced, the term "technology" can be used interchangeably with "capacity" in the context of my research.

[7] The logic behind this argument is not too distant from Kalyvas (2006)'s work, which establishes a link between armed groups' ability to use selective violence and collect accurate information on specific targets. My focus is merely on governing party elites using armed forces to intimidate opposition supporters with the purposes of winning elections.

individuals, they will have to confine their violent campaigns to their rivals' strongholds, where non-selective violence will be least likely to harm their own turnout. Thus, they strategically exclude the option of committing violence in competitive districts. In summary, it is only when political parties possess a high discrimination capacity, they expand their violent campaigns to competitive districts. Conversely, low discrimination capacity brings in a greater geographical divide, while advanced discrimination capacity enables selective violence across all districts.

Discrimination capacity may be a function of endogenous factors such as political parties' monitoring capability or exogenous constraints like the pervasiveness of ethnic voting, such that outward appearance is highly correlated with vote choice particularly in low-information elections (Conover & Feldman, 1989; Hurst, 2022; Anderson et al., 2020; Banducci et al., 2008; Kristín Birnir, 2007; Ferree, 2010; Posner, 2005; Barisione & Iyengar, 2016; Barreto, 2010; Bowler & Nicholson, 2018; Iyengar & Barisione, 2015; McDermott, 1998; Van Trappen, 2021). Hence, it can be a function of ethnic diversity, clientelistic networks or even information technologies.[8] If members of distinct ethnic groups can distinguish their own from the members of other groups in countries where co-ethnics tend to vote for same parties, parties can easily distinguish their own supporters from their rivals'. This attribute of discrimination capacity is more of an exogenous characteristic of the polity that parties cannot do much to improve. Alternatively, parties may collect information on voting behavior and/or party preferences of individuals through clientelistic networks. Under these circumstances, there may be brokers and/or party officials who develop a tracking system capturing the voting behavior of each individual and/or community at the local level. Governing parties may also monitor voters' behavior online and determine each

[8]The US would be a country with advanced discrimination capacity, where party volunteers use smart phone apps to code the political party preferences in each house when they are canvassing. These apps integrate the publicly available turnout information with the information entered by the canvassing official's observations such as whether the house has a yard sign for one party or the other, whether they answer the door in a supportive manner or not, along with any other interaction that reveals information on party preferences of the resident(s).

individual's precise location by information technology. Such technologies are available in all types of regimes. While they can also be used for marketing purposes by parties in democracies,[9] they can also be used for voter intimidation in unestablished democracies and authoritarian regimes.[10]

When political parties do not have the capacity to tell apart voters, they also lack the ability strategically between selective and indiscriminate violence. Kalyvas (2006) argues that the choice between selective versus indiscriminate violence depends on the political objectives of the perpetrators. If the governing party's aim is to eliminate key rival figures, suppress specific opposition parties and/or ethnic voting against the government, they tend toward selective violence (Kalyvas, 2006, 2008). Indiscriminate violence, however, can be counter-productive since it may strengthen the opposing political groups by instilling fear that may always create a backlash against the perpetrator (Kalyvas, 2006). With this perspective, committing violence in competitive districts may bring the risk of repressing their own turnout. Perhaps, as an off-the-path equilibrium, the absence of discrimination capacity could lead to indiscriminate violence which in turn can intimidate everyone in a competitive district regardless of party affiliation. In order to avoid repressing perpetrator's own turnout, parties choose to commit violence in their rival parties' stronghold districts when they do not have the capability of distinguishing amongst voters. Although the indiscriminate (or non-targeted) violence would arguably repress the turnout of the perpetrator's supporters in such a rival stronghold, the repression of the opponents will be greater than party supporters. This will still create an advantage to the perpetrating party in line with Kalyvas's contention that indiscriminate violence can benefit the perpetrator when the political objective is to establish dominance over the

[9]One would remember Cambridge Analytica scandal- the greatest leak in the history of the social media giant Facebook, which some argue that led to the victory of Donald Trump in 2016 US elections `https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html`

[10]China could be the best example of how the internet police track down individuals due to their anti-government (and/or pro-opposition) views.

rivals and discourage support for the opposing parties on a larger scale (Kalyvas, 2006). In sum, I argue that it is the discrimination capacity of political parties that determines whether there will be violence in competitive districts versus party strongholds.

This chapter contributes to the scholarship by formalizing the capability of political parties to distinguish their supporters from their opponents' supporters in a decision-theoretic model.[11] From a theoretical perspective, this helps bring together the conflicting findings in the literature. Political parties commit violence in competitive districts, as some scholars argue, but only in countries where they have the capacity to tell voters' party affiliations apart. In such settings, the parties will know who to target and can commit violence in competitive districts without jeopardizing their own turnout. In the absence of these capabilities, the violence will take place in rival strongholds which is in line with the recent findings in the literature that show political parties commit violence in party strongholds.

1.2 Conceptual Considerations

Electoral violence scholars have widely investigated the factors that cause pre-election violence at the national level. The most well-established factor at the national level is the level of competition or uncertainty in a national election. Pre-election violence is more associated with elections that are very close between contenders and/or with a high level of uncertainty around the likely winner at the national level (Hafner-Burton et al., 2014; LeBas, 2006; Boone, 2011). But, how do other factors influence the relationship between competitiveness and occurrence of pre-election violence? If competitiveness is a

[11] Formalizing similar concepts has been done by political violence scholars. A prominent example would be Kalyvas (2006) using a concept called "control" for the incumbents and insurgents as the two actors in his model. This is an all-encompassing concept integrating control over territory, population, and informational dimensions. In my model, I will use separate parameters for informational capacity and population's support for each party in the political competition with emphasis their effects on voter turnout.

great factor in determining whether there will be violence or not, it is a natural extension of this idea to theorize that institutions shaping competitiveness may also influence the occurrence of violence. With that, a recent study attempted to measure the impact of electoral systems across countries and argued that single-member plurality (SMP) systems raise the stakes of elections, which in turn increase the level of violence at the national level (Fjelde & Höglund, 2016). Given that electoral systems affect so many other factors that may directly or indirectly affect violence such as the number of political parties (Duverger, 1954), the level and perception of competitiveness in districts (Blais & Lago, 2009), and the size and number of districts, it is difficult to isolate the pure impact of varying electoral systems in the absence of counterfactuals. Fjelde & Höglund (2016)'s findings were limited to those of cross-national analysis and the within-country variation caused by electoral institutions was not completely explored in the analysis. Thus, the question regarding how competitiveness at the subnational level affects pre-election violence remains to be analyzed further at the district level.

This chapter argues that analyzing the interaction between competitiveness and pre-election violence at the subnational level can benefit the literature in multiple ways. First, it is still in question whether competitiveness brings more violence at the district level as Wilkinson (2006), Robinson & Torvik (2009), and Kasara (2014) advocate, or less violence as claimed by Rauschenbach & Paula (2019) and Wahman & Goldring (2020). Second, I argue that my findings at the district level can be aggregated to the national level, which may force us to revisit some of our national level findings that come from cross-national studies. For instance, when district dynamics do not give political parties any incentive to initiate violence (or my model's necessary condition for violence is not met), then there will be no violence in that district. If all the districts in a country are like this one district where there is no incentive for parties to pursue any violence, there will be no violence at the national level. Since the majority of the literature has followed a top-down approach, this new bottom-up approach aggregating micro findings to a macro level brings a new perspective and a set of new variables that were previously overlooked in the literature.

With this in mind, I contend that a factor that influences the relationship between competitiveness and the occurrence of pre-election violence is political parties' capabilities to tell their supporters apart from those of other parties. I argue that the ability to distinguish voters or "discrimination capacity" can be a useful parameter to predict the relationship between competitiveness and violence. Parties can discriminate between voters through different channels: (1) through their monitoring capacity at the local level, (2) identifiability through physical or ethnic cues. Monitoring capacity is a party characteristic, which the party elites may be able to advance by investing in clientelistic networks or collecting information on individual voters, among other methods. Identifiability of voters is more of a characteristic of voters over which voters only have partial control. Voters may hide their party preference or political stance by not wearing their party's symbols or try to remove ethnic or religious outfits to be less identifiable. However, in societies where ethnic groups have visible physical differences and when those ethnic groups have political alliances with particular parties, voters will not have much control over their identifiability and may more easily be subjected to selective/targeted intimidation prior to elections.

Regarding monitoring capacity, parties can have the ability to follow how each voter or at least small groups of voters vote in the elections. We know that the scholars in clientelism literature have used monitoring capacity as an important component on tracing voter behavior in return for the private goods and services delivered to them. For instance, Chandra gives examples of how party officials monitor elections in different ways to identify voting behavior of individuals or small groups of voters (Chandra, 2007, p.52). First, she shows that voting for one party for all the contested seats can easily be tracked even in democratic settings, where the ballot is considered secret. For instance, Chandra (2007) reports that voters were asked to simply pull a specific "party lever" in the voting machines when they wanted to vote a non-split ticket, and splitting the ticket would take so much more time in the municipal elections, which was observable to the party officials in the polling station in the municipal elections in New Haven, Connecticut (also see, Wolfinger, 1973, p.23). Chandra (2007) provides examples of government officials detecting voter behavior by strategically arranging polling stations. In instances like the 1993 elections in Senegal, they structured the stations to have an average of around 175 people per station. Despite the appearance of a secret ballot, this division of voters into smaller groups served as a form of "(collective) surveillance" (see also, Schaffer, 1998, p.136). In sum, party officials can develop the capability of detecting voting patterns of individuals or small groups even in democratic settings. This chapter adopts the theoretical stance that party officials are likely to utilize the already existing capacity to intimidate voters in competitive authoritarian regimes and new democracies with a history of (or vulnerability to) election violence.

Similarly, I argue that political parties can also use social networks to identify voting behaviors of individuals or small groups of voters before committing selective violence. We know from the literature on social networks that these networks can be ethnic, religious, clientelistic or merely partisan within the establishment of a political party (Larson & Lewis, 2017; Cruz, 2019; Koger et al., 2009; Gaines & Mondak, 2009). Since a small number of political elites need the aggregated votes of a large number of individuals to stay in power, networks can serve as a shortcut not only for elites to reach out to these voters for campaign appeals, but also to monitor, observe or collect information about their voting behavior. In this sense, elites' ability to distinguish individual voters can take place through any social network that may or may not overlap with clientelistic networks. For instance, North et al. (2009) state that patron-client networks can both limit violence by creating and distributing rent and structure its onset, which can then escalate within and across these networks (North et al., 2009, p.36). In addition, Kuhn (2015)'s discussion of "ethnic voting" can also shed light on the ways in which political parties can discriminate individual voters with the intention to use the information for selective violence before elections. Kuhn defines the concept as individuals in a certain ethnic group that is associated with being loyal supporters of a certain political party. In circumstances where there is widespread ethnic voting, party officials may be able to understand the party affiliation by looking at the attire (if religious attire is commonly used), facial features, names, spoken language, dialect or accent of that individual (Chandra, 2007). Chandra argues that some ethnic markers such as names, features, speech, dress can be used as informational shortcuts to collect costless data about voters (Chandra, 2007, 37-42).

Nonetheless, not all social networks are available for providing a costless opportunity to distinguish voters or a resource for data on voting tendencies. While information is roughly symmetric in the case of ethnic voting, positively identifying voters may be more difficult than positively identifying supporters when this identification is done through clientelistic networks. In such networks, the membership is not necessarily (or easily) observable from outside, and such information is only available to the members of that group. Since the effective identification of the group members depends on the information that will come from a member of that group, identification becomes more costly for the elites due to a lack of incentive-compatibility between the elites and the insider(s) providing that information which will be used for intimidation against their own group. In sum, the data to discriminate is more difficult to extract for rivals than the data needed to facilitate delivery of private goods for affiliated parties in the absence of visible markers.[12]

In conclusion, political parties employ various methods to gather data for differentiating among voters, determining whom to mobilize through campaign ads or private goods, and deciding whom to intimidate with violence before elections. With this in mind, this chapter

[12]Even in the cases where person having the insider information is not an actual member of the group such as a broker that works with several parties, the moment they deviate to provide that information to the rival party will be the moment s/he will be ousted from the network. In that sense, such information extraction methods are not only costly but also unsustainable for political parties in the long run.

aims to explore how political parties' capacity to distinguish among voters can help the elites to utilize violence across varying levels of competitiveness in districts. The chapter agrees with Birch (2020)'s notion that the literature needs to expand in the direction of describing the dynamics behind subnational variation in election violence. We are not certain why political parties pursue election violence in some districts and not in others. A better understanding of this question will inevitably help aggregate our district-level findings regarding the occurrence (or absence) of violence, prompting a reevaluation of our explanations for why some countries experience violence while others do not. The specific areas requiring further development in our understanding involve theorizing what distinguishes a violent district from a peaceful one and testing these theoretical claims. Once we understand what kind of incentives varying levels of competitiveness create for political parties regarding pursuing violence at the district level, we can then understand if those incentives (or lack of incentives) will aggregate to the presence (or absence) of violence at the country level. For that, it is beneficial to see under what circumstances political parties target rival party supporters in party strongholds versus competitive districts. The following section aims to provide responses to these questions.

1.3 A Decision-Theoretic Model for Pre-Election Violence

This section presents a decision-theoretic model with the governing party (G) being the main decision-maker determining the intensity and location of pre-election violence. There is a second political actor, an opposition party (O) which does not have the ability to initiate violence in the model. That is, violence (V) is a strategic tool in the hands of the government (G), who can use it to intimidate voters, causing them to abstain in elections. In this initial setup, the question is where G will choose to use violence as a strategic tool to repress the voter turnout. In order to answer this question, I formulate the decision-theoretic model as an optimization problem, where G seeks to maximize the vote difference between itself and the opposition, aiming to maximize a positive lead or minimize a negative gap. I construct the G's utility function in a country with n districts, where districts are denoted by D_i:

$$U_G = \sum_{i=1}^{n} G\text{'s } Vote \ in \ D_i - \sum_{i=1}^{n} O\text{'s } Vote \ in \ D_i - \sum_{i=1}^{n} Cost \ of \ Violence \ in \ D_i \tag{1.1}$$

In this initial framework, I incorporate two factors that determine each party's vote in a district: their initial support (α_i) and voter turnout levels (t_i). The two parties share the total public support that is normalized to 1: G's initial support is $\alpha_i \in [0, 1]$, whereas O receives the remaining support, $(1 - \alpha_i) \in [0, 1]$. Each party has its own turnout function: $t_{G,i}$ or $t_{O,i}$. With these two components, the parties' vote share in D_i is their initial support multiplied by turnout rates in that district. The total vote for each party at the national level is the sum of their respective vote shares in districts. With all these components, we can reformulate G's utility function in Equation 1.1 as follows:

$$U_G = \underbrace{\sum_{i=1}^{n} \overbrace{(\alpha_i)}^{G's\,Support} \cdot \overbrace{t_{G,i}(V_{G,i})}^{G's\,Turnout}}_{G's\,Total\,Vote} - \underbrace{\sum_{i=1}^{n} \overbrace{(1-\alpha_i)}^{O\text{'s } Support} \cdot \overbrace{t_{O,i}(V_{O,i})}^{O's\,Turnout}}_{O's\,Total\,Vote} - \underbrace{\sum_{i=1}^{n} k\,(V_{T,i})}_{G's\,Total\,Cost} \tag{1.2}$$

where the model's crucial component is the level of violence in each district, V. This parameter is indexed by i to indicate the district or location of violence. The subscripts G and O show which party's supporters that the respective levels of violence, V_G and V_O, is targeted at and/or victimizes, while V_T is to denote the total level of violence. By this definition, we have the equation below, which will later help incorporate the discrimination capacity as a parameter in the model.

$$V_{T,i} = V_{G,i} + V_{O,i} \tag{1.3}$$

In Equation 1.2, I assume that both turnout functions, $t_{G,i}(\cdot)$ and $t_{O,i}(\cdot)$, are monotone decreasing functions of violence against the supporters for each party, $V_{G,i}$ or $V_{O,i}$.[13,14] The inequalities to show this monotonicity would be as follows:

$$\begin{aligned} \frac{\partial t_{G,i}(V_{G,i})}{\partial V_{G,i}} < 0 \\ \frac{\partial t_{O,i}(V_{O,i})}{\partial V_{O,i}} < 0 \end{aligned} \tag{1.4}$$

I will use Equation 1.3 and Inequalities 1.4 to incorporate discrimination capacity (Δ) into the model, after Section 1.3.1 defines and discusses this parameter from a conceptual perspective.

1.3.1 Discrimination Capacity to Tell Voters Apart

This section introduces "discrimination capacity" as the governing party's capability of telling opposition supporters apart from their own supporters. This concept is the essential part of the model and incorporating it to the model will answer questions such as how ethnic networks and parties' monitoring capacities may play vital roles in determining the location and effect of pre-election violence. To carry out selective violence targeted at opposition supporters, governing parties must be able to differentiate individuals belonging to various voting groups. For that purpose, they need to develop effective monitoring

[13] This decision is based on the premise that violence increases the perceived risk of being harmed among citizens, which means that individuals' expected cost of voting increases. This modeling choice is in line with other formal models where scholars see violence a tool to repress turnout (e.g., Robinson & Torvik, 2009; Collier & Vicente, 2012)

[14] For further justification for the turnout function to be monotone decreasing, see the formalization of voters' cost function in Appendix.

capacities and/or gather information on each voter's ethno-religious background in settings where there is widespread ethnic voting among citizens for political parties led by co-ethnic elites.

I operationalize G's ability to identify its own supporters from the supporters of its rival party, O, using the parameter Δ. In extreme cases, such as when $\Delta = 0$, this implies that (1) the governing party lacks the capacity to monitor voting behavior or leverage information, and (2) physical characteristics (such as ethnic features, skin color, or religious attire) are not associated with voting patterns. Consequently, it becomes challenging for perpetrators to distinguish sympathizers from potential intimidation targets. In such instances, pre-election violence tends to be indiscriminate, causing widespread fear of becoming a victim.

Figure 1.1 visualizes the way in which violence affects voter turnout in the absence of discrimination capacity. The boxes on the left represent the portions of D_i voters having initial support for the governing party (G) versus the opposition party (O). The boxes on the right depict the reduction in turnout for both parties following the initiation of violence. When there is violence, voters are reluctant to go to the polls due to safety concerns, leading to a decrease in overall turnout in the district when $\Delta = 0$. This means that violence has an impact on the turnout for both groups of voters when G cannot discriminate among voters.

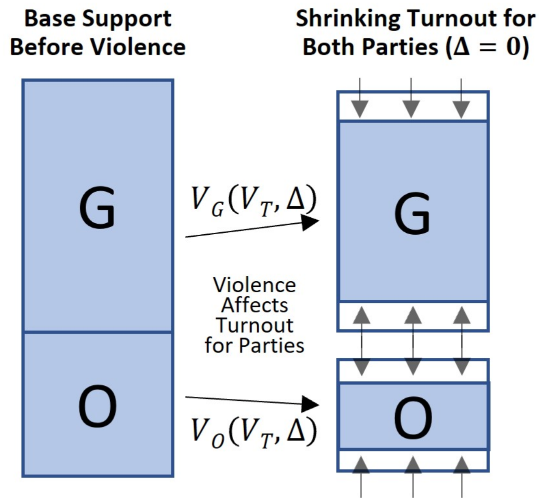

Figure 1.1: The Effect of Violence on Turnout ($\Delta = 0$)

When $\Delta = 1$, I assume that G can easily distinguish its own supporters from O's supporters. In these cases, G can pursue targeted violence against individuals and/or voter groups that support rival parties. In other words, the perpetrator will use selective violence targeted at rival supporters and will manage to repress the turnout only for party O without harming party G's turnout. Figure 1.2 illustrates the turnout repression through selective violence when G has the maximum level of discrimination capacity.

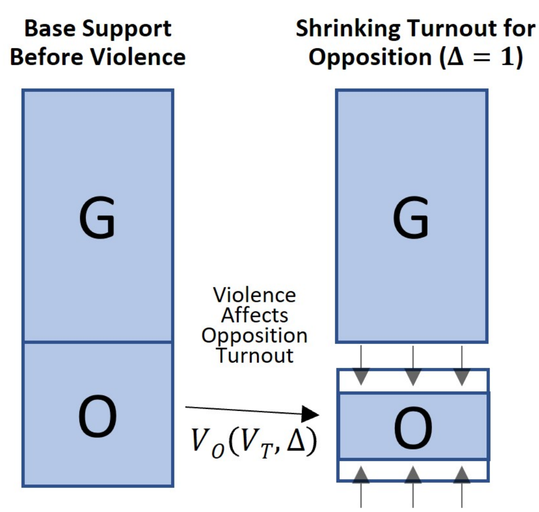

Figure 1.2: The Effect of Violence on Turnout ($\Delta = 1$)

As a final note, Figures 1.1 and 1.2 illustrate the corner cases where $\Delta = 0$ and $\Delta = 1$, the findings show that turnout for both parties will be affected at varying levels so far as $0 < \Delta < 1$. This means that as Δ approaches 0, the violence will hurt the perpetrator G more strongly, whereas when it approaches 1, the effect of repressed turnout will become more and more pronounced on the targeted opposition party, O.

How would we incorporate the new parameter Δ into the model? Equation 1.2 introduced violence, V, as an input in the turnout function for each party, t_G and t_O. However, V itself can be a parameter determined by other factors such as discrimination capacity. Adding this component to Equation 1.3, we define V_G as a function of Δ. This gives us the following equation:[15]

$$V_T = V_G(\Delta) + V_O(\Delta) \tag{1.5}$$

The parameter Δ in Equation 1.5 distributes the total violence between opposition and government supporters.[16] For high levels of Δ more of the violence will target the opposition supporters, while lower levels of Δ would bring indiscriminate violence that would both target both parties.[17]

How would we set up the behavior of turnout functions in relation to the Δ parameter? In order to do that, one should start with the behavior of V_G and V_O functions vis-à-vis changes in the value of Δ. I contend $V_G(\Delta, V_T)$ to be a monotone decreasing function with respect to Δ since for higher levels of Δ, less of the violence V_T would be directly targeted at G supporters. Similarly, $V_O(\Delta, V_T)$ would be a monotone increasing function since for higher levels of Δ, more of the violence V_T would be directly targeted at O supporters.

[15]For simplicity, I temporarily drop the i index in the notation since the location of violence is not integral to the section's discussion regarding the behavior of turnout function vis-à-vis discrimination capacity.

[16]Although both of the components of the V_T are functions of Δ, V_T does not necessarily have to be a function of Δ. See the Chapter Appendix for a more formalized discussion of this point.

[17]For a more formalized version of this contention, please see Chapter Appendix.

This means that the value of V_G would go down and V_O would go up as Δ increases for any given value of V_T. We can express these increasing and decreasing monotonic functions with respect to Δ as follows:

$$\begin{aligned} \frac{\partial V_G(V_T, \Delta)}{\partial \Delta} < 0 \\ \frac{\partial V_O(V_T, \Delta)}{\partial \Delta} > 0 \end{aligned} \tag{1.6}$$

Combining Inequalities 1.4 and 1.6 with the chain rule, we can conclude that turnout for G is a monotone increasing function while turnout for O is a monotone decreasing function with respect to Δ.

$$\begin{aligned} \frac{\partial t_G(V_G)}{\partial \Delta} > 0 \\ \frac{\partial t_O(V_O)}{\partial \Delta} < 0 \end{aligned} \tag{1.7}$$

To conclude, Inequalities 1.7 indicate that higher levels of discrimination capacity will increase the turnout among government supporters, while the opposite effect will take place for the opposition. The higher levels of discrimination capacity will bring more selectively targeted violence, which will be disproportionately harmful to opposition supporters' participation in elections.

1.3.2 The Effect of Discrimination Capacity (Δ) on the Location of Violence

1.3.2.1 Existence of an Optimum and Extreme Values of Δ

Where should we anticipate pre-election violence when political parties focus on maximizing their chances of winning? To establish the relationship between discrimination capacity and the parties' turnout, one has to examine the optimal level of violence under utility optimization. The governing party G is now going to maximize its utility U_G;

$$\underset{V_{T,1}, V_{T,2} \in \mathbb{R}^+}{\operatorname{argmax}} \sum_{i=1}^{2} \alpha_i \cdot t_{G,i}(V_{G,i}[V_{T,i}, \Delta]) - \sum_{i=1}^{2} (1 - \alpha_i) \cdot t_{O,i}(V_{O,i}[V_{T,i}, \Delta]) - \sum_{i=1}^{2} k(V_{T,i}) \tag{1.8}$$

where I use two districts D_i where $i \in \{1, 2\}$ for simplicity in comparison. I operationalize varying levels of competitiveness in a district using α_i follow a non-strict definition of a stronghold by assigning D_i to the political party as a stronghold by when that party has more than half of the vote in that district. For instance, $\alpha_1 > 0.5 > \alpha_2$ would mean D_1 is governing party and D_2 as a stronghold for the opposition.[18] A competitive district is a district where political parties share the total vote equally $\alpha_i = 0.5$. For instance, settings such as $\alpha_1 > 0.5, \alpha_2 = 0.5$ or $\alpha_1 = 0.5, \alpha_2 < 0.5$ enable a comparison between a party stronghold and a competitive district, whereas setting $\alpha_1 > 0.5 > \alpha_2$ enables comparing a government versus opposition stronghold. Proposition 1 will compare the cases of government versus opposition strongholds, and Lemma 1 will expand this comparison to the other two possible comparisons.

Proposition 1. *There exists a unique solution where initiating violence in both party strongholds is beneficial for the governing party, when $\Delta = 1$. In this case, the governing party will commit more violence in D_2 than in D_1 (i.e., $V^*_{T,2} > V^*_{T,1} > 0$).*[19]

Proof. See Appendix A.

Lemma 1. *Without loss of generality, Proposition 1 findings are expandable to other comparative cases involving (1) a government stronghold versus a competitive district and (2) a competitive district versus an opposition stronghold. In case (1), we observe more violence in a competitive district than in a government stronghold. In case (2), we observe more violence in an opposition stronghold than in a competitive district.*

Proof. See Appendix A.

[18]The non-strictness in the definition is not essential for reaching the present findings of the chapter. In fact, the model findings become stronger with stricter definitions of a stronghold.

[19]The proposition holds when the cost of perpetrating violence follows the same function in all districts (i.e., $\nexists\ k_i(\cdot)$). This is a justifiable assumption in countries where the governing party has comparable size of armed forces (e.g., police and/or military) in all districts.

Proposition 2. *When the governing party (G) is unable to distinguish its own supporters from the rival parties' supporters ($\Delta = 0$), it will have no incentive to commit violence in its own stronghold. It will have an incentive to initiate violence in rival party's stronghold (i.e., $V^*_{T,2} > V^*_{T,1} = 0$), when k is sufficiently low.*

Proof. In order for the government party to have an incentive to initiate violence in its own stronghold (D_1) where $\alpha_1 > 0.5$, the partial derivative of U_G with respect to $V_{T,1}$ must be greater than zero. That is, we have to have $\frac{\partial U_G}{\partial V_{T,1}} > 0$. To put if formally;

$$\frac{\partial U_G(V_{T,1})}{\partial V_{T,1}} = \alpha_1 \cdot \frac{\partial t_{G,1}(V_{G,1}[V_{T,1}, \Delta])}{\partial V_{T,1}} - (1 - \alpha_1) \cdot \frac{\partial t_{O,1}(V_{O,1}[V_{T,1}, \Delta])}{\partial V_{T,1}} - \frac{\partial k(V_{T,1})}{\partial V_{T,1}} \tag{1.9}$$

Following the chain rule and simplifying the notation, we obtain the following:

$$\frac{\partial U_G}{\partial V_{T,1}} = \alpha_1 \cdot \underbrace{\frac{\partial t_{G,1}}{\partial V_{G,1}}}_{<0} \cdot \underbrace{\frac{\partial V_{G,1}}{\partial V_{T,1}}}_{\geq 0} - (1 - \alpha_1) \cdot \underbrace{\frac{\partial t_{O,1}}{\partial V_{O,1}}}_{<0} \cdot \underbrace{\frac{\partial V_{O,1}}{\partial V_{T,1}}}_{\geq 0} - \underbrace{\frac{\partial k}{\partial V_{T,1}}}_{\geq 0} \tag{1.10}$$

When $\Delta = 0$, that means G can only initiate indiscriminate violence harming supporters on both sides. In expectation, the slopes for the $V_{G,1}(V_{T,1})$ and $V_{O,1}(V_{T,1})$ will be α_1 and $1 - \alpha_1$, respectively. I assume the same functional form for G and O's turnout functions which gives $\frac{\partial t_{G,1}}{\partial V_{G,1}} = \frac{\partial t_{O,1}}{\partial V_{O,1}}$. Since I assume linearity for these monotone decreasing functions, I equate the slopes of the turnout functions to $t < 0$. After plugging these in, we have the following equation:

$$\frac{\partial U_G}{\partial V_{T,1}} = \alpha_1 \cdot \underbrace{\frac{\partial t_{G,1}}{\partial V_{G,1}}}_{t} \cdot \underbrace{\frac{\partial V_{G,1}}{\partial V_{T,1}}}_{\alpha_1} - (1 - \alpha_1) \cdot \underbrace{\frac{\partial t_{O,1}}{\partial V_{O,1}}}_{t} \cdot \underbrace{\frac{\partial V_{O,1}}{\partial V_{T,1}}}_{1-\alpha_1} - \underbrace{\frac{\partial k}{\partial V_{T,1}}}_{\geq 0} \tag{1.11}$$

Algebraic simplification gives the following results:

$$\frac{\partial U_G}{\partial V_{T,1}} = \underbrace{(2\alpha_1 - 1)}_{>0} \cdot \underbrace{t}_{<0} - \underbrace{k'(V_{T,1})}_{\geq 0} \tag{1.12}$$

By definition, we have $t < 0$, $k'(V_{T,1}) \geq 0$, and $\alpha_1 > 0.5$ making $2\alpha_1 - 1 > 0$. This means that $\frac{\partial U_G}{\partial V_{T,1}} < 0$ for any $V_{T,1} > 0$. That is, G's utility falls for any value positive value of violence in its stronghold. Stated differently, G has no incentive to initiate violence in its own stronghold when it is unable to distinguish its supporters from the rival parties' supporters. This creates a corner solution when $\Delta = 0$, where the optimal value of violence in D_1 is 0 (i.e., $V^*_{T,1} = 0$).

The second part of the proof, which concerns G's incentive to initiate violence in O's stronghold (D_2), relies on the condition $\frac{\partial U_G}{\partial V_{T,2}} > 0$. By symmetry with Equation 1.12, we can express it as follows:

$$\frac{\partial U_G}{\partial V_{T,2}} = \underbrace{(2\alpha_2 - 1)}_{<0} \cdot \underbrace{t}_{<0} - \underbrace{k'(V_{T,2})}_{\geq 0} \tag{1.13}$$

By definition, $t < 0$, $k'(V_{T,2}) \geq 0$, and $\alpha_2 < 0.5$. This enables $\frac{\partial U_G}{\partial V_{T,2}} > 0$ when $(2\alpha_2 - 1) \cdot t > k'(V_{T,2})$. Therefore, G will have an incentive to commit violence in rival party's stronghold, when the cost of doing so is sufficiently low.

$\therefore$ When $\Delta = 0$, the optima for the violence levels are no violence in government stronghold and violence that is greater than 0 (zero) in the opposition stronghold (i.e., $V^*_{T,1} = 0, V^*_{T,2} > 0$). The results are independent from the cost function in D_1 and conditional upon the cost of violence being sufficiently low in D_2. $\blacksquare$

1.3.3 Comparative Statics

The previous section took up the cases of $\Delta = 0$ and $\Delta = 1$. But, how does the continuous case of Δ parameter affect the intensity and locationof violence? For that, we need the optimal level of $V_{T,i}$ for each district, which is the focus of this section. For simplicity in comparison, I set $\alpha_1 > 0.5 > \alpha_2$ to have D_1 as government and D_2 opposition strongholds. However, the findings are expandable for the other two pair-wise district level comparisons as discussed in Lemma 1. With that in mind, the First Order Condition (FOC), i.e., $\frac{\partial U_G}{\partial V_{T,i}} = 0$, provides us with the following:

$$\frac{\partial k}{\partial V_{T,i}} = \alpha_i \cdot \frac{\partial t_{G,i}}{\partial V_{G,i}} \cdot \frac{\partial V_{G,i}}{\partial V_{T,i}} - (1 - \alpha_i) \cdot \frac{\partial t_{O,i}}{\partial V_{O,i}} \cdot \frac{\partial V_{O,i}}{\partial V_{T,i}} \tag{1.14}$$

In line with the initial assumption of monotone increasing convexity for the $k(V_{T,i})$, I assume a generalizable functional form for $k(V_{T,i}) = k \cdot V_{T,i}^2$, where $k > 0$. In line with my linearity assumption for the $t_{G,i}$ and $t_{O,i}$ functions, I assume a generalizable form such as $t_{G,i} = t_{O,i} = t \cdot V_{T,i}$, where $t < 0$. Combining these with the formalized non-functional forms of the $V_{G,i}(V_{T,i}, \Delta)$ and $V_{O,i}(V_{T,i}, \Delta)$ (see Chapter Appendix):

$$\underbrace{\frac{\partial k}{\partial V_{T,i}}}_{2k \cdot V_{T,i}} = \alpha_i \cdot \underbrace{\frac{\partial t_{G,i}}{\partial V_{G,i}}}_{t} \cdot \underbrace{\frac{\partial V_{G,i}}{\partial V_{T,i}}}_{(1-\Delta)\cdot\alpha_1} - (1 - \alpha_i) \cdot \underbrace{\frac{\partial t_{O,i}}{\partial V_{O,i}}}_{t} \cdot \underbrace{\frac{\partial V_{O,i}}{\partial V_{T,i}}}_{1-\alpha+\Delta\alpha_i} \tag{1.15}$$

Subsequent to solving the equation for $V_{T,i}$, we have the following as the optimal level of violence in D_i:

$$V_{T,i}^* = \frac{(2\alpha_i - 1 - \Delta\alpha_i) \cdot t}{2k} \tag{1.16}$$

Since violence cannot be a negative value, when $V_{T,i}^* < 0$, G's utility is maximized at

$V^*_{T,i} = 0$, which means that we can conclude perpetrator's function for violence as follows:

$$V^*_{T,i}(\alpha_i, \Delta, t) = \begin{cases} \dfrac{(2\alpha_i - 1 - \Delta\alpha_i) \cdot t}{2k} & \textit{if } \alpha_i < \dfrac{1}{2-\Delta} \\ 0 & \textit{if } \alpha_i \geq \dfrac{1}{2-\Delta} \end{cases} \tag{1.17}$$

How would $V^*_{T,i}$ change with respect to the changes in Δ for the first case where $V^*_{T,i} > 0$? Differentiating $V^*_{T,i}$ with respect to Δ would give us the comparative statics for the effects of changes in Δ on $V^*_{T,i}$:

$$\frac{\partial V^*_{T,i}}{\partial \Delta} = -\frac{t\alpha_i}{2k} \tag{1.18}$$

This result reveals that the level of violence in D_i is expected to rise as Δ increases, as indicated by the positivity of the right-hand side of Equation 1.18 (i.e., $-\frac{t\alpha_i}{2k} > 0$). The parameters in the equation, including t, α_i, and k, play a moderating role in the impact of Δ on the level of violence.

The parameter t, by definition, reflects the sensitivity of the turnout function vis-à-vis the intensity of violence. A higher t signifies a more substantial reduction in turnout in response to increased violence for a given change in Δ. However, the comparative statics analysis reveals additional nuances in this relationship. Specifically, a larger t implies more effective returns from violence as Δ increases, benefiting the perpetrator.

In contrast, a larger k mitigates the effect of Δ on $V_{T,i}$. As the cost of violence, k, increases, it acts as a deterrent to the escalation of violence, thereby tempering the relationship between discriminatory capacity and the level of violence. This parameter exemplifies the district's capacity to withstand the disruptive effects of increased discrimination, not only in the form of costs to the perpetrator but also by dampening the effect of increased Δ on the optimal level of violence, $V^*_{T,i}$.

Regarding the α_i parameter, which reflects G's initial level of public support before the onset of violence, an interesting observation emerges. When the governing party, G, enjoys a stronger support base in a district, this implies a more pronounced relationship between Δ and the level of violence compared to districts with lower initial public support. In other words, an increase in Δ has a more significant impact on the level of violence in G's strongholds than in its rival's strongholds. This counterintuitive outcome is driven by the fact that indiscriminate violence in a government stronghold disproportionately hinders its own turnout at low levels of Δ. Consequently, identifying party supporters in such strongholds leads to a more substantial escalation of violence in previously non-violent districts.

This stands in contrast to opposition strongholds, where the impact of Δ on violence is less abrupt, having already experienced violence prior to any increase in discriminatory capacity. Stated differently, in opposition strongholds where violence was prevalent prior to any increase in discriminatory capacity, the influence of Δ on violence is less pronounced. This intricate interplay among support levels, discriminatory capacity, and violence dynamics underscores the multifaceted nature of the relationship between discriminatory capacity and its influence on the intensity and location of pre-election violence.

Drawing on insights from the comparative statics analysis, Proposition 3 elucidates the continuous and monotonically changing character of the optimal violence level $V^*_{T,\Delta}$ across the full range of potential discrimination capacity values. In essence, this proposition serves as a bridge connecting the results of the first two propositions, which concentrated on the specific cases for $\Delta = 1$ and $\Delta = 0$, encompassing the Δ's complete interval $(0 \leq \Delta \leq 1)$.

Proposition 3. *For all values of Δ, the optimal violence level $V^*_{T,\Delta}$ varies continuously and monotonically from $V^*_{T,\Delta=0}$ to $V^*_{T,\Delta=1}$ without any discontinuities in the closed interval of $\Delta \in [0, 1]$.*

Proof. I start the proof by identifying the 2 cases of $V^*_{T,i}(\Delta = 0)$ and build upon this initial starting point the trajectory of the $V^*_{T,i}(\Delta)$ function for the rest of the closed interval of $\Delta \in [0,1]$. The 2 cases following the formulation in piecewise Equations 1.17 are:

$$V^*_{T,i}(\Delta = 0) \begin{cases} V^*_{T,i} > 0 & \textit{if } \alpha_i < \dfrac{1}{2} \\ V^*_{T,i} = 0 & \textit{if } \alpha_i \geq \dfrac{1}{2} \end{cases} \tag{1.19}$$

In Case 1, we can combine this starting point with Equation 1.18 showing the comparative statics, which is a linear monotone increase in $V^*_{T,i}$, to build up the $V^*_{T,i}(\Delta)$ as a function any value possible for Δ for the interval of $0 \leq \Delta \leq 1$:

$$\begin{aligned} V^*_{T,i}(\Delta) &= V^*_{T,i}(0) + \int_0^{\Delta} \frac{\partial V^*_{T,i}}{\partial \Delta} d\Delta \\ &= V^*_{T,i}(0) + \int_0^{\Delta} \frac{-t\alpha_i}{2k} d\Delta \\ &= V^*_{T,i}(0) + \frac{-t\alpha}{2k} \Delta|^{\Delta}_{\Delta=0} \\ &= V^*_{T,i}(0) - \frac{t\alpha_1}{2k} \Delta \end{aligned} \tag{1.20}$$

where $t < 0$ and Δ is a continuous parameter on $\in [0,1]$. Hence, $V^*_{T,i}(\Delta)$ as a function will not have a discontinuity for any $\Delta \in [0,1]$.

For Case 2, where we have $V^*_{T,\Delta=0} = 0$, an additional step in the proof is required due to the existence of zero values for $V^*_{T,i} = 0$ even when $\Delta > 0$ (i.e., $V^*_{T,\Delta>0} = 0$). In order to determine this threshold in terms of a value expressed in Δ parameter, I reorganize the conditions for the function $V^*_{T,i}(\Delta)$ in Equation 1.17 as follows:

$$V^*_{T,i}(\alpha_i, \Delta, t) = \begin{cases} \dfrac{(2\alpha_i - 1 - \Delta\alpha_i) \cdot t}{2k} & \textit{if } \Delta > \dfrac{2\alpha_i - 1}{\alpha_i} \\ 0 & \textit{if } \Delta \leq \dfrac{2\alpha_i - 1}{\alpha_i} \end{cases} \tag{1.21}$$

This equation reveals that when Δ exceeds $\frac{2\alpha_i - 1}{\alpha_i}$, the option of initiating violence in

D_i starts to benefit the perpetrator. For simplicity, I denote this threshold as $\Phi = \frac{2\alpha_i - 1}{\alpha_i}$. Formally stated, if $\Delta > \Phi \Rightarrow V^*_{T,i}(\Delta) > 0$. When we add Φ into the Equations 1.20, we have the equations as follows:

$$\begin{aligned}
V^*_{T,i}(\Delta) &= V^*_{T,i}(0) + \int_0^\Phi \frac{\partial V^*_{T,i}}{\partial \Delta} d\Delta + \int_\Phi^\Delta \frac{\partial V^*_{T,i}}{\partial \Delta} d\Delta \\
&= \underbrace{V^*_{T,i}(0)}_{0} + \underbrace{0|^{\Delta=\Phi}_{\Delta=0}}_{0} + \frac{-t\alpha_i}{2k}\Delta|^{\Delta}_{\Delta=\Phi} \\
&= -\frac{t\alpha_i}{2k}(\Delta - \Phi)
\end{aligned} \tag{1.22}$$

We observe a continuous and monotonically increasing pattern in the optimal violence level $V^*_{T,i}(\Delta)$ in Case 2. By introducing the threshold $\Phi = \frac{2\alpha_i - 1}{\alpha_i}$, we establish that $V^*_{T,i}(\Delta) = 0$ for all Δ values below Φ. The threshold Φ marks the initiation of a linear increase in violence with respect to Δ. Beyond this threshold, the rate of change, denoted by $-\frac{t\alpha_i}{2k}$, indicates a consistent linear rise in violence for the Δ values between Φ and 1. Thus, the violence remains constant at 0 when $0 \leq \Delta \leq \Phi$, and it increases linearly when $\Phi \leq \Delta \leq 1$. Importantly, neither case entails any discontinuity. The transition from $V^*_{T,i}(\Delta) = 0$ to $V^*_{T,i}(\Delta) > 0$ at $\Delta = 1$ is continuous and well-behaved, devoid of sudden jumps.

$\therefore$ The optimal violence level, $V^*_{T,i}(\Delta)$, exhibits a monotone increasing behavior with respect to the continuous range of Δ values within the interval $\Delta \in [0, 1]$ in the two possible cases delineated in this proof.

$\blacksquare$

Figures 1.3 and 1.4 illustrate the change in $V^*_{T,1}$ and $V^*_{T,2}$ for varying levels of Δ, α_1, and α_2 parameters.[20]

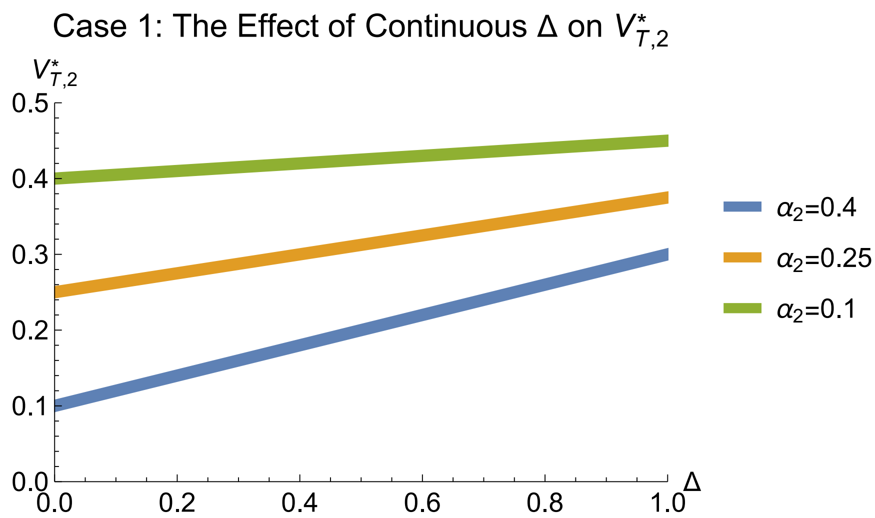

Figure 1.3: The Optimal Level of Violence with Varying Levels of α_2 in Opposition Strongholds

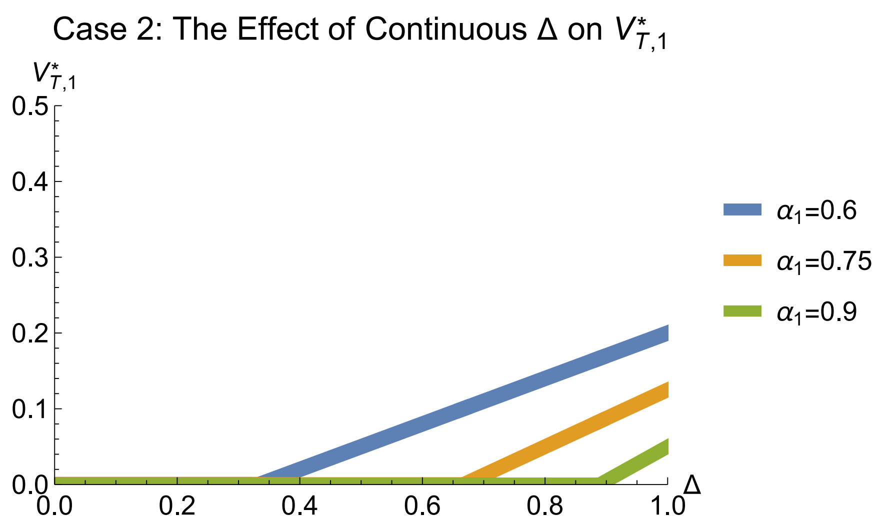

Figure 1.4: The Optimal Level of Violence with Varying Levels of α_1 in Government Strongholds

[20]See Appendix A for the functional forms and numerical examples used to create the corresponding graphs.

The results presented in Figures 1.3 and 1.4 align with Proposition 1, demonstrating a unique solution for districts with varying levels of α_i where $V^*_{T,2} > V^*_{T,1} > 0$ when $\Delta = 1$. Figure 1.4 corroborates the findings of Proposition 2. When the governing party (G) is unable to distinguish its own supporters from those of rival parties $(\Delta = 0)$, G lacks the incentive to commit violence in its own stronghold, while it is motivated to initiate violence in the rival party's stronghold $(V^*_{T,2} > V^*_{T,1} = 0)$. These visualizations also confirm the key finding that $V^*_{T,2} > V^*_{T,1}$ for any given Δ parameter.

Consistent with Proposition 3, the absence of violence persists until Δ reaches a specific threshold, Φ, determined by varying levels of α_i. In line with the comparative statics, an increase in Δ beyond Φ leads to an escalation of violence in all district types, whether it be a government stronghold $(\alpha > 0.5)$, a competitive district $(\alpha = 0.5)$, or an opposition stronghold $(\alpha < 0.5)$. Moreover, Figures 1.3 and 1.4 confirm the finding that that the increase in violence intensity is more pronounced in government strongholds than in opposition strongholds as Δ gains higher values. Crucially, the intensity of violence converges across all districts with varying levels α with each unit increase in Δ parameter.

1.4 Conclusion

This chapter reconciles conflicting perspectives in the literature by revisiting the theory of pre-election violence. While traditional scholarship suggested a strong link between national-level competitiveness and the likelihood of violence (Wilkinson, 2006; Wilkinson & Haid, 2009; Dhattiwala & Biggs, 2012; Kasara, 2014), recent studies challenged this view, proposing that violence is more likely in party strongholds, particularly in opposition strongholds (Wahman & Goldring, 2020; Rauschenbach & Paula, 2019).

This decision-theoretic model I proposed postulates that the location of violence is largely determined by the perpetrating party's ability to distinguish its own supporters from those of rival parties, which I defined as discrimination capacity. This concept aligned with Kalyvas's suggestion that belligerent groups tend to commit indiscriminate violence when they lack the capacity to acquire superior information about their targets Kalyvas (2006). In the context of my research, this capacity belonged to the incumbent government that used violence before elections with the purpose of winning those elections. Once discrimination capacity was incorporated, the government is able to pursue selective violence against opposition supporters and suppress their turnout successfully. When I operationalized this capacity as a continuous parameter, the model led to findings indicating that pre-election violence can occur both in competitive districts as well as party strongholds in countries, particularly when the perpetrating government possessed high discrimination capacity. In contrast, the absence of this capacity results in a more distinct geographical divide, with government-initiated violence primarily concentrated in opposition-dominated districts.

The formal model also shed light on governing parties' strategic engagement in pre-election violence based on factors such as the potential impact on voter turnout, initial support base prior to violence, and the options between selective violence targeting specific rival supporters, versus indiscriminate violence. Proposition 1 revealed that the perpetrating party has an incentive to initiate violence in both its own and opposition strongholds when possessing the maximum discrimination capacity. In such a scenario, the level of violence in the opposition stronghold is higher than the home base district since the rate of return is greater. This incentive transcends to competitive districts as indicated by Lemma 1, at a greater intensity than in a government stronghold and less intensity than in an opposition stronghold.

Proposition 2 explored the condition in which the perpetrating party is unable to distinguish its supporters from the rival's supporters. In this case, it refrains from initiating violence within its own district but may initiate violence in the opposition stronghold given specific factors, such as if the cost of violence is sufficiently low.

This chapter's significant contribution to the current scholarship lies in Proposition 3, establishing a continuous measure of discrimination capacity. This proposition revealed that increased detection of voting behavior leads to a heightened level of violence across all districts. Interestingly, high levels of discrimination capacity escalate violence at a greater rate in government strongholds compared to opposition strongholds.

In conclusion, this chapter delved into the nuanced relationship among incumbent governments' use of violence as a tool to manipulate upcoming elections, their state capacity to collect information on voters' partisan preferences, and how their base support at each district may play a role in determining where and how much violence they may choose to commit. By unraveling the intricate dynamics at the district level, it reconciled conflicting perspectives within the existing literature on the geographical distribution of pre-election violence, offering valuable perspectives for scholars, policymakers, and practitioners grappling with the impact of pre-election violence on democratic processes.

Chapter 2

Pre-Election Violence and Voter Turnout

2.1 Introduction

How do political parties use pre-election violence as a strategic tool to increase their chances of winning elections? Scholars have provided several compelling answers to this question. The most prevailing explanation posits that parties utilize violence before elections to suppress voter turnout through intimidation and coercion (Wilkinson, 2006; Blaydes, 2010; Collier & Vicente, 2012; Rauschenbach & Paula, 2019; Watch, 2010; Staniland, 2014; Höglund, 2009; Mac-Ikemenjima, 2017; Mohamed, 2018). Naturally, suppressing the voter turnout alone does not offer an advantage to the perpetrator unless the turnout for the rival parties is suppressed to a great extent than that of perpetrator's own supporters. A second widely accepted argument is that pre-election violence can have a positive effect on voter turnout, within certain groups of voters, by fostering a sense of collective identity and solidarity among supporters thereby potentially increasing turnout (Brass, 1997; Wilkinson, 2006; Hafner-Burton et al., 2018, 2014).[1] A smaller branch in this scholarly debate reveals null, mixed or contradictory findings regarding the effects of pre-election violence on voter

[1]Scholars have also drawn attention to other ways in which political parties may benefit from pre-election violence such as intimidated rival candidates withdrawing from the race and/or political parties boycotting elections due to intense violence campaigns against them (D. A. Bekoe & Burchard, 2017; Hafner-Burton et al., 2014).

turnout (D. A. Bekoe & Burchard, 2017).

Electoral violence scholars have reconciled these conflicting results through two distinct approaches. The first involves revisiting or establishing theories on the moderating conditions that determine whether the effect of pre-election violence on voter turnout will be positive or negative (e.g., Wilkinson, 2006; van Baalen, 2023). The second approach entails employing experimental designs to enhance causal inference allowing researchers to disentangle the impact of violence from the potential effects of unobserved confounders. For instance, Collier & Vicente's field experiment in Nigeria randomly assigned campaign materials against violence, providing solid causal evidence for the positive influence of anti-violence campaigning on voter turnout (Collier & Vicente, 2014). While they faced the inherent challenge of not being able to randomly assign violence as a treatment, they nonetheless established credible causal claims regarding the positive effects of anti-violence campaigning on increased voter turnout in a real-world setting (Collier & Vicente, 2014). Some researchers following experimental approach have employed hypothetical violence in randomized survey experiments as a remedy to circumvent our inability to assign violence as a treatment. Gutiérrez-Romero & LeBas (2020), for instance, found that presenting respondents with a choice between two candidates allegedly involved in electoral violence decreased voter turnout in their conjoint analysis.[2] In sum, recent scholarship has done remarkable well in showing the efficacy of innovative experimental research design when studying the effect of election violence on voter turnout.

This chapter aligns with the second group of scholars dedicated to enhancing our understanding of the impact of election violence on voter turnout. To achieve this objective, the chapter integrates two causal inferential methodologies. First, it utilizes an Unexpected Event during Survey (UEdS) design, which leverages event that occur during

[2] Recent evidence suggests that such conjoint experiments can yield effects similar to real-world events (Hainmueller et al., 2015), which reinforces the Gutiérrez-Romero & LeBas (2020) findings in the face of external validity criticism.

a public opinion survey to effectively create two comparable samples of respondents, one pre-treatment and the other post-treatment group. Muñoz et al. (2020) have reported the use of this research design in 44 articles, using a wide range of unexpected events such as the assassination of leaders, terrorist attacks, protests, policy reforms, and flu epidemics that coincide with survey administration. These articles frequently employ Regression Discontinuity (RD) or Interrupted Time Series (ITS) as their primary analytical tool. In ITS analysis, scholars face a trade-off between comparability and statistical power (Goldsmith et al., 2021). If they choose to maintain a narrow time interval between the pre- and post-event phases, they can minimize the influence of time-varying confounding variables and enhance comparability between pre- and post-treatment groups. On the other hand, if they choose to keep the bandwidth larger, this will bring greater statistical power or larger sample sizes, which is at the expense of reduced comparability due to the unobserved confounding variables (Wagner et al., 2002; Jandoc et al., 2015).

In order to overcome this challenge, I will incorporate a second causal inferential component in my research design. More specifically, I will use a combination of difference-in-difference (DD) analysis and matching, which has been used by scholars studying political violence from a spatial perspective (e.g., Zhukov, 2017; Lyall, 2009). The parallel trends assumption in DD design will account for time-varying unobservables. This in turn will ameliorate the trade-off between better comparability (with a narrow bandwidth) and greater statistical power (with a wide bandwidth) as in the case of RD or ITS analyses. In addition, I follow Lyall's advice and use matching in an effort to establish valid counterfactuals when conducting spatial analysis (Lyall, 2009). By utilizing this combined approach, I pursue two nuanced questions regarding the effect of pre-election violence on voter turnout: (1) whether pre-election violence negatively affects voter turnout exclusively in the locations where it is committed, and (2) whether it influences the turnout behavior of supporters differently when perpetrators and victims support opposing political parties.

The remainder of the chapter is comprised of five parts. First, I provide an overview of the current state of scholarship regarding the influence of pre-election violence on voter turnout. Second, I establish the theory and empirical expectations. The third and fourth sections will present the data and empirical findings. The fifth section will conclude with a discussion of the implications of my research and its contribution in light of the empirical findings.

2.2 Previous Scholarship

Why do political actors resort to violence against civilians? Over the past 30 years, political scientists have explored various explanations for this question. One perspective, rooted in the ethnic violence literature, suggests that elites employ violence to garner political support from their co-ethnics. This strategy involves spreading a discourse of fear derived from rival ethnic groups (Brass, 1997). Additionally, elites may use violence to demobilize other ethnic groups, exert control over the dominant discourse within their own co-ethnics, and suppress dissent more broadly (Gagnon, 2013). Another strand in this literature contends that violence is not always a result of premeditated planning by elites (Straus, 2007). Instead, it may stem from idiosyncratic, even psychological, factors at the individual level, such as personal resentment, greed, and revenge (Weinstein, 2006; Mueller, 2013; Midlarsky, 2005; Petersen, 2002), particularly during an outbreak of communal violence (Auster, 1996). However, it is hard to argue that such violence remains solely at the individual level, as we know from research findings that elites often exploit these violent episodes for their political gain by attempting to control the dominant narrative in the media (Snyder & Ballentine, 1996; Zimmermann, 1999) and deploying their own armed personnel into the crowds (Mueller, 2013).

Building on these insights, electoral violence scholars have often grounded their theories in the notion that pre-election violence serves the interests of elites. This aligns with the prevailing wisdom in the literature, which posits that political parties engage in pre-election violence to enhance their electoral performance (Wilkinson, 2006). Scholars have dissected this overarching contention into various theoretical components. Firstly, perpetrating parties anticipate reaping benefits from the ensuing political polarization triggered by violence. For instance, Wilkinson (2006) illustrates how the Bharatiya Janata Party (BJP) experienced a substantial surge in votes during the 1991 elections compared to 1989, especially in towns where nationalist Hindu leaders orchestrated riots by disseminating rumors of an imminent threat of violence from Muslims against Hindus (Wilkinson, 2006, pp. 49-51). Wilkinson argues that this increase in the BJP's vote share likely resulted from Hindus shifting their votes from more moderate parties to the nationalist BJP to prevent "the Muslim-supported parties and candidates" from gaining office (Wilkinson, 2006, pp. 49-51).

In addition to change in vote choice, a second theoretical dimension frequently discussed by scholars is the idea that perpetrators of pre-election violence can benefit from its effect on voter turnout. The impact of election related violence on voter turnout can be theorized in two directions: mobilization of the perpetrators' supporters and demobilization of the victimized party supporters. The literature offers evidence supporting both of these theoretical claims. Some scholars contend that violence may mobilize supporters to head to polling stations during elections (Travaglianti, 2013, 2015; Blaydes, 2010; Hafner-Burton et al., 2018; Robbins et al., 2013). For example, Wilkinson (2006) asserts that violent riots not only unified the Hindu vote but also substantially increased voter turnout among Hindus in several constituencies.[3] Conversely, other scholars have found evidence that election-related or other forms of violence can suppress voter turnout for the victimized

[3] For instance, the voter turnout in Bhopal North jumped from 62% in 1989 to 76% in 1993 (Wilkinson, 2006, pp. 49-51).

parties (Birch, 2010; Bratton, 2008; Höglund & Piyarathne, 2009; Klopp & Kamungi, 2007; Collier & Vicente, 2014; Gutiérrez-Romero & LeBas, 2020; Ley, 2018; Martinez i Coma & Morgenbesser, 2020). In summary, the effects on voter choice, mobilization, and demobilization can occur simultaneously, reinforcing one another, to the benefit of the perpetrators while undermining the victimized parties.

A critical question emerges with regard to these prevailing arguments, which emphasize the advantages for perpetrators: can such violence ever produce unintended consequences, undermining the objectives of the instigators? The answer to this question in the broader political violence literature would be affirmative, particularly when it is conducted in an indiscriminate fashion against civilians (e.g., Kalyvas, 2006, p.68).[4] But could the particular form of pre-election violence potentially shrink the electoral support base of perpetrating political party, lower the voter turnout among their remaining supporters, and/or even foster increased support and turnout for victimized parties? To explore this question from a qualitative perspective, one can turn to the case of Zambia: In the lead-up to the 2016 presidential elections, a significant degree of repression and election-related intimidation targeted the opposition in this country (Wahman & Goldring, 2020). This pattern of intimidation further intensified after the election cycle, culminating in the arrest and imprisonment of Hakainde Hichilema, the leader of the main opposition United Party for National Development (UPND), on treason charges in 2017 (*ACLED Zambia Data*, 2021). Remarkably, despite these challenges, Hakainde Hichilema ultimately secured victory in the 2021 elections and presently serves as the President of Zambia. This anecdotal evidence implies the potential for pre-election violence to backfire on perpetrators beyond its immediate short-term consequences. Beyond anecdotal examples like this, there is also a group of scholars producing inconclusive findings regarding the usefulness of election violence for its initiators with data used in cross-country empirical analysis. This stream

[4]For similar arguments regarding how violence can hurt the perpetrator, see Condra & Shapiro (2012) and Pape (1996).

of research is exemplified by the work of Burchard (2020), who contend that pre-election violence can be very costly to the incumbents, resulting in reduced levels of support, rather than enhancing their electoral prospects (Burchard, 2020).

In light of these -at times- contradictory findings, the following sections will unfold my theoretical framework, outline the primary hypotheses, and investigate potential moderating effects of individual voters' party affiliation and their proximity to violence. Subsequently, the chapter will delve into research design and identification strategies essential for establishing a valid comparison utilizing a quasi-experimental approach. This research design will help disentangle the divergent effects of pre-election violence on voter turnout theorized in Section 2.3.

2.3 Theoretical Considerations and Hypotheses

In line with the literature, does pre-election violence always benefit the perpetrators and harm the targeted groups? In order to answer this question, I propose examining the impact of violence on election participation in relation to (1) the voters' identification with perpetrating versus victimized political parties and (2) voters' proximity to violent events. This section will evaluate how these two factors may bring a variety of theoretical possibilities by drawing on several mechanisms from scholarly work. If our conventional wisdom is correct in the sense that election violence is likely to benefit the perpetrating political parties, this may happen in multiple ways.

As the foundation of my theory, let us assume that a government can effectively mobilize its supporters after committing an act of violence against the opposition. If we accept this as the starting point of our theory, we can anticipate the top two potential effects depicted in Figure 2.1:[5] (1) opposition accomplishes to mobilize its own supporters (polarizing

[5] In line with my model in Chapter 1 and the prevailing view in the literature on election violence (Hafner-Burton et al., 2014), I position the government as the perpetrating party and the opposition supporters as the victimized group when establishing the theoretical expectations.

effects) or (2) opposition elites fail to mobilize their supporters (differential effects). While the second scenario would clearly benefit a perpetrating government, the first scenario will only offer an advantage if the number of people mobilized for the government is greater than the number of voters mobilized in favor of the opposition.[6] In alignment with these two theoretical possibilities, I will investigate the following hypotheses:

H1: (*Polarizing Effects*) Subsequent to an election-related violent event, there will be an increase in support for both perpetrating government and victimized opposition parties.

H2: (*Differential Effects*) Following an election-related violent event, the gap between the turnout for governing and opposition parties will widen in a way to favor the perpetrating governing party.

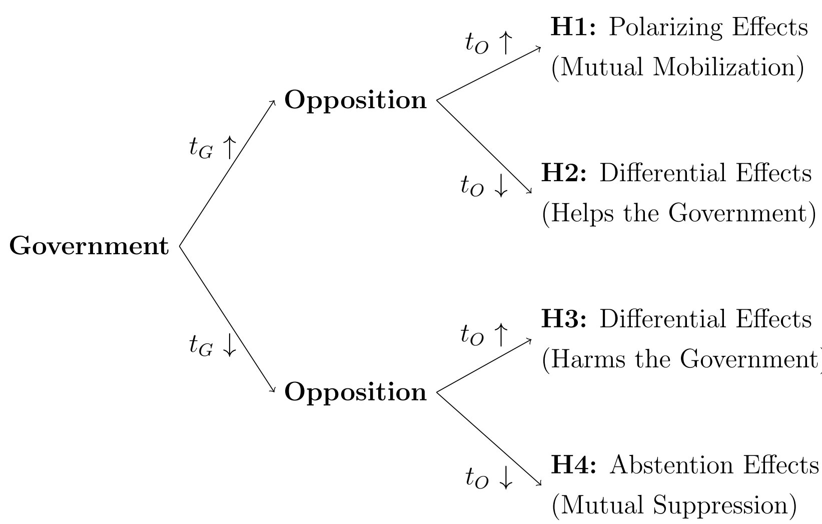

Figure 2.1: Potential Effects of Pre-Election Violence on Voter Turnout

[6]There can also be other scenarios where polarizing effects assist the incumbent government even when opposition gains are greater, may include cases where the increased government vote share help it reach a specific electoral threshold (e.g., 50 percent of the vote in a majoritarian system).

While Figure 2.1 presents two additional theoretical outcomes (i.e., H3 & H4), it is essential to consider the low likelihood of these effects from the perspectives of rational incentives and risk aversion, respectively. In the case of H3, where differential turnout effects clearly harms the government's chances of winning, the governing party has no incentive to initiate violence on a global scale. As for H4, it is theoretically possible for the government benefit from violence at the expense of reduced turnout among its own supporters, as long as the reduction in their turnout or total votes will be smaller than those of the targeted parties. But this scenario seems improbable in real-world contexts. Stated differently, it is unlikely for any rational government party to intentionally take risky actions that will diminish its own turnout prior to elections with the aim of winning those elections. Also, the existing electoral violence literature obviates the need or logic for establishing H4 as a viable theoretical expectation, albeit with limited findings[7] and qualitative accounts[8]. Scholars suggest that if governments resort to violence against their own supporters, this typically happens with the intention of coercing them into participating in the electoral process through threats of violence (See Travaglianti, 2015).

The proximity of violence plays an important role in my theory based on the following caveat regarding the lower half of Figure 2.1: When these elites anticipate that the H3 and H4 effects will remain localized, they may strategically employ violence targeting specific districts that they are less concerned about winning even at the expense of their own turnout. These districts can be areas where the prior knowledge that their party is

[7] One scholar making this argument is Travaglianti (2013), who states that governments can punish their own supporters if those supporters do not turn out to vote on the election day.

[8] Bratton (2008), for instance, reports that a Nigerian senior political scientist, John Ayaode, shared his personal observation with him at an Oxford University workshop in 2007: "the PDP [Nigerian ruling party] unleashed campaign repression in good part as a means to control its own members" (Bratton, 2008, footnote 16) although he admits that he only has anecdotal evidence to support this claim. Bratton adds that Ayaode's anecdote is in line with his own observations in Zimbabwe that "the ruling ZANU-PF intimidates its own followers as well as those of the opposition MDC" (Bratton, 2008, footnote 17). Similarly, Blaydes (2010) gives anecdotal examples from Mubarak's Egypt where police would not intervene when hired thugs would "force voters to support a certain candidate" (mobilization) and "prevent supporters of other candidates from voting at all" (demobilization).

likely to lose or the turnout among their supporters will be low among other reasons. In such cases, governments could initiate violence in select areas, hoping to reap the benefits of H1 or H2 effects in a greater number of regions that are more critical to maximizing their chances of winning the elections.[9] In sum, the contention that governments are likely to avoid H3 and H4 effects is limited to the cases where the governing party elites know that the damaging effects are only to occur in large portions of a country or even in all districts as a whole.

I argue that proximity to violence may play a vital role in the minds of perpetrators at this juncture, offering two possible outcomes. First is the case where voters have a distinct idea about the identities of the perpetrators and targeted. There can be political settings in some districts, where individual voters may perceive that violence against the rival group was necessary, as Wilkinson (2006) argued was the case in Hindu-Muslim ethnic riots in India. The opposite effect of decreasing turnout for the perpetrator may be due to different reasons. One such reason from the literature could be that voters can disapprove of violence even when such violence is committed by their own candidate (Gutiérrez-Romero & LeBas, 2020). Another reason could be that the government supporters may be afraid of retaliation and therefore going to the polls when they are in the minority in the opposition strongholds (Wahman & Goldring, 2020). This brings cases where government-initiated violence mobilizes the opposition and reduces the turnout for the governing party. However, I do not expect elites to engage in such violence unless this backfiring effect is limited to local areas that are in close proximity to violence as opposed to a larger phenomenon across a country.

H3a: *(Proximity & Differential Effects)* Following an election-related violent event, the gap between the turnout for governing and opposition parties will widen in a way to favor the targeted opposition party in violent areas.

[9] This possibility was investigated thoroughly from a theoretical perspective in Chapter 1.

As an alternative theoretical scenario, mutual suppression may also take place in a non-global fashion in a country. This can be because various feelings could drive an individuals' behaviors in response to violence. These may include disapproval of violence as a political tool, solidarity for the victims among other feelings, which may manifest as decreased turnout for the perpetrating political party. Similarly, the victimized targeted party's supporters feel intimidated and concerned about becoming victims themselves, leading them to abstain from participating in elections all together. This may bring abstention effects for both parties following violence between parties. Like its alternative hypothesis (H3a), I expect the following hypothesis to be localized if there is evidence that it is taking place:

H3b: *(Proximity & Abstention Effects)* The turnout amongst voters will be lower subsequent to an election-related violent event transpiring in its immediate proximity, in comparison to the voters in distant/other locations.

One final theoretical expectation is about the varying baseline turnout levels for each voter group. If pre-election violence has long-term effect on voter behavior, I argue that groups with a long history of violence and marginalization may have lower baseline levels of voter turnout compared to groups outside this category. Specifically, individuals who are more often victimized by violence exhibit lower levels of political participation as a long-term response to violence. This leads me to the following expectation:

H4: *(Differential Baselines)* The intention to vote among voters who are frequently targeted by violence will be lower than among those who support the perpetrating party.

2.4 Research Design

This chapter pursues a quasi-experimental approach to overcome some of the difficulties previously faced by empirical studies in making causal inferences. A causal identification approach is particularly advantageous when re-evaluating observational studies that yield null results on the link between pre-election violence and voter turnout within a country across time (e.g., D. A. Bekoe & Burchard, 2017). It is plausible that voters may choose not to participate in the political process or abstain from voting in a particular year if they anticipate intimidation based on past experiences of violent elections. In such cases, the oppressors may not necessarily initiate any violence observing the absence of participation from the repressed group.

Consequently, the perpetrators' past intimidation will have the continued 'benefit' of violence (i.e., repressed turnout) without initiating violence that specific year, owing to the deterrent effects of past violence and the perception of potential recurrence. Therefore, the null results seen in such observational designs might be a product of an inherent selection issue since the effect of an unobserved variable (perceived possibility of violence) is replaced with a misleading value (of no violence) in the explanatory variable. This will result in null results showing that there is statistically no difference in voter turnout between violent and non-violent elections. In fact, such selection bias and endogeneity issues have been discussed extensively in other literatures such as compliance (e.g., Downs et al., 1996) and deterrence (e.g., Danilovic, 2001) in international relations. With this in mind, I contend that utilizing a causal inference methodology is appropriate to address such selection issues and the inherent endogeneity between election-related violence and voter turnout.

I have identified Zimbabwe as a case where an unexpected violent event occurred during a survey conducted by Afrobarometer (AB). AB is an organization that conducts public opinion surveys across the African continent. Their round 6 survey in Zimbabwe was conducted from November 16$^{\text{th}}$ to November 29$^{\text{th}}$, 2014, coinciding with an inter-party violent event that took place on November 22$^{\text{nd}}$. There were two actors in this violent event- the youth organization of the governing Zimbabwe African National Union-Patriotic Front (ZANU-PF) and a newly formed opposition party at the time, called Transform Zimbabwe (TZ). During the event, the president of TZ and his supporters were violently attacked by ZANU-PF's youth organization. While that November had witnessed other violent events, such as ZANU-PF members and elites being assaulted by other factions within the ZANU-PF party structure, this was the first instance of inter-party violence witnessed by voters in Zimbabwe in the month of November 2014.

The violent event that occurred in Zimbabwe was identified as a survey-interrupting event for several reasons. First and foremost, the timing of the event coincided with the survey window, dividing the total sample of $n = 2400$ into nearly identically sized subsamples with pre-violence group having $n = 1120$, post-violence group having $n = 1088$ with the number of respondents being interviewed on the event of the day being $n = 192$ (see Table 2.1). This chapter will take advantage of the event during the survey to examine the effects of inter-party violence on voters' perception.

Table 2.1: Number of Respondents
vis-à-vis Timing of Violence

Groups	**N**
Pre-Violence	47 % (1120)
Day of Violence	8 % (192)
Post-Violence	45 % (1088)
Total N	2400 (0 NA)

Second, the content met the crucial criterion regarding the description of the event such as the identity of the actors and their apparent motivation. In this case, the violence was committed by one political party (ZANU-PF) against another (TZ), with the seeming intent to suppress a political rival in elections. This type of violence can be referred to as "inter-party violence," as its purpose is to repress votes for a rival political party.[10] Taking these factors into account, I specifically sought "inter-party violent event" in analysis.[11]

One final remark regarding why the violent event in Zimbabwe qualifies as a "sufficiently" interrupting event has to do with the size of this event. In general, interrupting events should be large enough to capture the attention of the national audience (as opposed to smaller violent events or daily harassment against individual local politicians that are unknown to the greater public). However, they also should not be so large and impactful (perhaps catastrophically so) to a point where they bias all the other variables in the post-violence responses. One could raise the example of the 9/11 terror attacks being such catastrophic events that they induced bias on people's perceptions of life, happiness levels along with response rates (or perhaps many other variables such as political participation, party affiliation, perceptions of economy) in the post-treatment sample, if it were to be used as an interrupting event. For these reasons, I decided that the size and impact of the violent assault on the opposition party were optimal to qualify as an appropriate unexpected violent event that coincides with a public opinion survey that can be used for the purposes of this chapter.

[10] I contend that the term "pre-election violence" does not fully capture the nature of this type of violence since it limits the event (as most scholars do) to the 6 months before an actual election. This approach places emphasis on the timing of violence rather than the content and intent of violence. On the other hand, the name "inter-party violence" does a better job of describing the violence against political rivals with the intention of dominating the victims in the elections. This type of violence occurs all the time and is not necessarily confined to 6 months leading up to an election.

[11] As opposed to an event that would qualify as a "pre-election violent event" since some inter-party violent events may not necessarily occur within the 6-month window leading up to the elections as many scholars define "pre-election violence".

2.4.1 Data

I operationalize the main concept of interest, -intent to vote-, using the AB survey question "If a presidential election were held tomorrow, which party's candidate would you vote for?" When (and if) the respondents reveal their preference, the interviewers record that political party's code. When the respondents state that they would not vote in the presidential elections, coders write that down as "would not vote." In order to constitute a binary DV, I recode any particular party choice as "1" and "would not vote" as "0."[12] Table 2.2 shows the recoded values and the number of observations in each of the pre-, during and post-violence groups in the survey.

Table 2.2: Respondents' Intent to Vote, by Survey Timing

Vote if a presidential election tomorrow?	**Pre-Violent Event**	**Day of Violence**	**Post-Violent Event**
Would vote	68% (756)	69% (133)	67% (729)
Would not vote	6% (67)	6% (11)	5% (52)
Refused to answer	22% (248)	21% (41)	26% (278)
Do not know	4% (49)	4% (7)	3% (28)
N	**1120** (0 NA)	**192** (0 NA)	**1087** (1 NA)

All categories except for the "Refused to answer" have approximately equal percentages across the three survey windows as summarized in Table 2.2. The ratio of people refusing to answer the question seems to witness a 4% jump from the pre-violence group to the post-violence group. In order to unpack this discrepancy and the key variable of interest

[12] This is a proxy measure since the question does not directly ask respondents whether they intend to vote. Also, the question wording does not leave any option for respondents who want to say that they intend to vote without revealing their vote choice. A better formation would be to separate the question into two parts first asking, "If a presidential election were held tomorrow, would you turn out to vote?" and then "If yes, which party's candidate would you vote for?" In that case, the first part of the restructured question would be a better way to measure the intention to vote. Under the current formation, it is possible that some respondents may refuse to answer the question and/or choose to say they "don't know." So, the respondents who may want to reveal they intend to vote without revealing their party preference are forced to choose an option, which likely introduces a bias toward reduced turnout.

“Would vote”, I establish a party affiliation from two pertinent AB survey questions. In comparison to the vote choice question, the question wording and structure deals better with potential biases by first asking whether the respondent feels affinity to a political party (Q1: “Do you feel close to any particular political party?”) Following this question, there is a follow-up question asking specifically for the party name (If yes, Q2: “which party is that?”) In the empirical analysis section, I will use categories coded by these two “Closest Party” responses to investigate the larger question of whether violence affects turnout behavior differentially across different party supporters and independents in the following section.[13] In sum, the data on party affiliation will facilitate in-depth analysis of polarization effect versus differential effects of election violence on political participation across party lines among respondents.

Before proceeding to investigating the effect of violence on turnout intent in light of the hypotheses in Section 2.3, Table 2.3 provides insights into how respondents’ revealed party preferences in relation to the timing of the violent event .

[13] Baker & Renno (2019) classify the initial yes/no question on party identification as a “partisan-discouraging” item in surveys such as Afrobarometer. They argue that giving a “non-partisan option” to the respondents offers them an “easy way out” of the survey, which in turn creates a substantial measurement error with false negatives when researchers construe “No” responses as an indication of being “nonpartisan” or “independent” (Baker & Renno, 2019).

Table 2.3: Closest Party by Survey Timing

Closest Party?	**Pre-Violent Event**	**Day of Violence**	**Post-Violent Event**
None	29% (322)	29% (56)	24.5% (267)
ZANU-PF	39% (433)	39% (75)	40% (430)
MDC-T	17% (194)	21% (40)	17% (185)
Small Parties	2% (20)	0.5% (1)	1.5% (19)
NA/DK (Q1)*	5% (61)	2.5% (5)	7% (75)
NA/DK (Q2)**	8% (90)	8% (15)	10% (112)
N	**1120** (151 NA)	**192** (20 NA)	**1088** (187 NA)

* 131 respondents refused to answer Q1 and 10 respondents said "don't know" or had missing responses.

** 208 respondents refused to answer Q2 after having said yes to Q1 without revealing their party affiliation, and 9 respondents said "don't know" or had missing responses.

Out of the entire AB sample (N=2,400), 1,614 (versus 645) respondents answer the first question positively (versus negatively) stating that they feel close to a particular political party. Among this group, 938 state that they feel close to the governing ZANU-PF, 419 to the largest opposition party MDC-T and 40 to smaller opposition parties. It is interesting to note that nearly 360 respondents either choose the response "don't know" or refuse to answer the question. As reported in Table 2.3, 208 respondents refuse to reveal their party affinity in the follow-up question after having stated that they feel close to a particular political party. This may be an indication of their fear of being harmed or anxiousness regarding revealing their party affiliation. Such tendency would create a bias against the expected empirical relationship as the people who are expected to be less likely to turn out to vote will also be less likely to report their party affiliation and drop out of the analysis. The following section will introduce the empirical strategy on how to partially mitigate the effect of such potential bias in the analysis.

2.5 Empirical Analysis

This section empirically tests the hypotheses laid out in Section 2.3 using a DD design by taking advantage of an unexpected event during surveys. There has been a large volume of scholarship offering various ways to deal with concerns regarding the lack of randomized assignment of a key variable of interest and our ability to establish valid counterfactuals when aiming to achieve causal inference with observational data. Although scholars using an unexpected event during survey (UEdS) design take an important step towards dealing with concerns regarding randomization of a treatment variable, this approach does not comprehensively address the issue of absence of valid counterfactuals in the face of possible strategic interaction between actors, selection issues in the data and/or interdependence of the variables. As a remedy to these concerns, methodology used by some violence scholars such as has a great deal to offer to the pre-election violence scholarship.

Particularly, the main concern remains to be whether we can identify the respondents who would serve as the control groups before and after the treatment after the identification of an unexpected violent event during a survey. In establishing such counterfactuals, one can benefit from Lyall's discussion in his 2009 article (Lyall, 2009). The first possible counterfactual has to do with how the respondents in a violent region would have reacted to the idea of a hypothetical presidential election had the violent event not happened in their region. Particularly, in case of a region where violent events are frequent, it is difficult to distinguish the unobservable global trends in the data as opposed to the unobservable trends that are particular to the violent region that are taking place *because* of the violent event. Although there is no perfect remedy to this issue, a DD design creating a pre-treatment baseline comparison group both for the treated and the non-treated may capture some of the unobservable trends that take place both in the region that is violent and outside the region (or non-violent regions).

The second counterfactual is regarding our lack of knowledge on how the respondents would have reacted to the party affiliation question had there been no violent event. As Table 2.3 has shown there has been an increase in the number of NA/DK responses following the violent incident against an opposition party in Zimbabwe. Considering that most of these missing values come from respondents who have refused to answer which party they feel close to after admitting in the initial question that they *do* feel close to a political party. There may be possible mechanisms at work here, some canceling out each other. For instance, some opposition supporters may have chosen to hide their party affiliation following the violent event due to increased concerns about their safety, whereas some independents may have decided to side with the victims against the incumbent party's violent acts against the opposition. Similar to the solution formulated in the previous paragraph, I will use a DD design to establish the baseline groups for the treated group -the opposition or potential victims- and the control group in the pre-violence sample. Different from the first DD design, however, I will also add matching based on propensity scores coming from a logistic regression predicting the likelihood of respondents to be an opposition supporter in the pre-violence sample.[14] In sum, the research will use DD design along with matching as some scholars used in the study of geographical aspects of violent conflict (e.g., Lyall, 2009; Zhukov, 2017).

2.5.1 Differential Effects of Pre-Election Violence on Partisans

This section will explore whether pre-election violence may have varying effects on different groups. As discussed in Section 2.3, the violence could result in differential effects on supporters of different parties. Specifically, the turnout may increase among the supporters of one party and decrease or remain unchanged for the other party. Section 2.3 discussed

[14]The reason I do not use this method in the first DD is simple. This bias in reporting party preference following a violent event may be affected by the violence itself, whereas the act of truly reporting where the interview was taken place will not be an artefact of violence.

polarization, as an alternative theoretical possibility. Perhaps, it is the case that both perpetrators and victimized parties benefit from election-related violence. A Difference-in-Differences design would provide an appropriate way to test these competing claims comparing the differences between supporter groups before and after the violent event. One complication is that the violent event may interfere with respondents' tendencies to reveal their true partisan identities. The ensuing analysis intends to verify whether such bias in the data is a valid concern. The results seemingly confirm that respondents are more likely to refuse to reveal their party preference in the post-violence group as seen in Table 2.4.

Each of the logistic regression models in Table 2.4 has a different binary indicator as their dependent variable. The dependent variable in Model 1 indicates whether the respondent refused to answer the first party preference question, while the dependent variable in Model 2 codes whether the respondent refused to answer the second party preference question after saying 'Yes, I feel close to a political party' in the first question. The third dependent variable indicates whether the respondent has refused to answer the first or second question combining the dependent variables of the first two models. Finally, the dependent variable in Model 4 combines all the respondents who refused to answer the party preference question and those responded with an "I do not know." The results indicate that there is a significantly higher number of respondents who refuse to answer and/or respond with "I do not know" to one of the two party preference questions in the post-violence group than the pre-violence group. This significant difference between the groups may bring an imbalance between the pre- and post-treatment groups, which Section 2.5.2 will investigate further with balance tests.

Table 2.4: Respondents Refusing to Reveal Partisanship

	DV: Respondents Refusing to Answer Party Preference Question(s)			
	Refuses Q1	Refuses Q2	Refuses Q1 or Q2	Refuses or Says 'DK'
	(1)	(2)	(3)	(4)
Post Violence	0.125	0.282*	0.240*	0.246*
	(0.211)	(0.169)	(0.137)	(0.135)
In-Region	−0.472	0.229	−0.050	−0.038
	(0.398)	(0.301)	(0.248)	(0.245)
Post Violence × In-Region	0.269	−0.713*	−0.330	−0.266
	(0.480)	(0.400)	(0.314)	(0.307)
Fear	0.145*	−0.013	0.054	0.049
	(0.078)	(0.064)	(0.051)	(0.050)
Age	0.002	−0.011*	−0.006	−0.006
	(0.006)	(0.006)	(0.004)	(0.004)
Female	0.302	0.069	0.171	0.172
	(0.191)	(0.154)	(0.124)	(0.123)
Education	−0.017	0.130**	0.075*	0.070*
	(0.063)	(0.053)	(0.042)	(0.041)
Rural	−0.587**	0.240	−0.102	−0.113
	(0.234)	(0.199)	(0.157)	(0.155)
Constant	−2.853***	−2.784***	−2.052***	−1.987***
	(0.530)	(0.444)	(0.353)	(0.348)
Observations	2,184	2,184	2,184	2,184
Log Likelihood	-463.329	-640.379	-890.609	-910.049
Akaike Inf. Crit.	944.658	1,298.757	1,799.219	1,838.098

Notes: *p<0.1; **p<0.05; ***p<0.01, and std. errors are in parentheses.

2.5.2 Balance Tests between Pre- and Post-Violence Groups

In an ideal experimental setting, the expectation is that samples exhibit balance *a priori*, given the random assignment of treatment. With that in mind, the forthcoming balance tests will focus on key demographic characteristics, including age, gender, education levels, and urban versus rural residency. I anticipate that these variables should demonstrate balance *a priori* under my independence assumption regarding potential outcomes and treatment assignment. However, even in a meticulously designed random experiment, certain demographic features or other pivotal characteristics influencing treatment effectiveness may inadvertently concentrate in one group over another due to chance alone.

Besides this random chance component, my anticipation for balance in demographic covariates aligns with the expectation in an ideal experimental setting. This assumption rests on the notion that a respondent's affiliation with a particular demographic group should not be influenced by the occurrence of the violent event during the survey, nor should it be the consequence thereof. Given this exogeneity assumption, I expect these demographic variables to display balance across pre- and post-violence groups.

Within the context of my natural experiment, the concern regarding potential bias or sample imbalance stems from the conceivable impact of fear on respondents' willingness to disclose their party affiliations truthfully. This concern is empirically testable, with a focus on assessing whether there is an increased ratio of respondents unwilling to answer the second question on party affiliation after affirming their proximity to a political party in response to the first question. Nevertheless, the presence of such an imbalance is not a substantive concern, as it aligns with theoretical expectations. Specifically, it is anticipated that variables such as fear and political affiliation may inherently manifest imbalances, the latter expected to demonstrate a higher mean in the post-violence group, as expounded upon in Section 2.3.

Table 2.5 presents the mean values of each variable in both the pre- and post-violence groups. It is crucial to reiterate that while certain imbalances are expected and theoretically grounded, such as fear levels and party affiliation, there are other covariates, such as the demographic variables, whose imbalance would be problematic. These critical covariates, which warrant close scrutiny, are detailed in the subsequent discussion.

In summary, the focus of the balance tests will be on characteristics such as age, gender, education levels, and whether the respondent lives in an urban versus rural area. Additionally, I included other variables, such as fear and political affiliation, which may naturally have a significantly higher mean in the post-violence group due to theoretical reasons discussed earlier. Table 2.5 shows the mean of each of these variables in the pre- and post-violence groups.

Table 2.5: Balance Table for the Pre- and Post-Violence Groups

Variables	**Pre-Violence Mean**	**Post-Violence Mean**	**p-values**	
			Unadjusted	**Bonferroni**
Living Conditions	2.42	2.49	0.21	0.84
Previously Assaulted	0.28	0.28	0.90	1.00
Legal Discrimination	1.65	1.68	0.46	1.00
Elite Crimes	1.81	1.76	0.28	1.00
Female	0.49	0.48	0.78	1.00
Age	39.31	37.88	0.04*	0.20
Urban	0.94	0.93	0.32	1.00
Education = 0	0.05	0.05	0.85	1.00
Education = 1	0.00	0.00	0.55	1.00
Education = 2	0.10	0.07	0.02*	0.08
Education = 3	0.15	0.12	0.04*	0.16
Education = 4	0.21	0.23	0.31	1.00
Education = 5	0.37	0.34	0.17	1.00
Education = 6	0.08	0.10	0.11	1.00
Education = 7	0.01	0.02	0.07†	0.28
Education = 8	0.02	0.05	0.00**	0.00**
Education = 9	0.00	0.02	0.00**	0.00**
Fear = 0	0.38	0.37	0.89	1.00
Fear = 1	0.19	0.20	0.77	1.00
Fear = 2	0.18	0.17	0.67	1.00
Fear = 3	0.25	0.26	0.79	1.00
Government Supporters	0.38	0.40	0.40	1.00
Independents	0.28	0.25	0.05†	0.20
Opposition Supporters	0.21	0.20	0.62	1.00
Refusers and ‘DK’ers	0.13	0.16	0.07†	0.28

Signif. codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$

The results of the balance tests[15] indicate an absence of statistically distinguishable differences between pre- and post-violence groups concerning the distributions of gender, fear levels, government supporters, and opposition supporters. However, respondents in the post-violence group exhibit a discernible tendency to be younger (approximately two years on average) and more educated compared to their counterparts in the pre-violence group. Furthermore, there appears to be a notable decrease in the number of independents and an increase in refusals in the post-violence group relative to the pre-violence group. This observation may be indicative of a heightened inclination to conceal true political affiliations, where independents, feeling vulnerable, might have identified themselves as government supporters or opted to refrain from responding to the partisanship question. It is noteworthy to highlight that these observed imbalances, specifically the elevated count of "Independents" and "Refusers and 'DK'ers," potentially result from the treatment/violence as an outcome, aligning with our theoretical expectations. They may also be a product of multiple testing as this statistically significant difference disappeared when p-values were adjusted with a Bonferroni correction.

2.5.3 Covariate Balancing Propensity Score (CBPS) Matching

The following matching process is based on covariate balancing propensity scores (CBPS) offered by Imai & Ratkovic (2014). This approach seems as the most appropriate since there is a theoretical link between the likelihood of a respondent reporting him or herself as a government versus opposition supporter when the violent act is perpetrated by the supporters of the governing party (i.e., ZANU-PF) against the supporters and elite of an opposition party (e.g., TZ). CBPS method creates balanced pre- and post-violence samples in terms of the distribution of covariates after taking into consideration how influential each of these observable covariates on the likelihood of being in the treatment group before

[15] The RItools package was employed for conducting balance tests Hansen & Bowers (2008), and the Cobalt package in R facilitated ggplot visualizations Greifer (2022).

any treatment is assigned.

In the context of the Zimbabwean survey, I designate respondents who openly declare their opposition to the government as well as those who refuse to disclose their party affiliation prior to the occurrence of violence as members of the treatment group. This categorization is informed by the assumption that these two subsets are particularly concerned about potential targeting and reprisals through violence. [16] To elaborate, respondents anticipating the likelihood of experiencing violence may opt to conceal their political affiliations, while those openly acknowledging their opposition support may be perceived as likely targets.

Conversely, I posit that pre-violence government supporters can serve as a baseline or an untreated control group in a Difference-in-Differences setting. This assertion is grounded in the understanding that these respondents are less likely to be targeted by government violence, and any potential retaliation from opposition parties is unlikely due to their fragmentation (De Jager & Du Toit, 2013).

This delineation yields four distinct groups, each associated with their respective potential outcomes:

1. **Group 1:** Opposition supporters before the violence ($\mathbb{E}[Y_0(0)|T = 1]$)
2. **Group 2:** Government supporters before the violence ($\mathbb{E}[Y_0(0)|T = 0]$)
3. **Group 3:** Opposition supporters after the violence ($\mathbb{E}[Y_1(1)|T = 1]$)
4. **Group 4:** Government supporters after the violence ($\mathbb{E}[Y_1(1)|T = 0]$)

These groups represent the treated and untreated treatment groups (Groups 1 and 3) and the treated and untreated control groups (Groups 2 and 4) in a Difference-in-Differences framework.[17] This categorization enables a robust examination of the treatment

[16] I base this assumption on the qualitative data I collected through my interviews with Zimbabwean political activists in May 2023.

[17] For a visual representation of these four groups and the ensuing matching process, refer to Figure B.1 in Appendix B.

effect by accounting for potential confounding factors, aligning with the principles of a Difference-in-Differences analysis.

An important component of the CBPS matching is determining the propensity scores. What determines a respondent's likelihood to be in the opposition group? I predict the answer with variables measuring economic, political, legal and security related concerns of the respondents. With that, I argue that respondents will be more likely to support the opposition if they think that their living conditions are worsening under the current government, if they think they face discrimination in front of the law, if they think that political elites go unpunished when *they* commit crimes, and whether they or members of their family were physically assaulted in the past one year. Many of these variables also determine whether a respondent will be fearful of being victimized by violence, which is an advantage of this approach. I also added some demographics such as age, gender, education level along with whether the respondent lives in an urban area to ensure balance in these control variables. Table 2.6 presents the logistic regression models that are used to determine the propensity scores. The dependent variable in the model is a binary indicator showing whether or not the respondent is in Group 1.

Table 2.6: Propensity Scores for Covariate Balancing Propensity Score (CBPS) Matching

	Logistic Regressions for Propensity Scores *DV: Opposition Supporter or Refuser*		
	Groups 1 & 2 (combined sample)	Groups 1 & 3 (combined sample)	Groups 1 & 4 (combined sample)
Living Conditions	-0.279^{***}	0.001	-0.068^{***}
	(0.064)	(0.018)	(0.014)
Previously Assaulted	0.292^{*}	0.050	0.053
	(0.152)	(0.041)	(0.033)
Legal Discrimination	0.122	-0.026	0.014
	(0.081)	(0.024)	(0.018)
Elite Crimes	0.183^{**}	0.014	0.069^{***}
	(0.083)	(0.025)	(0.017)
Age	-0.004	0.002	-0.0002
	(0.005)	(0.001)	(0.001)
Female	-0.052	0.002	-0.012
	(0.141)	(0.039)	(0.030)
Urban	0.019	0.078	0.026
	(0.284)	(0.072)	(0.061)
Education = 1	-13.569	-0.390	-0.280
...	(882.743)	(0.508)	(0.468)
Education = 6	0.600	-0.095	0.158^{*}
...	(0.399)	(0.106)	(0.085)
Education = 9	-13.924	-0.488^{***}	-0.208
	(471.971)	(0.185)	(0.202)
Constant	-0.443	0.354^{**}	0.317^{***}
	(0.558)	(0.149)	(0.120)
Observations	998	695	966
Log Likelihood	-605.577	-487.463	-616.866
Akaike Inf. Crit.	1,245.154	1,008.925	1,267.733

Notes: *p<0.1; **p<0.05; ***p<0.01, and std. errors are in parentheses.

With respect to the logistic regression results utilized to finalize matching between the groups, it seems plausible that a respondent's living conditions are negatively associated with their likelihood of being an opposition supporter (or one of the respondents who refuse to reveal their partisanship). This finding is evident in the first and last columns of Table 2.6 when comparing Groups 1 and 2, and Groups 1 and 4. That suggests respondents in the opposition camp are likely to have worse living conditions than those in the governing supporting group. It is also not surprising to see virtually no difference between the living conditions and all the other characteristics (other than high end of the educational background) between the Groups 1 and 3, since there are the supposedly the most similar groups, both of the groups being in the non-government camp. Respondents in Group 1 seem to agree strongly with the statement that crimes committed by public/state officials can go unpunished when compared to Groups 2 and 4 (pre- and post-violence governments supporters and independents). It appears plausible that a respondent's security concerns exhibit a positive association with their likelihood of being in the non-government supporter. Similarly, respondents in Group 1 express a strong agreement with the statement that crimes committed by public/state officials can go unpunished when contrasted with Groups 2 and 4 (pre- and post-violence government supporters and independents).

2.5.4 Difference-in-Differences Analysis Results

Table 2.7 presents the results of a Difference-in-Differences analysis examining the impact of post-violence conditions on the intent to vote binary outcome. The coefficient associated with the variable "Post-Violence" (Column 1) indicates a statistically significant positive effect of 0.150 ($p<0.01$) on the intent to vote binary. This implies that, on average, respondents in the post-violence period are significantly more likely to express an intent to vote compared to the pre-violence period, holding other variables constant. Interestingly, respondents who disclose their preference for an opposition party, are more likely to vote, with a coefficient of 0.186 ($p<0.01$).

The interaction term "Post-Violence $\times$ Opposition Supporter," as the key variable producing the DD results, has a negative and statistically significant effect of -0.120 ($p<0.01$). This finding is crucial since it implies that the causal effect of violence on an opposition member or a person who refuses to identify his party affiliation is negative on their likelihood to have strong intentions to vote in elections. This, following the parallel trends assumption, means that even with the positive impact of post-violence conditions, the intent to vote is attenuated among opposition supporters following a violence exposure.

The second model delves into a comparison of the mean intent to vote between government supporters and the rest of the respondents. The analysis reveals that non-government supporters demonstrate a diminished likelihood of voting for a specific party on election day. These results imply an initial higher propensity among government supporters to cast their votes compared to the broader sample. However, the DD finding, revealed by the interaction term in the second column, indicate a drop in the determination of government supporters subsequent to the inter-party violent event. This observed drop in intent to vote among the ZANU-PF supporters aligns with the findings of Gutiérrez-Romero & LeBas (2020), who argue that supporters of the perpetrating party do not always condone their party's violent attacks against the elites of a small opposition party. In this case, the party leader attacked by the ZANU-PF youth organization is a well-known political figure with prior affiliation to the governing party, ZANU-PF, in Zimbabwe.

Table 2.7: Difference-in-Differences Results

	Dependent Variable:	
	Intent to Vote Binary	
	(1)	(2)
Post-Violence	0.150***	−0.005
	(0.020)	(0.028)
Opposition Supporter	0.186***	
	(0.016)	
Post-Violence × Opposition Supporter	−0.120***	
	(0.035)	
Opposition or Independent		−0.155***
		(0.022)
Post-Violence × Opposition or Independent		0.075**
		(0.036)
Fear = 1	−0.008	0.030
	(0.019)	(0.020)
Fear = 2	0.046**	0.117***
	(0.020)	(0.020)
Fear = 3	0.024	0.091***
	(0.018)	(0.018)
Age	0.001***	0.001**
	(0.0005)	(0.0005)
Female	−0.001	−0.013
	(0.014)	(0.014)
Urban	−0.105***	−0.110***
	(0.015)	(0.016)
Previously Assaulted	0.001	0.021
	(0.015)	(0.015)
Education	0.003	0.006
	(0.005)	(0.005)
Constant	0.760***	0.926***
	(0.035)	(0.039)

Notes: *p<0.1; **p<0.05; ***p<0.01, and std. errors are in parentheses.

The DD methodology employed here is particularly well-suited for capturing the causal impact of post-violence conditions on political behavior by leveraging the comparison between opposition supporters and government supporters before and after the violence. The interaction terms allow for a nuanced understanding of how violence exposure interacts with political affiliation. Section 2.5.5 will follow a similar empirical strategy to test the proximity effects of violence on voter turnout.

2.5.5 Proximity Effects of Pre-Election Violence on Voter Turnout

This section will test whether the data are consistent with the expectation that voters who are in closer proximity to a violent inter-party event will be more or less likely to turn out to vote in elections. If we witness a general increase (decrease) in intent of turning out to vote, this may be consistent with the mobilization (demobilization) argument. However, a general increase or decrease in voter turnout may not be indicative whether perpetrators are reaching their aims without knowing whether it is the supporters of the opposition or governing party. For this first DD analysis where the focus is on the regional proximity effect, I will use the party affiliation as a control variable before moving the focus onto differential effects in the ensuing analysis. Table 2.8 shows the number of respondents who are interviewed in the region where the violent event took place, namely Harare, and whether the interview took place before or after this event. There are nearly 200 or more respondents in each category, which provides a powerful sample size to make meaningful comparisons.

Table 2.8: Time vs. Location of the Interview

	In Harare	Outside Harare
Pre-Violence	43% (192)	48% (928)
Day of Violence	7% (32)	8% (160)
Post-Violence	50% (224)	44% (864)
N	**448** (0 NA)	**1952** (0 NA)

While the effects of being in Harare versus being in the post-violence group with their large enough sample sizes may help us to investigate possible changes in voter turnout levels, using either of these as a sole parameter to see the effect of violence may raise concerns whether we can establish valid counterfactuals due to unobserved heterogeneity as discussed previously. For instance, respondents in the post-violence group may report lower levels of intention to turn out to vote, but this may be due to due to possible time-variant unobservables that took place in the time window between the pre- and post-violence worlds. In other words, any change in the mean turnout levels in the post-violence group may be due to unobservables that are independent from the presumed treatment effect (i.e., the effect of the violent event in Harare). For that reason, following a Difference-in-Differences design provides a way to address concerns of omitted variable bias. I follow this approach by assuming that people in the violent region are the treatment group due to their proximity to violence whereas people outside the Harare area can establish a control group.

$$\underbrace{\mathbb{E}[Y_1(1) - Y_1(0)|T=1]}_{\textit{Causal effect of violence on turnout}} = \underbrace{(\mathbb{E}[Y_1|T=1] - \mathbb{E}[Y_0|T=1])}_{\textit{Turnout difference in Harare}} - \underbrace{(\mathbb{E}[Y_1|T=0] - \mathbb{E}[Y_0|T=0])}_{\textit{Turnout difference outside Harare}} \tag{2.1}$$

where Y denotes the potential outcome of turnout denoted $Y_1(1)$ as the respondents' average level of intent to vote in the treatment group and $Y_1(0)$ denoting the counterfactual turnout of the respondents in the treatment group. That is, the LHS of Equation 2.1 denotes the effect of the treatment on the treated. The difference between the observed turnout level after the violence takes place in Harare and the unobserved turnout level in the same group if the violence had not occurred in Harare. On the RHS, we see the subtraction of the two differences- difference in mean turnout in the Harare region (treatment group) over time and difference in voter turnout outside the Harare region (control group) over time. Each of these differences in the RHS takes care of time invariant unobservables since confounders that stay stable before and after within each group cancel out one another. The DD approach takes care of the time-variant unobservables by taking the difference between these two differences with the parallel trends assumption that suggests any unobserved confounder causing the change across time should be the same within these two groups. As long as this assumption holds, the DD offers an unbiased estimate of the treatment effect on the treated units.

Although it is not difficult to calculate the two differences within each group in the RHS, I partially follow Angrist & Pischke's suggestion to use a regression formulation of DD since this can serve as a convenient way to construct coefficient estimates and the standard errors (Angrist & Pischke, 2009, p.234):

$$Voter\ Turnout_i = \beta_0 + \beta_1 \cdot In\ Region_i + \beta_2 \cdot Post\text{-}Violence_t + \beta_3 \cdot In\ Region_i \cdot Post\text{-}Violence_t + \varepsilon_{it} \tag{2.2}$$

where i denotes the individual respondent, and t denotes time of the interview. In this equation, the key variables -"In Region" and "Post-Violence"- are binary indicators respectively showing whether the respondent resides in the same region as the location of violence and whether the individual is interviewed after the violence. In this regression formulation, the $\widehat{\beta_3}$ is equivalent to the value on the LHS of Equation 2.1 and is expected to provide an unbiased estimator of the effect of violence on the people in Harare region in line with the parallel trends assumption. In line with the general DD structure, I will use a linear probability model with my DV coming from individual respondents being a binary indicator.

Although the DD in the case of Zimbabwe country survey seems to be an appropriate design from a causal inference point, it is not entirely immune to any other types of biases. One concern can be the fact that the violence takes place in the capital city, which is also the most populous city in the country. Although this only partially addresses the issue, I add whether the respondent lives in an urban versus rural area as a control variable along with other demographic characteristics such as such as respondents' age, gender, and education level.

Table 2.9: Linear Probability Models Predicting Intent to Vote

	Dependent Variable:	
	Intent to Vote (Binary)	
	(1)	(2)
Post-Violence	0.022	0.010
	(0.013)	(0.013)
In Harare	0.053**	0.016
	(0.025)	(0.025)
Post-Violence × In Harare	0.024	0.026
	(0.032)	(0.032)
Fear = 1	−0.021	0.011
	(0.017)	(0.017)
Fear = 2	0.013	0.061***
	(0.018)	(0.018)
Fear = 3	−0.004	0.056***
	(0.016)	(0.016)
Opposition Supporter	0.103***	
	(0.015)	
Opposition Supporter		−0.130***
or Independent		(0.013)
Age	0.001***	0.001**
	(0.0004)	(0.0004)
Female	0.003	−0.004
	(0.012)	(0.012)
Education	−0.003	0.005
	(0.004)	(0.004)
Urban	−0.120***	−0.070***
	(0.016)	(0.017)
Constant	0.900***	0.935***
	(0.030)	(0.030)

Notes: *p<0.1; **p<0.05; ***p<0.01, and std. errors are in parentheses.

The DD results do not provide support for violence for H1 where people in close proximity will be less likely to turn out to vote following a violent event since the key interactive variable (Post-Violence x In Harare) is not statistically significant. However, results seem to be consistent with the differential baselines (H4) argument. That is, opposition supporters seem to be more likely to turn out to vote when the reference category is everybody else in the sample regardless of the recent violence. When I group opposition supporters and independents, this leaves the reference category as the government supporters. One can infer that government supporters are more likely to turn out to vote compared to opposition supporters and independents. This can be interpreted as both opposition and government supporters are more likely to show up at the polls in comparison to independents.[18]

2.6 Conclusion

This chapter investigated the effect of pre-election violence on voter behavior by merging theoretical exploration with causal inference methodologies. After reviewing the broader political violence literature, the theoretical section scrutinized the potential effects of pre-election violence, including mutual mobilization for political parties, suppression of voter turnout for party supporters, or differential effects, manifesting as heightened voter turnout for one party and diminished turnout for rival parties. The differential effects component included the conventional anticipation of increased turnout for the governing party and repressed opposition turnout, as well as the less-explored prospect of a backlash against the perpetrators– especially when the violence is orchestrated by the governing party's elites. Additionally, I examined how the proximity to violence may influence voter turnout, considering these factors within the strategic calculus of political party elites

[18]This effect may also due to a confounding factor that was discussed earlier in the chapter: opposition supporters may identify themselves as "independent" and/or say "no" to the first party preference question in order to preempt the second question that will ask them the specific party.

when deciding where and to what extent to initiate or commit violence.

To address these questions, I employed a causal identification strategy that leveraged an inter-party violent event during an Afrobarometer survey that divided the sample into comparable before and after violence groups. This event, I posit, serves as an unexpected and thus exogenous proxy for pre-election violence, akin to an 'as-if' randomly assigned treatment. I argued that the exogeneity assumption holds and this inter-party violent event can be incorporated as a substitute for pre-election violence in the absence of upcoming elections since the event involved the members of ZANU-PF's youth organization assaulting the prominent leader of an opposition party, Transform Zimbabwe (TZ). If this event had occurred right before elections, scholars would have categorized it as a pre-election violence event.

Occurring unexpectedly amidst the survey, it provided an exogenous source of variation meeting the independence assumption between the assignment of the treatment and potential outcomes. Following the guidance in political violence scholars' work such as Zhukov (2017) and Lyall (2009), I integrated my Difference-in-Differences (DD) analysis with matching techniques to construct valid counterfactual locations and voter profiles, addressing what would have occurred had the violence not transpired. Building upon the political violence work on the spatial dimensions of conflict, and the burgeoning spatial studies of pre-election violence, I leveraged the location of my unexpected event to explore the proximity effects of violence from a causal perspective. The combination of these tools, integrated with the Unexpected Event during Survey (UEdS) design, reinforced the causal validity of my findings within the distinctive context of Zimbabwe.

The first DD findings revealed a scenario characterized by differential effects. Both opposition members and government supporters demonstrated heightened mobilization after exposure to violence, while independents exhibited a diminished inclination to express any intent to vote on election day. This finding suggests that while violence may indeed mobilize the opposition, the absence of a corresponding shift among independents hampers its substantial impact against opposition gains from the mobilizing effect of pre-election violence. The secondary DD results did not support the proposition that proximity to violence diminishes voter turnout. This may be attributed to the specific location of the violence—Harare, one of the largest city centers and a competitive district, notwithstanding its status as the capital city of Zimbabwe. These characteristics of Harare may have introduced a confounding effect on the proposed relationship between proximity to inter-party violence and voter turnout, potentially contributing to the absence of clear results in the analysis.

Chapter 3

Geography of Fear and Voter Turnout

3.1 Introduction

The relationship between fear and political participation constitutes a pivotal inquiry within the realm of political science. At its core, this research question probes the fundamental factors shaping citizens' engagement with the electoral process, unraveling the complex interplay between emotional states and democratic participation. In the landscape of comparative politics, two prominent strands of literature emerge: one that highlights the mobilizing effect of traumatic violence, and another emphasizing the suppressive impact of fear on voter turnout as a consequence of election violence. The trauma literature posits a compelling argument that traumatic experiences can galvanize individuals, compelling them to partake in the political process in response to adversity (Blattman, 2009; Bellows & Miguel, 2009; Shewfelt, 2009). Conversely, recent work in the election violence literature asserts that fear, particularly the dread of coercion and violence, can erode citizens' trust in institutions and their willingness to engage in democratic elections (e.g, van Baalen, 2023; von Borzyskowski et al., 2021; Mac-Ikemenjima, 2017).

In this chapter, I aim to bridge the gap between these opposing narratives on the relationship between fear and political participation by utilizing a spatial analysis tool.

Drawing inspiration from the vastly diverse fabric of Nigerian society, I propose that both trauma-driven mobilization and fear-induced abstention are plausible responses, and that their manifestations are mediated by local dynamics.[1] I ground the mechanisms underlying these divergent paths in the contention that citizens' reactions can vary widely from feelings of perceived isolation and helplessness to expressions of solidarity within their larger communities. I argue that these contrasting reactions to violence are largely driven by the presence (or absence of) support networks and shared identities within local communities.

My theory incorporates this vast diversity across communities in Nigeria as a conceptual component in my argument, suggesting that it is local dynamics that determine whether fear of violence leads to mobilization at the polls or results in intimidation against taking part in the elections. Consequently, understanding and analyzing such political dynamics necessitates a methodological tool that takes into account this broad spectrum of local diversity across communities in Nigeria.

To disentangle this unobserved heterogeneity over the diverse topography of Nigeria, I employ a multifaceted approach. First, I introduce a theoretical framework that underscores the collective sentiments of helplessness and solidarity. Second, my focus on the Nigerian context capitalizes on the aftermath of traumatically violent months preceding the Afrobarometer survey, offering a unique opportunity to examine the influence of fear on political engagement. Next, I utilize Geographically Weighted Regression (GWR) analysis, leveraging the geo-coded Afrobarometer dataset, to capture the spatial variations in the relationship between fear and participation across Nigeria's regions. By amalgamating these facets, this research contributes a fresh perspective to the discourse on citizens' responses to extreme fear in the context of political participation, bridging the divide

[1] Nigeria is the most populous country marked by a rich history of various ethno-religious identities, cultures, and with the highest number of (more than 500) languages spoken in the African continent. This diversity in Nigerian landscape positions each local community as an entity distinct with its own internal dynamics.

between election violence and trauma literatures.

In the subsequent sections, I delve into the intricate tapestry of fear, political participation, and local dynamics within Nigeria. This chapter unfolds as follows: Section 3.2 reviews the extant literature, providing a comprehensive overview of the trauma and election violence narratives before Section 3.3 elaborates on the conceptual framework underpinning this research with a focus on the moderating role of local dynamics. Section 3.4 details case selection and data, while Section 3.5 delineates the methodological approach, presents the empirical findings, unveiling the nuanced relationship between fear and political engagement across Nigerian regions. Finally, Section 3.6 offers concluding reflections, emphasizing the significance of these insights within the broader landscape of political science research.

3.2 A Tale of Two Narratives: Trauma versus Repression

Why would political actors engage in election related violence? Traumatic political violence elicits contrasting effects on political participation, as scholars propose varying mechanisms to explain these impacts. While one group of scholars contends that trauma heightens political engagement, another asserts the opposite. One prevailing theoretical argument posits that traumatic political violence can enhance political participation through multiple mechanisms. For instance, the forging of identity and group solidarity can foster a sense of community (Walsh, 2007; Muldoon et al., 2023), and empowerment along with agency can empower individuals to advocate for change (Bussey & Wise, 2007; Dass-Brailsford, 2007; Hernández et al., 2007; Montiel, 2000). Additionally, catharsis and healing often provide avenues for emotional recovery. In alignment with these propositions, one could assert that violence may intensify personal connections to political issues and social networks, consequently mobilizing individuals. Furthermore, external attention and recognition can lend legitimacy to their cause, particularly after enduring victimization or subjugation to sustained violence. These mechanisms, collectively generating heightened levels of perceived threat, may evoke survival instincts, thereby igniting a desire for political action and participation.

On the other hand, the mechanisms proposed to explain decreased political participation following traumatic political violence are similarly straightforward. Psychological distress and anxiety may impede individuals from engaging, leading to erosion of political trust (Albertson & Gadarian, 2015; Myers & Tingley, 2016; von Borzyskowski et al., 2021). This type of political alienation may further foster disengagement. Moreover, extreme fear and trauma can lead to social isolation (Pain, 2022; Ryu & Park, 2018; Gorst-Unsworth & Goldenberg, 1998), resulting in reduced exposure to political discourse. Coping with trauma and its aftermath consumes significant emotional, financial, and temporal resources for both individuals and the local communities they rely on during times of distress (Paphitis et al., 2023; Canetti et al., 2010; Walter et al., 2010; Hobfoll et al., 2016; Talabi et al., 2023). This resource depletion can constrict the capacity and willingness to bear the costs required for active political participation.

In order to reconcile these divergent viewpoints, I pursue a dual approach. From a theoretical perspective, I argue that an individual's response depends on their relationship with their local community. Specifically, whether an individual reacts to traumatic political violence with heightened political participation driven by trauma or opts for political disengagement fueled by fear depend on their perception of isolation from or their experience of solidarity with their surrounding community. From a methodological viewpoint, I contend that local and regional dynamics introduce non-stationary spatial heterogeneity into data analysis. In other words, many of the interconnected mechanisms I discuss above influence each other, exhibiting significant geographical variation both in their presence and in their (direct or moderating) effects on the outcome variable. In this context, I argue that using linear (or non-linear) regression models that implicitly assume a singular relationship at the national level forces scholars to assume spatial homogeneity (and therefore, overlook spatial heterogeneity). Thus, I advocate for a judicious application of spatial econometrics tools that account for the simultaneous existence of divergent effects and non-stationary spatial heterogeneity in the analysis.

3.3 Community Solidarity as a Crucial Mediator

I argue that an individual's relationship with their local community is an essential determinant of their reaction to extreme levels of political violence. Specifically, whether a victimized individual responds with trauma-driven political participation or fear-induced political disengagement hinges on their sense of isolation from or solidarity with their community. From one perspective, trauma resulting from political violence can galvanize a sense of shared experience within communities, reinforcing collective identity and group solidarity (Scholz, 2008; Páez et al., 2007; Kimura, 2003). Consequently, extreme levels of fear within a community will lead to heightened political participation in regions where such communal ties are firmly established.

Considering this perspective, I argue that individuals residing in regions where their collective identity dominates over identities associated with the opposing side of the conflict are likely to encounter heightened levels of community solidarity. When confronted with traumatic political violence, extreme fear in these communities will act as a unifying force strengthening the collective determination of individuals. The shared experience of fear becomes a rallying point for such close-knit communities, fostering feelings of empowerment and a heightened sense of agency among these individuals. In such circumstances, fear-driven motivations transform into political action, leading to an upswing in political participation. Therefore, I propose that the presence of a supportive community will drive heightened political engagement as a coping mechanism in response to fear induced by traumatic violence. To formalize this hypothesis:

H1: Extreme fear will positively influence political participation in communities where individuals from a conflicting side constitute the majority.

Conversely, in communities where individuals from a conflicting side represent the minority, the amplification of fear stemming from traumatic political violence can exacerbate sentiments of social isolation. The absence of a strong communal network sharing the same identity weakens the mechanisms of empowerment and agency. In such circumstances, fear-induced distress may lead individuals in these communities to disengage from political participation, perceiving their voices as marginalized and unsupported. As individuals experience their fears of victimization by violence in an isolated manner, without the support of a larger community, this results in lower political engagement. The following hypothesis highlights the role of community dynamics in moderating the impact of extreme fear on political engagement, particularly in areas where the individual voter does not associate with the larger commonly shared identity in his or her community.

H2: Extreme fear will have a negative effect on political participation in communities where individuals from a conflicting side are in the minority in their community.

In conclusion, I argue that individuals' reactions to political violence, whether characterized by fear-induced disengagement or trauma-enhanced participation, are contingent upon their sense of isolation or solidarity within their communities. The theoretical conjectures presented in H1 and H2 demonstrated how the dynamics between fear and political participation may differ across diverse local communities within a country's geographical landscape. The next section will delve deeper into the role of geographical variation and spatial heterogeneity as critical moderating factors in the relationship between extreme fear and political participation.

3.4 Case Selection and Data

The Afrobarometer (AB) conducted its survey in Nigeria between December 2014 and January 2015. During the six months preceding the survey, Nigeria experienced intensifying levels and frequency of violence either in the hands of Boko Haram or in the fight against this violent group. The timing of these unfortunate events makes it reasonable to assume that fear of political violence remained vivid in the minds of survey respondents. If these fears are fresh in the respondents' minds, this also allows for a unique exploration of citizens' responses to traumatic violence and its subsequent impact on respondents' political behavior. That is, Nigeria's recent history, characterized by collective trauma as result of political violence, renders the Nigeria as an appropriate setting for testing the conjectures derived from the existing literatures on trauma and violence (as detailed in Sections 3.2 and 3.3).

In addition, the presence of geo-coded survey data was a key factor qualifying Nigeria as an appropriate case study. The Afrobarometer survey in Nigeria provides the geo-location of the respondents, which enables it to make a spatial comparison between the location of respondents vis-à-vis the location of violent events. Figure 3.1 reveals an intriguing pattern regarding the intensity of violence: the most violent Boko Haram attacks, or the largest symbols indicating 20 or more deaths per incident, are concentrated in the northeastern corner of the country.[2] Stated differently, the severity of violence—quantified through casualties and the frequency of incidents—increases substantially as one moves eastward and northward. Another trend is that the violence spatially converges: the locations of violent events become closer to one another as one would move toward the northeastern regions.[3] On the one hand, the concentration of violence in the northeastern corner of the

[2] In addition to this trend in the data, multiple recent academic works, including Ikpe et al. (2023); Mahmoud (2023); Ter Abagen & Yusuf (2023); Rodríguez & Mugica (2023); Idika-Kalu (2023); Tenuche et al. (2023); Pate & Jibril (2023); Paphitis et al. (2023), have documented that Northeastern Nigeria is the region with the most concentrated and intense political violence.

[3] For visual clarity, I picked only three categories with fatalities greater than or equal to 5, 10 and 20.

nation makes it considerably easy to test whether proximity to violence influences political participation negatively (3.1). On the other hand, the use of respondents' geo-locations and spatial tools such as geographically weighted regressions (detailed in Section 3.5) enables to disentangle seemingly strong negative impact of proximity to violence on political participation, and delve more into the local variations in the relationship between fear and participation across regions. All these factors make the Nigerian case an intriguing backdrop for spatial analysis.

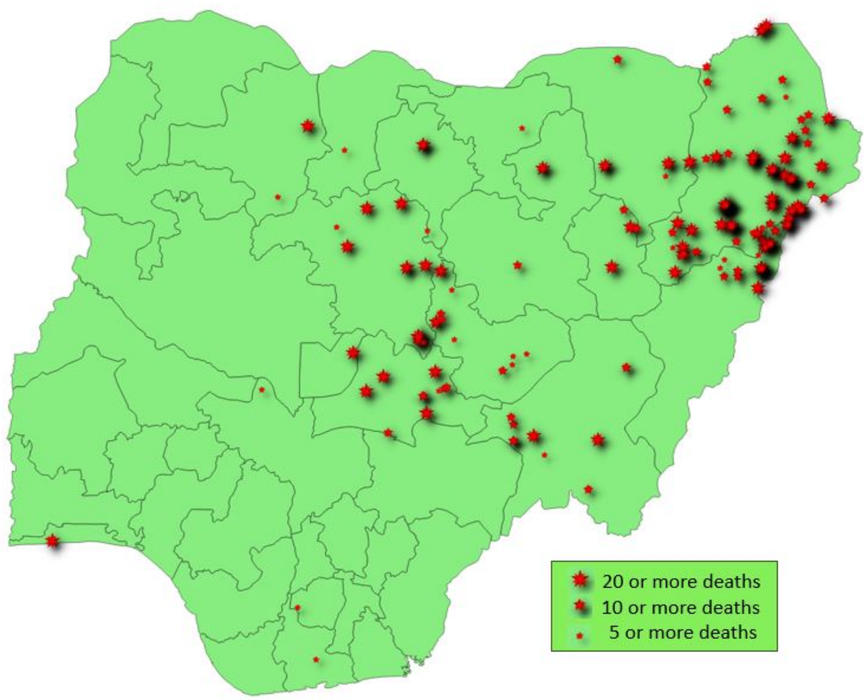

Figure 3.1: Boko Haram Violent Attacks between June and December in 2014 (Source: ACLED)

Finally, the profound nature of the Boko Haram attacks, marked by abductions, injuries, and fatalities, adds a poignant dimension to evaluating fear's impact on political engagement. Notably, the distinct alignment of Boko Haram with a fundamentalist interpretation of Islam allows for an examination of how respondents' identification with

The increasing trend in severity and frequency of violence as one approaches the northeastern corner of the country is robust to other categorizations.

different religious groups shapes their reaction to fear-inducing events. The availability of respondents' religious identity data from the Afrobarometer serves the purposes of this analysis.

3.4.1 Naïve Regression Analysis

This section employs an ordinary regression analysis to establish a foundational reference for comparison, highlighting the contribution of GWR analysis in the subsequent section. While traditional regression approaches often overlook non-stationary spatial heterogeneity, the tools available for spatial analysis are confined to the respondents' location or proximity to a political phenomenon of interest and regionally clustered standard errors to adjust for the bias in the analysis. It is worth noting that GWR takes a more nuanced approach, providing distinct coefficient estimates for each observation. This differs from ordinary regression with clustered standard errors, which assumes a singular relationship between fear and turnout across the entire country.

Table 3.1 bases its dependent variable (DV), a respondent's intention to vote, upon the AB question "If a presidential election were held tomorrow, which party's candidate would you vote for?" The independent variable for fear is derived from the question, "During election campaigns in this country, how much do you personally fear becoming a victim of political intimidation or violence?" The other key variables are the religious identity question ("What is your religion, if any?") and geo-locational coordinates (e.g., Latitude and Longitude). I include whether the respondent lives in an urban or rural area since voter turnout may have different dynamics in urban versus rural areas, along with other control variables such as demographics (e.g., age, gender, education), socioeconomic status (e.g., living conditions), and political views (e.g., on whether elites in Nigeria go unpunished when they commit crimes) for each respondent.

A noteworthy decision pertains to the inclusion of Latitude and Longitude variables, serving as a proxy for proximity to violence. As discussed earlier, the northeastern region stands as the focal point of Boko Haram violence. This suggests that respondents' reactions to violence may hinge on their perceived risk of being victimized and/or the intensity of traumatic events in their perception of the world. Consequently, proximity to the epicenter of violence—particularly the most afflicted areas—could influence their political participation behavior. Notably, Nigeria spans latitudes 4.27° N to 13.89° and longitudes 3.58° E to 14.68° E, with both coordinates increasing towards the northeastern regions. That would mean that if proximity to violence has a negative impact on voter turnout, these two variables should indicate negative and significant relationships in a linear regression.

The results indicate a robust association between extreme levels of fear and abstention across various model specifications. An interesting insight comes from the contrasting behavioral patterns between Christians and Muslims when those individuals are among the respondents that reveal that they are highly fearful of potential victimization from election-related violence. For Muslims, the prediction aligns with the trauma argument, substantiating that heightened fear correlates with an increased propensity to participate in voting. Conversely for Christians, the model presents outcomes consistent with the repression argument from the electoral violence literature. Furthermore, the coordinate variables provide additional implications; respondents' proximity to the northeastern region corresponds with an increased likelihood of electoral engagement, in alignment with the expectations of the trauma argumentation.

Nonetheless, these initial findings leave an unanswered question due to the conventional regression assumption that presumes a singular relationship between key variables. It is plausible that the interplay between fear and voter turnout may be influenced by collective sentiments of solidarity within community members or individual respondents' perceived isolation from their community, particularly as members of a marginalized minority. More specifically, the inquiry remains: "Do Muslims consistently experience mobilization across different regions even when surrounded by Christians?" The flip side of the coin pertains to the apparent demobilization of Christians. Conceivably, Christians might experience mobilization when they are in the majority, reflecting communal solidarity, while Muslims may feel demobilized when in the minority, mirroring sentiments of isolation as outlined in the earlier theoretical framework.

Table 3.1: Linear Probability Model for Intention to Vote

	Dependent Variable:			
	Intent to Vote (Binary Indicator)			
	(1)	(2)	(3)	(4)
Extreme Fear	−0.076***	−0.090***	−0.131***	−0.050*
	(0.018)	(0.018)	(0.024)	(0.026)
Muslim			−0.018	
			(0.022)	
Extreme Fear × Muslim			0.092***	
			(0.035)	
Christian				0.021
				(0.022)
Extreme Fear × Christian				−0.074**
				(0.035)
Age	−0.003***	−0.002***	−0.002***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Female	−0.046***	−0.039***	−0.040***	−0.040***
	(0.015)	(0.015)	(0.015)	(0.015)
Education	−0.011**	−0.008*	−0.008*	−0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Urban	−0.075***	−0.028*	−0.027*	−0.028*
	(0.015)	(0.016)	(0.016)	(0.016)
Living Conditions	0.003	−0.002	−0.001	−0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Elite Crimes	−0.031***	−0.032***	−0.031***	−0.031***
	(0.008)	(0.008)	(0.008)	(0.008)
Legal Discrimination	0.005	0.00002	−0.0003	−0.0001
	(0.007)	(0.007)	(0.007)	(0.007)
Latitude		0.009***	0.008*	0.009**
		(0.003)	(0.004)	(0.004)
Longitude		0.029***	0.030***	0.030***
		(0.004)	(0.004)	(0.004)
Constant	1.109***	0.776***	0.790***	0.766***
	(0.042)	(0.057)	(0.057)	(0.063)
R^2	0.042	0.079	0.082	0.081
Adjusted R^2	0.039	0.075	0.077	0.076
Residual Std. Error	0.357	0.351	0.350	0.350
F Statistic	12.473***	19.413***	16.830***	16.612***

Notes: *p<0.1; **p<0.05; ***p<0.01, and std. errors are in parentheses.

3.5 Methodology and Findings

3.5.1 Geographically Weighted Regression

The theory laid out in Section 3.3 postulates that there is spatial heterogeneity in our estimates predicting the relationship between heightened fear and political participation. A methodological tool that is particularly beneficial in capturing such unobserved heterogeneity is geographically weighted regression (GWR) analysis (Cho & Gimpel, 2010; Brunsdon et al., 2002; Huang & Leung, 2002). While traditional regression analysis assumes constant relationship across space, GWR aims to capture spatial non-stationarity by allowing the model parameters to vary spatially geographical regions. Stated differently, GWR is a spatial statistical technique used to model spatially varying relationships between a dependent variable and one or more independent variables.

In the context of my research, the linear probability model in Table 3.1 shows the following equation:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \varepsilon_i \tag{3.1}$$

This model follows a standard linear regression, where Y_i is the dependent variable, Intent to Vote, for observation i, and $\beta_0, \beta_1, \beta_2, \ldots,$ are the global model parameters; vectors $X_{i1}, X_{i2}, \ldots,$ are the independent variables (e.g., Extreme Fear, Muslim) for observation i, and ε_i is the error term. In GWR, however, the relationship is allowed to vary spatially by introducing local parameters:

$$Y_i = \beta_{i0} + \beta_{i1} X_{i1} + \beta_{i2} X_{i2} + \ldots + \varepsilon_i \tag{3.2}$$

where $\beta_{0i}, \beta_{1i}, \beta_{2i}, \ldots,$ are the local model parameters for observation, i. This means that the difference (between Equations 3.1 and 3.2) is that GWR results produce a distinct set of regression coefficients for each observation that has a unique geo-location in the dataset.

In operationalizing GWR, a key decision is the selection of spatial weight matrix, W. This decision involves several methodological and theoretical components. First, methodological: If we rewrite Equation 3.2 to highlight the uniqueness of each regression coefficient, we remove the i subscript and replace it with the location coordinates for each observation as follows:

$$Y_i = \beta_0(u_i, v_i) + \beta_1 X_1(u_i, v_i) + \beta_2 X_2(u_i, v_i) + \ldots + \varepsilon_i \tag{3.3}$$

where the difference from Equation 3.2 is that the spatially varying coefficient estimates $(\beta_{i0}, \beta_{i1}, \ldots)$ for location i are now shown with the coordinates (u_i, v_i) of each location in Equation 3.3. If report the these coefficient estimates in matrix form, it would produce the following $nx(k+1)$ matrix;[4]

$$\begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \beta_2(u_1, v_1) & \ldots & \beta_k(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \beta_2(u_2, v_2) & \ldots & \beta_k(u_2, v_2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \beta_2(u_n, v_n) & \ldots & \beta_k(u_n, v_n) \end{bmatrix}$$

If we now take a step back to computation of $\hat{\beta}$ for Equation 3.1 would be $\hat{\beta} = (X^T X)^{-1} X^T Y$. In comparison, GWR analysis or Equation 3.2 would require the inclusion of a spatial weight matrix, W, in the coefficient equation altering it to $\hat{\beta}_i = (X_i^T W_i X_i)^{-1} X_i^T W_i Y_i$ where $\hat{\beta}_i$ represents the estimated coefficients for the i-th observation and W_i is the spatial weight matrix for the i-th observation, which reflects the influence of neighboring observations on the estimation of $\hat{\beta}_i$.

In the analysis, I use the `spgwr` package in R and employed spatially adaptive weights. My theory incorporates two components that inform the selection of a kernel function which in turn creates a spatial weight matrix based on the spatial distribution of respondents' data. The first component is the theorized inverse relationship between the distance

[4] This section uses the same notation used by scholars Cho & Gimpel to maintain consistency across political science works that use the GWR methodology.

between individuals and how those individuals influence one another's political behavior. This negative relationship postulates that the kernel should incorporate an inverse decay function like an exponential, Gaussian or bi-square kernel function. Second, I argue that people outside an individual's community should not have an impact on that individual's political behavior. This means that there should be a cut-off point, or a "bandwidth", to delineate the boundaries of a local community and its impact on the individuals within that community. Among the inverse decay functions that assign zero weight to observations beyond a bandwidth, the functional form of the bi-square kernel aligns the best with my theoretical expectations as opposed to uniform, triangular kernel functions.[5] To be specific regarding the functional form, the bi-square kernel can be defined as:

$$w(d) = \begin{cases} (1 - \frac{d^2}{c^2})^2 & \text{if } d \leq c \\ 0 & \text{if } d > c \end{cases}$$

where $w(d)$ is the weight assigned to an observation based on its distance d from the focal point, the location of observation i. c is the bandwidth or the critical distance beyond which observations receive zero weight. This polynomial functional form along with the c cutoff point make the bi-square kernel function less sensitive to extreme outliers distinctly from other inverse decay functions such as exponential or Gaussian kernel functions.

[5]Among the options, one was the uniform kernel function which assigns equal weight to all the neighboring observations within a bandwidth disregarding the distance within a community. Another was the triangular kernel that assigns weights based on a linearity assumption between the impact of a neighbor and their impact. I did not have a theoretical reason to assume such linearity in the relationship between distance and effect of a neighbor.

3.5.2 Spatial Variability in the Impact of Extreme Fear on Intent to Vote

Table 3.2 juxtaposes the results of the GWR analysis with Linear Probability Model's results (from Table 3.1). On the one hand, the linear regression using the global Nigerian data seem to offer a clear cut picture indicating a negative effect of extreme fear on intention to vote for a particular political party. GWR results, on the other hand, show a more complex relationship with positive coefficients as big as "0.215" in some regions, which is three times larger than the OLS prediction of "-0.076" in the opposite direction, unveiling an effect that would have been overlooked in naïve regression analysis: extreme levels of fear can lead to heightened political participation.

Table 3.2: Summary Statistics for OLS versus GWR Coefficients

	OLS	**GWR**			
Variable	**Estimates**	Min	Max	Mean	Median
Extreme Fear	-0.076***	-0.511	0.215	-0.107	-0.069
	(0.018)				
Age	-0.003***	-0.010	0.006	-0.001	-0.001
	(0.001)				
Female	-0.046***	-0.162	0.085	-0.039	-0.028
	(0.015)				
Education	-0.011**	-0.046	0.043	-0.009	-0.011
	(0.004)				
Urban	-0.075***	-0.222	0.297	-0.007	-0.010
	(0.015)				
Living Conditions	0.003	-0.037	0.083	-0.000	0.001
	(0.007)				
Elite Crimes	-0.031***	-0.149	0.046	-0.027	-0.021
	(0.008)				
Legal Discrimination	0.005	-0.097	0.062	-0.008	-0.006
	(0.007)				
Intercept	1.109***	0.624	1.478	1.038	1.053
	(0.042)				
N	2275				
R^2	0.042				
AIC	1786.835	1363.348			

Notes: *p<0.1; **p<0.05; ***p<0.01, and std. errors are in parentheses.

Figure [3.2](#) exposes the intriguing spatial variation that would have been overlooked by the linear predictions of the naïve regression model. Notably, we observe a departure from the previous model's estimation of a decline in individuals' likelihood of participating in elections due to extreme fear. Quite to the contrary, high levels of fear appear to exert a positive effect on mobilization in the western and central regions, while the anticipated mobilizing effect, as suggested by the ordinary regression, is apparent in the northern and southernmost areas of the country.

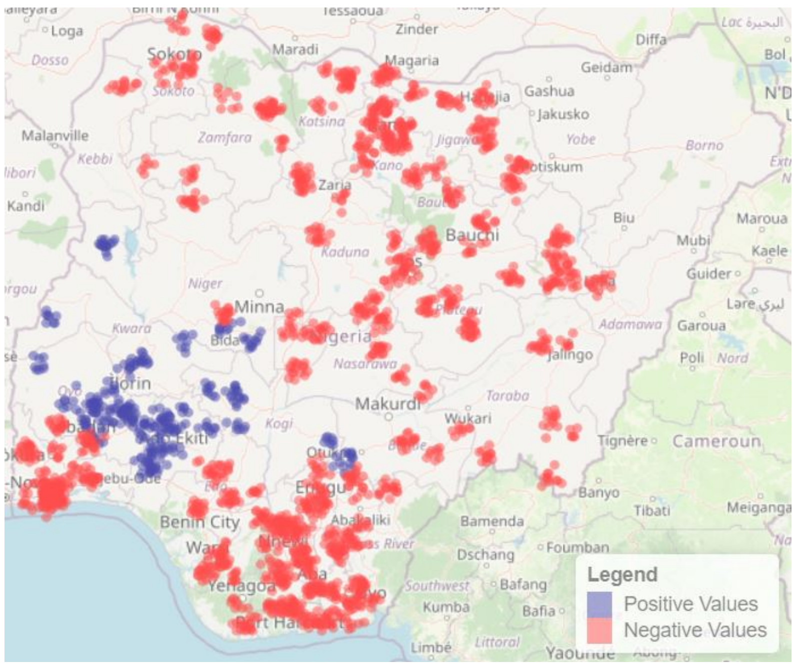

Figure 3.2: GWR Coefficient Estimates for Extreme Fear

With the primary objective of this section being to address the crucial research question concerning the divergent impacts of heightened fear levels stemming from traumatic violence, a lingering query pertains to the potential mobilization of Muslims. The ensuing map compiles the coefficients associated with interactive terms, specifically those involving extremely fearful Muslims (Muslim x Extreme Fear), and exclusively displays coefficients with a p-value under 0.05. It is important to note the concerns of multiple testing in GWR analysis (da Silva & Fotheringham, 2016), where approximately 5 percent of the total number of regressions would be expected to yield significance merely by chance. On the other hand, my GWR analysis reveals that 15 percent of the distinct regressions exhibit significance at the 0.05 level while 23 percent of regressions are significant at the 0.1 level. The subsequent map in Figure 3.3 visually portrays the location of these regression coefficients, additionally indicating whether they exert a positive or negative influence on individual respondents' intended voter turnout.

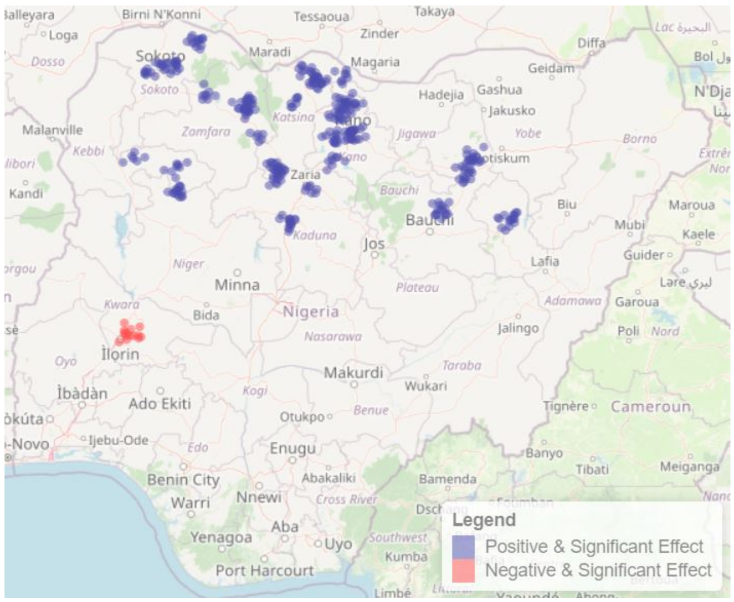

Figure 3.3: GWR Coefficient Estimates
for Muslims who are Extremely Fearful

Similarly, when I use Christian and Extremely Fearful as the interactive variable in GWR analysis, around 15 percent of the total regressions show statistical significance at the 0.05 level. Table 3.4 exemplifies the distinctiveness of the model's findings. Notably, regions witnessing demobilization among Christian voters predominantly lie in the northern part of the country, where Muslims constitute the majority, while mobilization is evident in areas where Christians form the majority.

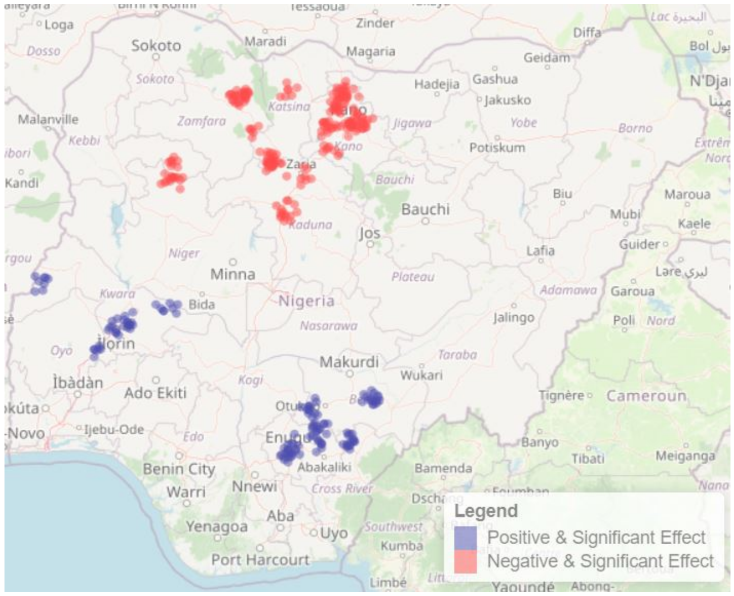

Figure 3.4: GWR Coefficient Estimates
for Christians who are Extremely Fearful

3.6 Conclusion

The chapter aimed to bring a dual contribution to the existing literature. First, it advocated for the integration of advanced spatial econometric techniques with geo-coded datasets, allowing us to move beyond broad generalizations that naïve regression analysis can lead us to as scholars. In order to achieve this, the chapter delved into the relationship between extreme fear and political participation within the Nigerian context. The initial OLS results revealed a highly significant and negative relationship between extreme levels of fear and the respondents' intention to vote for a particular party in the elections.

Through geographically weighted regression (GWR) analysis, I showed that the relationship between high levels of fear and voting behavior is inherently tied to geographic context, challenging conventional assumptions of singular relationships offered by traditional OLS regressions. In particular, findings illustrated that the presence of non-stationary spatial heterogeneity accentuates the critical role of geographic context in shaping voter behavior in the context of Nigeria. This more nuanced spatial analysis of the data revealed that extreme fear leads to more participation for Christians in southern Nigeria and for Muslims in northern Nigeria, where both of these religious groups form the majority.

These findings underscore that fear operates both as a catalyst for mobilization and a deterrent to participation, contingent upon the specific geographic context across Nigeria's diverse regions, and that taking OLS results for face value can be misleading for researchers working with data overlooking the possibility that the behavior of their respondents, subject, or data points may be influenced by other observations that are surrounding them. This exploration of the spatial dynamics established that the mobilization argument posed by the trauma literature holds true in certain regions, while the predictions of fear's repressive effects advanced by the election violence literature find applicability in others. By incorporating spatial heterogeneity, the GWR analysis challenged the notion of stable relationships across subnational units and contributed to a more holistic understanding of the dynamics between heightened fear and political participation.

In conclusion, we find ourselves at a juncture where the growing availability of geo-coded data opens new avenues for enriching our understanding of socio-political dynamics through the lens of spatial econometrics. The findings from this chapter underscore the necessity for spatial methodologies when examining the complexities of extreme levels of fear and political participation. This not only informs the scholarly discourse but also provides practical insights for policymakers and electoral practitioners, helping them understand the complex spatial variation in the relationship between fear and political participation across different geographic contexts.

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Appendix A

Supplemental Information for Chapter 1

A.1 Formal Definition of Discrimination Capacity (Δ)

This section of the Appendix A formalizes the role of discrimination capacity. Succinctly, the parameter Δ plays a role in the distribution of government-initiated violence between two forms of violence: The violence that hurts the government supporters (V_G) versus the one that harms the opposition supporters (V_O). Stated differently, the *discrimination* capacity parameter (Δ) affects the model in terms of how selectively (or *indiscriminately*) the total violence (V_i) will be targeted towards voters. In the two extreme cases ($\Delta = 0$ versus $\Delta = 1$), the level of violence experienced by each party's supporter group will be categorically different. In the $\Delta = 0$ case, perpetrator G will not have the ability to effectively target the O supporters. In this case, the violence will be indiscriminate, making the probability of being victimized by a violent event equal to the distribution of initial support in the district. When $\Delta = 1$, G will be able to pursue a highly effective selective violence campaign against targeted individuals and/or small groups of O supporters. In this case, the G supporters will experience 0 (zero) level of violence when the totality of violence will be directed at O supporters. The following table shows the expected level of violence that supporters of each party will be exposed to in District i.

Table A.1: Distribution of Violence across Δ's Corner Cases

	$\Delta = 0$	$\Delta = 1$
Government	$\alpha_i \cdot V_{T,i}$	0
Opposition	$(1 - \alpha_i) \cdot V_{T,i}$	$V_{T,i}$

Table A.1 helps us to create the continuous Δ parameter. When $\Delta = 0$, G is not in control of how much of its violence will victimize its own supporters versus opposition supporters. In this case, turnout functions will have to share the total violence between parties in line with the distribution of party support. When $\Delta = 1$, G will be able to avoid indiscriminate violence and its supporters will not be exposed to any violence. In this case, $V_{T,1}$ will go to the opposition supporters in its entirety. For the cases in between, I integrated a continuous $\Delta \in [0, 1]$ to produce the expected levels of violence against government and opposition supporters as $(1-\Delta)\ \alpha_i V_{T,i}$ and $(1-\alpha_i+\Delta\alpha_i)\ V_{T,i}$, respectively. Plugging in $V_{G,1} = (1 - \Delta)\alpha_1 V_{T,1}$, $V_{O,1} = (1 - \alpha_1 + \Delta\alpha_1)V_{T,1}$, $V_{G,2} = (1 - \Delta)\alpha_2 V_{T,2}$, and $V_{O,2} = (1 - \alpha_2 + \Delta\alpha_2)V_{T,2}$ into equation, we will have the following utility function for G:

$$\begin{aligned} U_G = \alpha_1 \cdot t_{G,1}[(1-\Delta)\alpha_1 V_{T,1}] - (1-\alpha_1) \cdot t_{O,1}[(1-\alpha_1+\Delta\alpha_1)V_{T,1}] - k(V_{T,1}) \\ +\alpha_2 \cdot t_{G,2}[(1-\Delta)\alpha_2 V_{T,2}] - (1-\alpha_2) \cdot t_{O,2}[(1-\alpha_2+\Delta\alpha_2)V_{T,2}] - k(V_{T,2}) \end{aligned} \tag{A.1}$$

where the turnout ($t(V_i) \in [0, 1]$) and cost $k(V_i)$ functions are twice differentiable by assumption. For simplicity, I assume that $t(V_i)$ is a linear monotone decreasing function, whereas $k(V_i) \geq 0$ is convex and monotonically increasing.[1] As mentioned previously, I assume that initial vote share in the districts are $\alpha_1 > 0.5 > \alpha_2$, and that our key concept discrimination capacity follows $0 \leq \Delta \leq 1$.

This formalization of Δ also shows why V_T does not necessarily have to be a function of Δ. In fact, claiming that total level of violence V_i is a function of Δ would suffer from a circular logic since Δ is set up in a way to distribute total level of violence between violence against opposition and government supporters. To show this formally, one can see that the summation of all the four cells in Table A.1 which can be used to calculate the total level of V_i is equal to V_i, by definition.

[1] These assumptions are sufficient for a unique optimum for $(V^*_{T,1}, V^*_{T,2})$.

A.2 Proofs for Proposition 1 and Lemma 1

Proposition 1. This proof includes two parts. First, I show the existence of a unique optimum by proving the strict concavity of the U_G. Second, I show that that unique solution is $V^*_{T,2} > V^*_{T,1}$ (as opposed to $V^*_{T,1} > V^*_{T,2}$) through First Order Conditions (FOCs).

(1) Strict Concavity of U_G

Showing that Hessian matrix of U_G is negative definite will suffice to prove that G's utility function, $U_G(V_{T,1}, V_{T,2})$, is strictly concave (See Theorems 17.13-14 in Sydsaeter, Knut & Hammond, Peter J (1995)).[2] The Hessian matrix of the function (Hess $U_G(V_{T,1}, V_{T,2})$) is follows:

$$\text{Hess } U_G(V_{T,1}, V_{T,2}) = \frac{\partial^2 f}{\partial x_i \partial x_j} = \begin{bmatrix} \dfrac{\partial^2 f}{\partial V_{T,1}\partial V_{T,1}} & \dfrac{\partial^2 f}{\partial V_{T,1}\partial V_{T,2}} \\ \dfrac{\partial^2 f}{\partial V_{T,2}\partial V_{T,1}} & \dfrac{\partial^2 f}{\partial V_{T,2}\partial V_{T,2}} \end{bmatrix}$$

From Young's Theorem, we know that the Hessian matrix of a function with two variables is a symmetric matrix. We also know that a n x n symmetric matrix is negative definite only and only if its leading principal minors follow the condition: $(-1)^l D_l > 0$ for $l = 1, ..., n$. Hence, if the first-order leading principal minor $|D_1| < 0$ and second-order leading principal (or the determinant of the matrix) $|D_2| > 0$, the Hessian matrix of U_G is negative definite.

In 2 x 2 matrices such as $U_G(V_{T,1}, V_{T,2})$, $|D_1| = \dfrac{\partial^2 f}{\partial V_{T,1}\partial V_{T,1}}$. Therefore, $|D_1| = \alpha_1^3 \cdot (1-\Delta)^2 \cdot t''_{G,1}((1-\Delta)\alpha_1 V_{T,1}) - (1-\alpha_1)((\Delta-1)\alpha_1+1)^2 t''_{O,1}(V_{T,1}(\alpha_1\Delta - \alpha_1 + 1)) - k''(V_{T,1})$. Due to our linearity assumption for $t(\cdot)$ and convexity assumption for $k(\cdot)$, we have $t''(\cdot) = 0$ and $k''(\cdot) > 0$. Thus, $|D_1| < 0$.

$|D_2| = |\text{Hess } U_G(V_{T,1}, V_{T,2})|$, and $|\text{Hess } U_G(V_{T,1}, V_{T,2})| = \dfrac{\partial^2 f}{\partial V_{T,1}\partial V_{T,1}} \cdot \dfrac{\partial^2 f}{\partial V_{T,2}\partial V_{T,2}} - \dfrac{\partial^2 f}{\partial V_{T,1}\partial V_{T,2}} \cdot \dfrac{\partial^2 f}{\partial V_{T,2}\partial V_{T,1}}$. Since $\dfrac{\partial^2 f}{\partial V_{T,1}\partial V_{T,2}} = \dfrac{\partial^2 f}{\partial V_{T,2}\partial V_{T,1}} = 0$, we have

$$|\text{Hess } U_G(V_{T,1}, V_{T,2})| = |D_1| \cdot \frac{\partial^2 f}{\partial V_{T,2}\partial V_{T,2}}$$

where $\dfrac{\partial^2 f}{\partial V_{T,2}\partial V_{T,2}} = \alpha_2^3(\Delta-1)^2 t''_{G,2}(\alpha_2(\Delta-1)(-V_{T,2})) + (\alpha_2-1)(\alpha_2(\Delta-1)+1)^2 t''_{O,2}(\alpha_2(\Delta-1)V_{T,2} + V_{T,2}) - k''(V_{T,2})$. Since $t''(\cdot) = 0$ and $k''(\cdot) > 0$, $\dfrac{\partial^2 f}{\partial V_{T,2}\partial V_{T,2}} < 0$.

[2] These theorems suggest that if the Hessian matrix of a function is negative definite, that function is *strictly* concave.

Since $|D_1| < 0$ and $\dfrac{\partial^2 f}{\partial V_{T,2} \partial V_{T,2}} < 0$, $|\text{Hess } U_G(V_{T,1}, V_{T,2})| > 0$. This proves that Hessian matrix is negative definite.

We know from our theorem that if Hessian matrix of U_G is negative definite, then U_G is strictly concave. $\therefore U_G$ has a unique optimum for $(V^*_{T,1}, V^*_{T,2})$.

(2) $V^*_{T,2} > V^*_{T,1}$

Proof by contradiction ($\otimes$): The following equations provide the First Order Conditions (FOC) through partial derivatives of U_G with respect to $V_{T,1}$ and $V_{T,2}$ ($\dfrac{\partial U_G}{\partial V_{T,1}} = 0$, $\dfrac{\partial U_G}{\partial V_{T,2}} = 0$). Let us denote the solution as $(V^*_{T,1}, V^*_{T,2})$.

$$\begin{aligned} -(1-\alpha_1) \cdot t'_{O,1}(V^*_{T,1}) &= k'(V^*_{T,1}) \\ -(1-\alpha_2) \cdot t'_{O,2}(V^*_{T,2}) &= k'(V^*_{T,2}) \end{aligned} \tag{A.1}$$

Let us assume $V^*_{T,1} \geq V^*_{T,2}$. If $V^*_{T,1} \geq V^*_{T,2} \Rightarrow k'(V^*_{T,1}) \geq k'(V^*_{T,2})$ since $k(\cdot)$ is a convex monotone increasing function. Combining with the equations in (A.1), we have the following:

$$(1-\alpha_1) \cdot t'_{O,1}(V^*_{T,1}) \leq (1-\alpha_2) \cdot t'_{O,2}(V^*_{T,2}) \tag{A.2}$$

Since we assumed linearity and same functional form for G and O's turnout functions, $t'_{O,1}(V^*_{T,1})$ and $t'_{O,2}(V^*_{T,2})$ cancel each other out changing the direction of the inequality since $t(\cdot) < 0$. This leaves us with $(1-\alpha_1) \geq (1-\alpha_2)$. In contrast, we know that $\alpha_1 > \alpha_2 \Rightarrow (1-\alpha_1) < (1-\alpha_2)$ by definition. $((1-\alpha_1) \geq (1-\alpha_2) \wedge (1-\alpha_1) < (1-\alpha_2)) \rightarrow \otimes$. $\therefore V^*_{T,2} > V^*_{T,1}$. Putting this together with the first part of the proof, we can conclude that $V^*_{T,2} > V^*_{T,1}$ is a *unique* solution. ■

Lemma 1. For case (1), we can compare the levels of violence between a government stronghold (D_1) and a competitive district (D_2) by setting $\alpha_1 > 0.5$ and $\alpha_2 = 0.5$ in Inequality A.2. This choice maintains the contradiction used in the proof, leading to the conclusion that $V^*_{T,2} > V^*_{T,1}$. Consequently, there will be more violence in a competitive district than in a government stronghold. For case (2), we can set $\alpha_1 = 0.5$ and $\alpha_2 < 0.5$. This allows us to conclude that an opposition stronghold will experience higher levels of violence compared to a competitive district. ■

A.3 Functional Forms & Numerical Examples

In order to illustrate the findings, I chose the following functional formals:

$$
\begin{aligned}
\mathrm{tg1} &= 0.8\ - \alpha 1(1-\Delta)\mathrm{v1} \\
\mathrm{tg2} &= 0.8\ - (1-\alpha 1)(1-\Delta)\mathrm{v2} \\
\mathrm{to1} &= 0.8\ - ((1-\alpha 1)(1-\Delta)\mathrm{v1} + \Delta \mathrm{v1}) \\
\mathrm{to2} &= 0.8\ - (\alpha 1(1-\Delta)\mathrm{v2} + \Delta \mathrm{v2}) \\
\mathrm{k1} &= \mathrm{v1}^2 \\
\mathrm{k2} &= \mathrm{v2}^2
\end{aligned}
$$

When we maximize the $U_G(V_{T,1}, V_{T,2})$ through FOC, we find the following optimal values:

$$
\begin{array}{lll}
V^*_{T,1} = -0.1 + 0.3\Delta & V^*_{T,2} = 0.05 + 0.1\Delta & \text{for } \alpha_1 = 0.6 \\
V^*_{T,1} = -0.25 + 0.375\Delta & V^*_{T,2} = 0.125 + 0.0625\Delta & \text{for } \alpha_1 = 0.75 \\
V^*_{T,1} = -0.4 + 0.45\Delta & V^*_{T,2} = 0.2 + 0.025\Delta & \text{for } \alpha_1 = 0.9
\end{array}
$$

Appendix B

Supplementary Information for Chapter 2

B.1 Covariate Balancing Propensity Score (CBPS) Matching Process

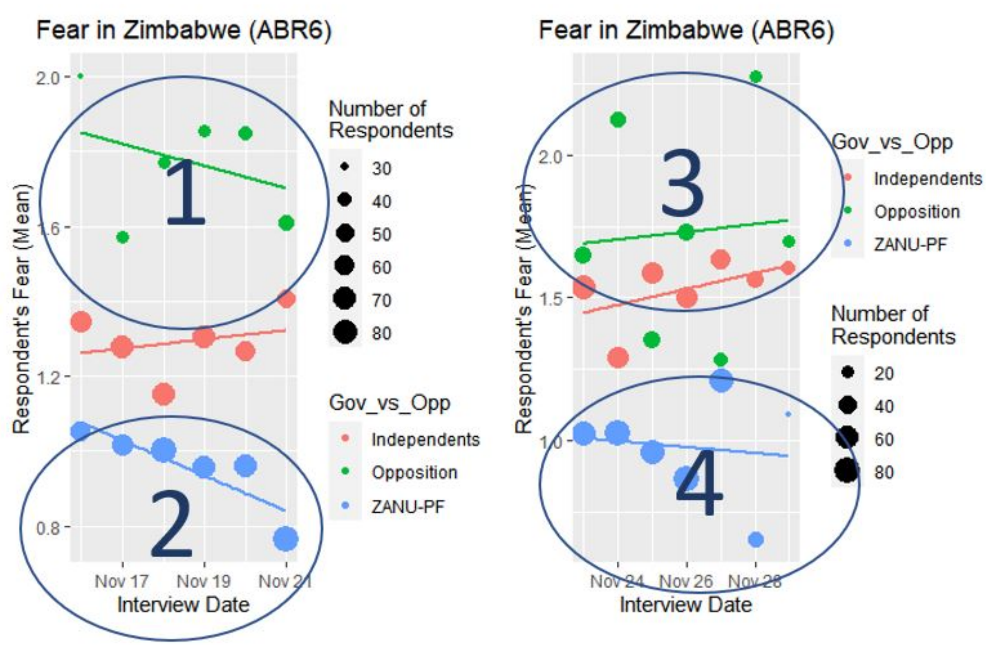

Figure B.1: Matching Strategy with Covariate Balancing Propensity Scores (CBPS)

B.2 Balance After Covariate Balancing Propensity Score (CBPS) Matching

The Covariate Balancing Propensity Score (CBPS) matching included three phases: Matching between groups 1 and 2, 1 and 3, and 3 and 4. The following love plots and histograms detail the before-and-after comparisons:

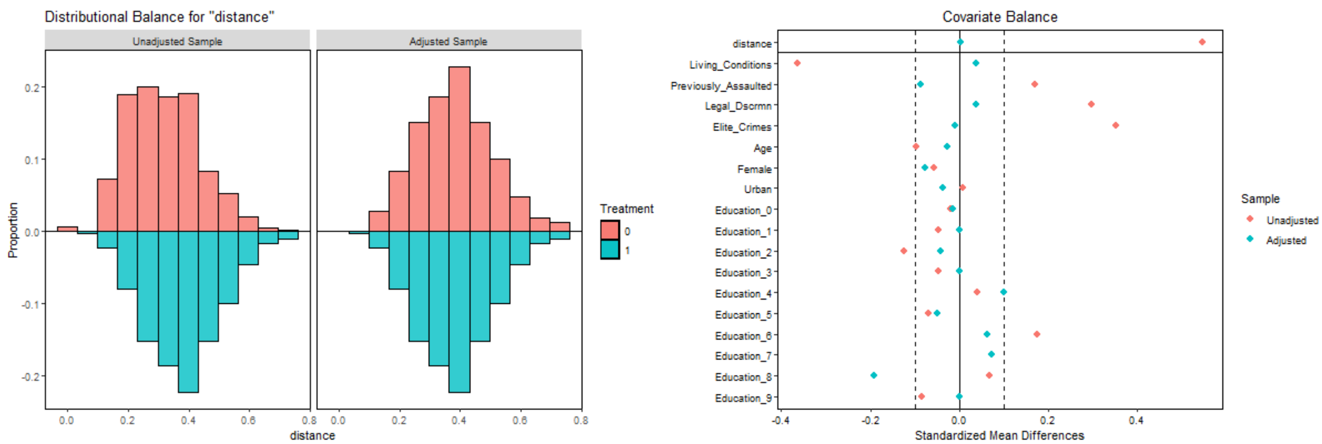

Figure B.2: Covariate Balancing Propensity Score (CBPS) Matching Between Groups 1 and 2

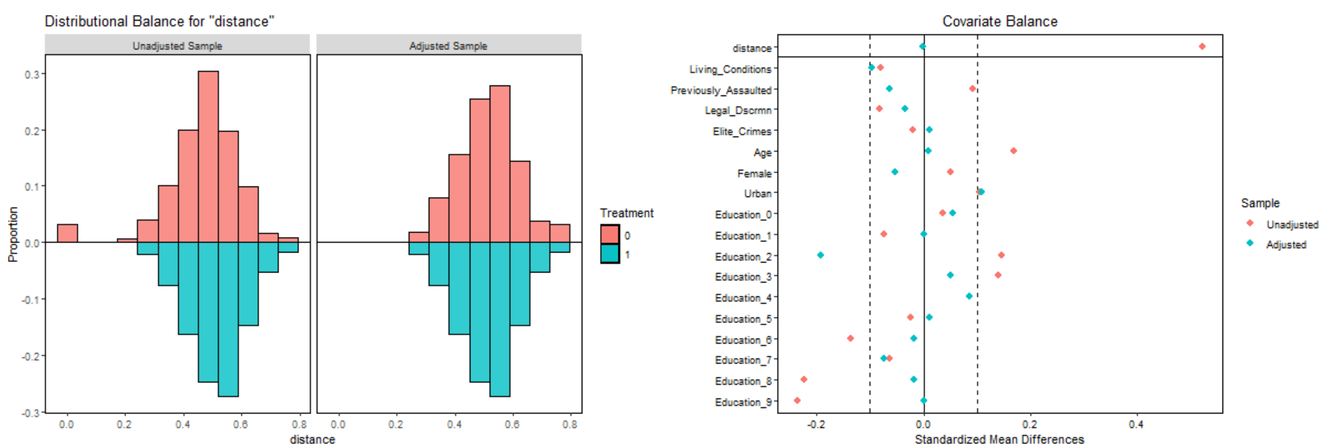

Figure B.3: Covariate Balancing Propensity Score (CBPS) Matching Between Groups 1 and 3

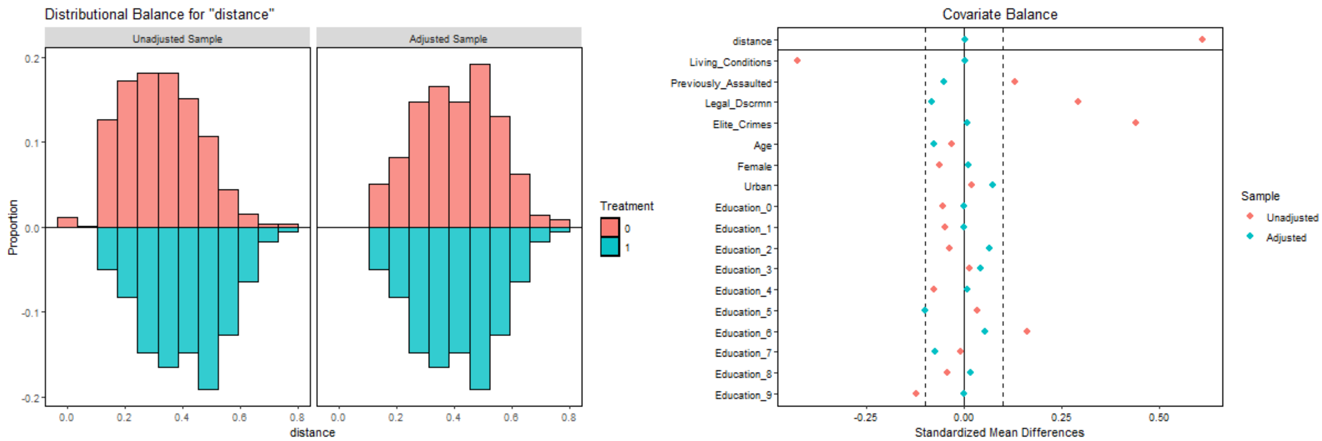

Figure B.4: Covariate Balancing Propensity Score (CBPS) Matching Between Groups 1 and 4

Combining all the three samples together, I culminate with the balance test results in Table B.1 in Appendix B.3.

B.3 Post-Matching Balance Tests

Table B.1: Balance Test Results After Covariate Balancing Propensity Score (CBPS) Matching

Variables	Pre-Violence Mean	Post-Violence Mean	p-values Unadjusted	Bonferroni
Living Conditions	2.19	2.29	$0.10^{\dagger}$	0.90
Previously Assaulted	0.33	0.33	0.80	1.00
Legal Discrimination	1.82	1.80	0.68	1.00
Elite Crimes	2.01	1.91	$0.06^{\dagger}$	0.54
Female	0.47	0.47	0.88	1.00
Age	38.49	37.99	0.56	1.00
Urban	0.94	0.93	0.39	1.00
Education = 0	0.05	0.04	0.59	1.00
Education = 1	0.00	0.00	1.00	1.00
Education = 2	0.09	0.07	0.46	1.00
Education = 3	0.14	0.13	0.51	1.00
Education = 4	0.21	0.21	0.86	1.00
Education = 5	0.35	0.37	0.61	1.00
Education = 6	0.12	0.12	0.87	1.00
Education = 7	0.01	0.03	$0.07^{\dagger}$	0.63
Education = 8	0.03	0.03	0.64	1.00
Education = 9	0.00	0.00	1.00	1.00
Fear = 0	0.29	0.33	$0.09^{\dagger}$	0.81
Fear = 1	0.18	0.17	0.83	1.00
Fear = 2	0.22	0.19	0.25	1.00
Fear = 3	0.31	0.30	0.65	1.00
Government Supporters	0.10	0.31	0.00^{***}	0.00^{***}
Independents	0.08	0.22	0.00^{***}	0.00^{***}
Opposition Supporters	0.50	0.25	0.00^{***}	0.00^{***}
Refusers and 'DK'ers	0.32	0.22	0.00^{***}	0.00^{***}

Signif. codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$