The Geography of Conflict Mediation: Proximity and Success in Armed Conflict Resolutions

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Abstract

As conflicts persist across the globe, the complexity of conflict resolution has grown, with numerous variables influencing the success of mediation efforts. One critical, yet often overlooked, factor is the geographical dynamics of mediation: does the physical distance between conflict zones and mediation events shape the likelihood of successful peace outcomes? Newly available conflict mediation data allows us to address this question in robust and meaningful ways. This study examines the spatial dynamics of conflict mediation and its impact on the signing of peace agreements and the de-escalation of violence. Utilizing spatial autocorrelation techniques, the Getis-Ord Gi* statistic is employed to identify and map hotspots of mediation activity. The empirical analysis further explores the relationship between the Great Circle distance from mediation locations to conflict zones and two key measures of mediation success: the formalization of peace agreements and the reduction in violent events. The findings reveal a nuanced relationship: while distant mediation efforts are more likely to yield peace agreements, closer proximity to the conflict zone is linked to a greater reduction in violence. These results suggest that while distant mediation may foster agreements through perceived neutrality, proximity may be more effective in directly mitigating conflict. This study offers new insights into the spatial strategies of conflict resolution, providing valuable implications for future peacemaking efforts.

Unresolved conflicts continue to have widespread repercussions, highlighting the challenges of achieving durable peace. While existing research has focused heavily on mediator characteristics, negotiation processes, and the broader political context, the role of geography in conflict mediation remains underexplored (Melin & Olander, 2019; Duursma, 2020; Lundgren & Svensson, 2020). Specifically, the distance between conflict zones and mediation locations may influence the likelihood of a successful peace outcome. Research such as the Duursma (2020) study of local mediation in Darfur points to the importance of spatial proximity, showing that conflict severity can drive localized mediation efforts. However, systematic investigations into the broader spatial dynamics of conflict mediation remain sparse. This study addresses this gap by examining how the geographical distance between conflict sites and mediation events affects the success of peace processes, measured both by the signing of peace agreements and by reductions in conflict intensity.

Recent studies in conflict research have underscored the role of geography in shaping armed conflict risk and dynamics. For instance, Xie et al. (2023) leveraged spatial models to analyze conflict risk across sub-Saharan Africa, revealing that spatial factors enhance our understanding of conflict drivers. Despite these advancements in spatial analysis in the conflict and peace literature, few studies have extended such methodologies to the mediation arena. As the thesis of this work suggests, greater distance may confer perceived neutrality to mediation processes, potentially facilitating formal peace agreements, whereas proximity might allow for more effective violence reduction through a better contextual understanding of local conflict dynamics (Duursma, 2020). This overlooked spatial dimension represents a significant gap in the literature, providing a jumping off point for this study.

By addressing this gap, the current research contributes to the literature by linking spatial analysis techniques with conflict mediation outcomes. This integration not only bridges the gap between traditional conflict resolution discourse and spatial conflict analysis, as emphasized by prior work in the field, but also offers practical insights for policymakers. Understanding whether geographically distant mediation efforts, which are often perceived as more neutral, or locally embedded efforts that might leverage intimate knowledge of the conflict context, are more effective, could significantly inform the strategic decision-making in peace processes. Thus, this paper aims to offer a more nuanced account of how geography influences the success of mediation efforts, advancing our theoretical and empirical understanding of conflict resolution.

This paper makes a novel contribution by utilizing newly available geospatial data on conflict mediation events to analyze the spatial dynamics of conflict resolution. This work employs spatial autocorrelation and econometric modeling techniques to assess the relationship between the distance of mediation events from conflict zones and key indicators of mediation success.

The findings have important implications for both scholars and practitioners in conflict resolution. Results suggest a complex relationship between distance and mediation outcomes: greater distance between mediation events and conflict zones is associated with a higher likelihood of a peace agreement being signed, while closer proximity is linked to greater reductions in fatalities. These insights can inform strategies for the location of peace talks and guide the allocation of resources, suggesting that distant mediation may facilitate formal agreements, whereas local efforts may be more effective at reducing conflict intensity.

The paper is structured as follows: the next part discusses the theoretical underpinnings of proximity in conflict mediation, followed by the presentation of testable hypotheses derived from these theories. The subsequent section details the empirical approach, including data, key variables, and methods. Afterward, the results are reported, and the paper concludes with implications for future research and policy.

Theories of Proximity in Conflict Mediation

In recent years, conflict resolution processes have become increasingly fragmented, with multiple actors and organizations simultaneously mediating the same conflict (Peter, 2024). This proliferation of mediation efforts has resulted in a geographical dispersion of mediation events (see Figure 1), highlighting the growing complexity in the locations and contexts in which mediation occurs. As more actors become involved, it is essential to consider how the location of mediation events may influence the success of these efforts, particularly in terms of both formal peace agreements and the intensity of conflict on the ground. This section explores the theories behind the proximity of mediation efforts, highlighting the impact that both geographical context and the increasing complexity of mediation processes have on conflict resolution.

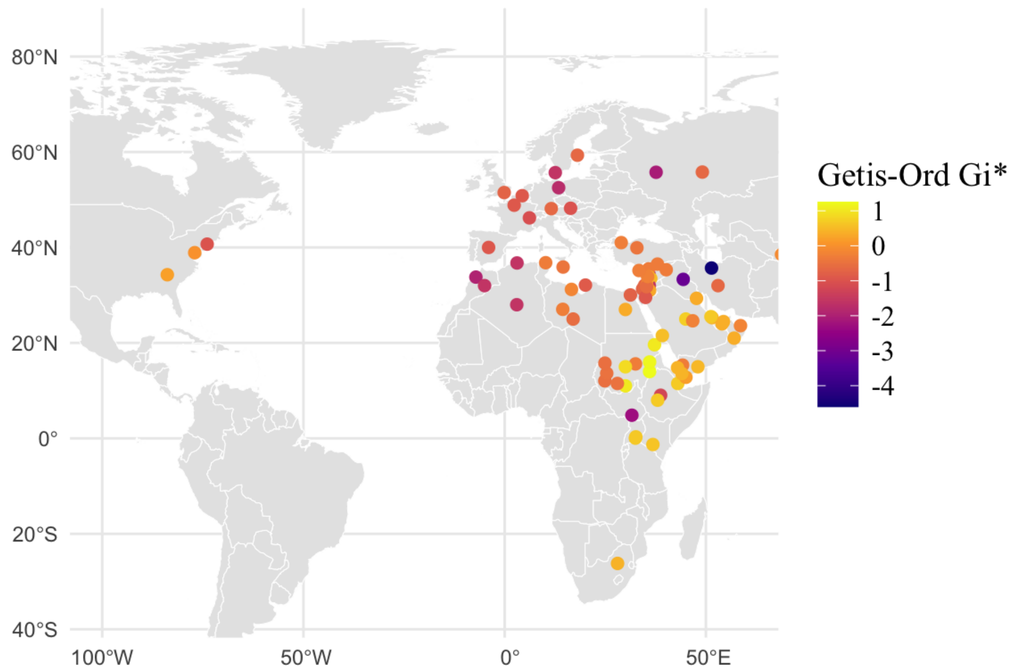

Figure 1. Hotspot Mapping of Mediation Events (2018-2024). See Appendix A for methodology.

Neutrality and Complexity

The location of mediation in armed conflicts is likely a strategic factor that can significantly influence the success of mediation efforts. Various theories have emerged to explain how and why mediation location might affect outcomes. The predominant theories can be categorized into several key areas: the geographical context of mediation, the cultural implications of location, the strategic interests of the parties involved, and the logistical considerations that arise from different mediation settings.

One of the primary theories posits that the geographical context of mediation plays a crucial role in shaping the dynamics of conflict resolution. Greig (2013) research highlights that the choice of mediation location can be influenced by the parties' strategic objectives, where they may seek to gain a tactical advantage or leverage their position in the conflict. This perspective is supported by Wallensteen & Svensson (2014), who argue that the geographical setting can affect the power dynamics between conflicting parties, potentially leading to more favorable conditions for negotiation. Furthermore, the authors emphasize that the location can impact the accessibility of mediators and the willingness of parties to engage in dialogue, as certain locations may be perceived as neutral ground while others might be viewed as biased or hostile (Wallensteen & Svensson, 2014).

Cultural implications of mediation location also play a significant role in the success of conflict resolution efforts. For example, cultural factors inherent in specific locations can influence the mediation process, as local customs and practices may dictate the acceptability of certain negotiation styles or approaches (Lundgren & Svensson, 2020). This is particularly relevant in contexts where indigenous reconciliation methodologies, such as sulh in Arab-Islamic cultures, are integrated into the mediation process (Dosari & George, 2023). The effectiveness of such culturally sensitive approaches can be contingent upon the chosen mediation location, which may either facilitate or hinder the acceptance of these practices by the conflicting parties.

Strategic interests of the parties involved in the conflict further complicate the relationship between mediation location and success. The work of Ruhe (2015) suggests that the intensity of conflict and the perceived likelihood of victory for each party can influence their willingness to engage in mediation, with certain locations potentially providing a more conducive environment for negotiation when both parties are equally matched. This notion is also supported by DeRouen, Bercovitch & Pospieszna (2011), who argue that the type of conflict and its duration can also affect the choice of mediation location, with longer conflicts often leading to a greater likelihood of mediation occurring in neutral or third-party locations. The strategic calculus of the parties may thus dictate their preferences for specific mediation venues, impacting the overall success of the mediation process.

Logistical considerations associated with different mediation locations are another critical factor that can influence outcomes. The accessibility of the mediation venue, the availability of resources, and the presence of supportive infrastructure can all affect the feasibility of mediation efforts. For instance, logistical challenges can hinder the participation of key stakeholders, thereby limiting the effectiveness of mediation (Wall & Dunne, 2012). Additionally, political fragility and the timing of mediation may be influenced by logistical factors, which may vary significantly depending on the chosen location (Beckerman, 2022). These logistical elements can create barriers to effective communication and negotiation, ultimately impacting the success of mediation.

Moreover, the evolving nature of armed conflicts and the increasing complexity of mediation processes necessitate a nuanced understanding of how location affects mediation outcomes. The work of Haspeslagh (2013) suggests that the global proscription regime and the legal implications of engaging with certain armed groups can further complicate the choice of mediation location, as mediators must navigate the political landscape surrounding the conflict. This complexity underscores the importance of considering both the immediate and broader geopolitical context when evaluating the impact of mediation location on conflict resolution.

Taken together, these theoretical perspectives underscore the multifaceted ways in which mediation location can influence conflict resolution outcomes. Geographic, cultural, strategic, and logistical considerations all shape the environment in which negotiations occur. Yet, a common thread across these factors is the importance of perceived neutrality: locations that are geographically removed from the immediate conflict zone may mitigate biases, reduce security risks, and create more balanced conditions for dialogue. Building on this foundation, this study advances the theory that greater physical distance between the conflict site and the mediation venue increases the likelihood of achieving a peace agreement by enhancing the perceived neutrality and legitimacy of the process.

Voice and Conflict Intensity

The increased localization of negotiations in armed conflicts may play a role in peace outcomes (Peter, 2016). Some literature highlights how localized negotiations can foster trust, address specific grievances, leverage social proximity, and create a sense of urgency, all of which may contribute to reducing conflict intensity.

One of the primary mechanisms through which localized negotiations can decrease conflict intensity is by fostering trust and understanding among the parties involved. Research indicates that when mediation occurs in familiar settings, parties may perceive the mediator as more relatable and trustworthy, which can enhance the dialogue process (Bogacz, Pun & Klimecki, 2020). This is particularly important in asymmetrical conflicts where the power dynamics can be more effectively addressed in a context that is familiar to both parties. For instance, localized mediation allows mediators to better understand the specific cultural and social nuances that influence the conflict, thus tailoring their approach to meet the needs of the parties involved (Minko, 2024). This increased understanding can lead to more effective communication and a greater likelihood of reducing violence.

Localized negotiations also have the advantage of addressing specific grievances that may be overlooked in broader, more formal mediation settings. By focusing on local concerns, mediators can facilitate discussions that resonate more deeply with the parties, potentially leading to quicker management strategies and a decrease in conflict intensity. For example, localized mediation can empower communities by giving them a voice in the process, fostering a sense of ownership over the outcomes, which can further reduce tensions (Muigua, 2015). This empowerment may help to ensure that the solutions reached are relevant and acceptable to those most affected by the conflict, reinforcing the potential for a sustained reduction in violence.

The dynamics of social proximity further enhance the effectiveness of localized negotiations. Research suggests that social support and familiarity among parties can mitigate conflict, as individuals are more likely to empathize with one another when they share a common context (Weisser, 2024). Close physical proximity facilitates reconciliation by allowing for more direct and personal interactions, which can help alleviate tensions and foster understanding (Link, Scheffran & Ide, 2016). The ability to engage face-to-face in familiar environments builds personal relationships that can transcend the conflict, making localized mediation particularly effective at lowering hostility and fatalities.

Moreover, localized negotiations can create a sense of urgency and immediacy that may not be present in more distant mediation settings. As conflicts escalate, parties may be more inclined to seek immediate solutions when negotiations occur within their own communities (Adegbonmire, 2015). The awareness of ongoing violence in their immediate surroundings can motivate parties to engage more earnestly in mediation efforts. This immediacy, fostered by close proximity, acts as a catalyst for reducing conflict intensity by pushing actors toward quicker and more committed management strategies.

Taken together, these mechanisms suggest that geographically closer mediation efforts are particularly effective at reducing violence and conflict fatalities, supporting the broader argument that proximity can play a vital role in shaping peace outcomes.

In conclusion, while neutral and distant mediation locations are often associated with formal peace agreements, the fact that peace agreements and conflict de-escalation may occur in geographically different areas should signal to peacemakers that the concept of "conflict resolution" needs to be redefined. Successful agreements may be signed far from the conflict zone, but de-escalation often takes place closer to the area of violence through the engagement of local actors and direct intervention. Peacemakers should thus not solely focus on formal settlements but also consider localized processes that contribute to reducing conflict. The geographical disparity between where agreements are signed and where violence occurs underscores the need for a broader understanding of conflict resolution, one that values both formalization and local efforts to address ongoing violence.

Hypotheses

Theories explored in the previous section suggest that mediation location influences conflict outcomes in two distinct ways. Greater distance from the conflict zone may enhance perceptions of neutrality and foster formal peace agreements, while proximity to the conflict area may facilitate trust-building with local actors and reduce conflict intensity. These dynamics highlight the need to consider the spatial relationship between mediation efforts, peace agreement signings, and sites of ongoing violence.[1] Based on these theoretical foundations, I propose the following hypotheses:

> *H_1:* The further the distance between a mediation event and a conflict area, the higher the likelihood of a peace agreement being signed.

Mediation efforts located farther from the conflict zone may increase the chances of a peace agreement by providing a neutral setting, reducing local political pressures, and allowing parties to negotiate without immediate emotional or security concerns.

> *H_2:* The closer the distance between a mediation event and a conflict area, the lower the intensity of conflict in that area.

Conversely, mediation conducted closer to the conflict zone may directly engage local actors, foster more immediate trust, and enable faster responses to emerging violence, thus contributing to conflict de-escalation.

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[1]

While formal peace agreements are likely to be signed in neutral, distant locations, the reduction of conflict intensity may depend more on localized mediation processes. By bringing local stakeholders into negotiations, proximity-based mediation may achieve de-escalation even in the absence of formal agreements. Thus, although distance may favor formal settlement success, proximity is likely to play a critical role in mitigating violence on the ground.

Empirical design

This work investigates the spatial dynamics of conflict mediation in seven conflict locales between 2018 and 2024,[2] specifically examining the relationship between the geographical distance of mediation events from conflict locations and the success of these mediations across two metrics. The study captures success both in terms of agreement signing and battle death reduction, combining spatial analysis techniques with econometric regression modeling.

Data

The primary data source for mediation events is the Mediation Events and Negotiators (MEND) dataset from PeaceRep (Peter et al., 2025).[3] This dataset includes information on the location of mediation events (city names and coordinates), date, event type, and outcome (agreement signed or not) of mediation events. The variables included in the Hypothesis 1 models include the spatial clustering of mediation events and the spatial clustering of mediation events that resulted in agreements. The *signing of agreements* in the given mediation events serves as the dependent variable in Hypotheses 1, capturing a metric of a *successful* mediation.

Data which captures *battle deaths* is drawn from the UCDP Georeferenced Event Dataset (GED) Global version 24.1 (UCDP, 2022). This dataset pro-

[2]See Appendix B.

[3]The MEND dataset is part of an ongoing research project. The data utilized in this study are drawn from the Version 1.0 of the dataset. The dataset includes mediation events involving exogenous third-party mediators—that is, mediators (whether states, IGOs, NGOs, or others) originating from outside the conflict locale. This data also integrates PA-X Peace Agreement data (Bell & Badanjak, 2019).

vides georeferenced battle death information on violent events which servas as the dependent variable of Hypotheses 2.

The primary independent variable of the analyses in Hypotheses 1 and 2 is the geographical *distance* between mediation event locations and conflict event locations. This distance is operationalized as the great-circle distance using the Haversine formula (see Equation 1).[4]

$$d = 2R \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos\varphi_1 \cos\varphi_2 \sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \tag{1}$$

where d is the great-circle distance between two points, R is the Earth's radius, φ_1 and φ_2 are the latitudes of the two points (in radians), and λ_1 and λ_2 are the longitudes of the two points (in radians).

This method accounts for the Earth's curvature, providing accurate distance measurements in meters, unlike a simple Euclidean distance calculation on latitude and longitude coordinates, which would be distorted. By focusing on the great-circle distance, the study aims to isolate the effect of spatial proximity on mediation success, hypothesizing that closer proximity may influence both the likelihood of peace agreement signings and the intensity of conflict events.

In addition to the primary independent variable of *distance*, this analysis incorporates several control variables including *conflict duration* (logged) to capture the temporal dynamics of the conflict, and the total number of *violent events* (logged) to control for the overall level of violence (Davies et al., 2024). *Incompatibility*, a measure of the issues dividing the conflict parties, is included to account for the nature of the conflict itself (Davies et al., 2024). *Political stability* and *regulatory quality*, sourced from the World Bank's Worldwide Governance Indicators, are used to control for the broader political and institutional context (World Bank, 2024). *Liberal democracy* scores from V-Dem are included to account for the influence of political regime type (Coppedge et al., 2024). Finally, a *spatial lag* of the dependent variable is included to account for potential spatial autocorrelation in the outcome variable, thereby addressing the influence of neighboring areas (Ward & Gleditsch, 2018).

[4]This method utilizes the `distVincentySphere` function from the `geosphere` R package.

The spatial lag of the dependent variable was created to account for potential spatial autocorrelation in the outcome. Spatial autocorrelation occurs when the values of a variable at one location are influenced by the values of the same variable at neighboring locations.[5] Specifically, a k-nearest neighbor approach was employed (see Equation 2).[6]

$$y_{\text{lag},i} = \sum_{j=1}^{N} w_{ij} y_j \tag{2}$$

where $y_{\text{lag},i}$ is the spatially lagged dependent variable for location i, w_{ij} is the spatial weight between location i and location j, and y_j is the dependent variable at location j. Since a k-nearest neighbor approach with $k = 5$ is used, each location i only considers its five closest neighbors. The weights w_{ij} are row-standardized, ensuring that:

$$\sum_{j=1}^{N} w_{ij} = 1. \tag{3}$$

The resulting data used in the subsequant analyses leverage multiple geospatial, socio-economic, and conflict-related datasets to examine the relationship between mediation events, agreement signing, conflict intensity, and spatial proximity. By integrating data from the MEND dataset, UCDP GED, and a variety of political and institutional measures, the analysis systematically accounts for both the spatial distribution of mediation and the contextual factors that shape conflict dynamics (Peter et al., 2025; UCDP, 2022). The great-circle distance calculation ensures accurate spatial measurement, while the inclusion of a spatial lag variable controls for potential spatial autocorrelation. Through this approach, the study aims to provide a more comprehensive understanding of how the geographic proximity of mediation efforts influences both the likelihood of successful agreements and the persistence of violent conflict.

[5] To address this, a spatial weights matrix was first constructed using the `knn2nb` and `nb2listw` functions from the `spdep` package in R (Bivand, Pebesma & Gómez-Rubio, 2013).

[6] where k was set to 5 (the maximum possible neighbors), meaning that each location was considered a neighbor to its five closest locations. This created a list of neighbors for each location, which was then converted into a spatial weights matrix with row-standardized weights.

Methodology

The empirical analysis of this study involves estimating the effect of distance between mediation event and conflict on (1) peace agreement signing, and (2) battle-related deaths.

For Hypothesis 1, predicting the singing of peace agreements, a logistic regression model (see Equation 4) with mixed effects (see Equation 5) is employed to analyze the relationship between distance between mediation event and conflict on the likelihood of a peace agreement. This allows for controlling for time-invariant characteristics of mediation locations and for the nested structure of the data multiple mediation events within locations. The primary independent variable is the great-circle distance between the mediation event and the conflict location and control variables are included to account for potential confounding factors such as: logged average conflict duration to capture the temporal dynamics of conflict, total deaths and total violent events to control for the intensity of the conflict, government incompatibility between conflict parties to account for the nature of the issues at stake, political stability to reflect the broader political context, and liberal democracy scores to account for regime type (World Bank, 2024; Coppedge et al., 2024; Davies et al., 2024). Finally, robust standard errors are clustered by mediation location.

$$\text{logit}\left(P(\text{Agreement}_{ij} = 1)\right) = \beta_0 + \beta_1 \log(\text{Distance}_{ij}) + u_j \tag{4}$$

$$u_j \sim \mathcal{N}(0, \sigma_u^2) \tag{5}$$

where $P(\text{Agreement}_{ij} = 1)$ is the probability of a peace agreement for mediation event i in mediator location j, given the distance between the mediation and conflict locations. $\log(\text{Distance}_{ij})$ is the primary independent variable, representing the log-transformed great-circle distance between the mediation event and conflict location. u_j is the random effect for mediator location j, capturing unobserved location-specific variation, assumed to follow a normal distribution with mean zero and variance σ_u^2. The model estimates the log-odds of a peace agreement as a function of distance and mediator location effects, with β_0 as the intercept and β_1 as the coefficient for the distance variable.

For Hypothesis 2 which investigates the relationship between mediation proximity and conflict intensity, a zero-inflated negative binomial (ZINB) model is employed (see Equations 6-7). This model is chosen due to the count nature of the dependent variable, total conflict-related deaths, which exhibits both over-dispersion and a potential excess of zero values (see Appendix C for over-dispersion estimates).[7] The primary independent variable is the logged great-circle distance between mediation events and conflict locations. Additional control variables include the logged conflict duration, regulatory quality to account for institutional context, and total violent events to control for the overall level of violence (Davies et al., 2024; World Bank, 2024). A spatial lag of total conflict deaths is also included to account for the influence of conflict deaths in neighboring locations, acknowledging the spatial interdependence of violence. This model allows for a robust estimation of the effect of mediation proximity on conflict intensity, while controlling for other relevant factors and accounting for the specific distributional characteristics of the outcome variable.

$$P(Y_i = 0) = \pi_i, \quad \text{and} \quad Y_i | Y_i > 0 \sim \text{NegBin}(\mu_i, \theta) \tag{6}$$

where $P(Y_i = 0) = \pi_i$ is the probability of observing a zero count for the battle-related deaths outcome variable Y_i, modeled with a logistic function, and $Y_i|Y_i > 0$ follows a negative binomial distribution with mean μ_i and dispersion parameter θ. The count model for μ_i is specified as:

$$\log(\mu_i) = \beta_0 + \beta_1 \cdot \text{Distance}_i + \cdots + \epsilon_i \tag{7}$$

where μ_i represents the expected number of battle deaths in location i, and Distance_i is the logged great-circle distance between mediation events and conflict locations. The control variables are represented by the ellipsis $(\dots)$, the error term ϵ_i accounts for unobserved factors, and the coefficient β_1 estimates the effect of mediation proximity on battle deaths, while π_i in the zero-inflation part estimates the probability of observing zero battle deaths.

This study explicitly incorporates the spatial dimension of conflict mediation, examining the geographical proximity between mediation efforts and conflict zones. By leveraging two distinct measures of mediation suc-

[7] The ZINB model is well-suited for analyzing battle deaths, as these data often exhibit over-dispersion—where the variance exceeds the mean—and an excess of zeros due to periods of no conflict. Many regions experience lulls or ceasefires, during which mediation efforts may help prevent escalation. By addressing both over-dispersion and excess zeros, the ZINB model provides a more accurate representation of conflict fatalities, accounting for the spatial and temporal dynamics of violence in relation to mediation proximity.

cess—peace agreement signings and battle death reduction—the study provides a deeper and more nuanced understanding of the effectiveness of mediation. The analyses employ regression models to estimate the effect of mediation proximity on peace agreement signing and battle-related deaths, while controlling for confounding factors and accounting for the spatial interdependence of conflict dynamics. Model specification strategies, robustness checks, and the inclusion of relevant variables are further discussed in the robustness section.

Results

This section presents the results of the statistical analyses designed to evaluate the hypotheses proposed in this study. Central to the analysis is the geographical distance between mediation events and conflict zones, which is examined as a key explanatory variable for two outcomes. First, the effect of distance on the likelihood of peace agreement formation is assessed. Second, the relationship between distance and the incidence of conflict fatalities is analyzed.

Hypothesis 1: Greater Distance Favors Agreements

The first hypthesis in this work estimated that the further from the conflict that the mediation event takes place, the more likely a peace agreement is to be signed. This hypothesis is based on arguments of neutrality and bargaining spaces. Table I presents the results of the mixed effects logistic regression model examining the relationship between the distance of a mediation event from the conflict area and the likelihood of a peace agreement being signed.[8]

[8] The model incorporates fixed effects for mediation location and clustered robust standard errors to account for the non-independence of observations within the same mediation venue.

Table I. Hypothesis 2: Distance and Peace Agreements

	Dependent variable:
	Agreement (Logit)
Distance (log)	0.133^{**}
	(0.046)
GDP (log)	-4.587
	(6.604)
Infant Mortality Rate	0.407
	(0.447)
Battle Deaths	0.0004^{*}
	(0.0002)
Conflict Duration (log)	$-0.024^{\cdot}$
	(0.012)
Intercept	0.244
	(50.333)
Fixed Effects	Yes (by mediation location)
AIC	1089.6
Null Deviance	1912.02 (df = 4584)
Residual Deviance	967.65 (df = 4524)
Fisher Scoring Iterations	20
Observations	4,585

Note: $^{\cdot}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

The coefficient for the logged distance between the mediation event and the conflict area, the main independent variable of interest, is positive and statistically significant ($\beta = 0.133, p < 0.01$). This finding supports Hypothesis 1, indicating that as the geographical distance between a mediation event and a conflict area increases, the likelihood of a peace agreement being signed also increases. This suggests that mediation events held in more geographically distant locations from the conflict zone are more likely to result in formal peace agreements. The log odds indicate that for every additional "far away" mediation event from the conflict area, the odds of a peace agreement being signed increase by approximately 14.2%.[9]

Among the control variables, the number of battle deaths is positively and significantly associated with the likelihood of an agreement ($\beta = 0.0004, p < 0.05$). For every additional 100 battle deaths, the odds of a peace agreement being signed increase by (4%) increase in the odds. This could suggest that as the human cost of the conflict escalates, the warring parties may become more willing to negotiate and formalize an end to the violence. This finding aligns with the idea that higher conflict intensity can create a 'ripe moment' for peace, where the costs of continued conflict outweigh the perceived benefits of further fighting (Harris, 2010; Pruitt, 2011; Moghaddam, 2021; Porat, Halperin & Bar-Tal, 2013; Wohl, Porat & Halperin, 2015). Other control variables were not statistically significant.

The model demonstrates a reasonable fit to the data, as indicated by the difference between the null and residual deviance. The inclusion of fixed effects for mediation location improves the model's ability to account for unobserved heterogeneity across different mediation venues.

Hypothesis 2: Closer Mediation, Fewer Deaths

Table II presents the results of the ZINB model, which investigates the relationship between the distance of a mediation event from the conflict area and the number of battle-related deaths.[10]. The model includes random effects for year-month and mediation location to account for temporal and spatial dependencies in the data. The dependent variable, battle deaths, is lagged by one month to account for the potential time lag between mediation efforts and their impact on conflict intensity.

[9] To interpret this coefficient in terms of odds, the coefficient is exponentiated: $\exp(0.133) \approx 1.142$.

[10] The ZINB model is employed due to the over-dispersed count nature of the battle deaths data, with a potential excess of zero values. The ZINB model consists of two parts: a count model (negative binomial) for positive outcomes and a binary model (logistic) for the probability of a zero outcome.

Table II. Hypothesis 2: Distance and Fatalities

	Dependent variable:
	Battle Deaths
Distance (log)	0.046*
	(0.025)
Rule of Law	0.154
	(0.122)
Infant Mortality Rate	0.050·
	(0.026)
Log Spatial Lag Battle Death	0.654***
	(0.025)
Conflict Intensity	0.861***
	(0.172)
State-Based Conflict	0.579*
	(0.242)
Constant	-2.214*
	(0.980)
Observations	2453
Log Likelihood	-8340.0
AIC	16700.1
BIC	16758.1

Note: $^{\cdot}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.
Model includes random effects for Year-Month and Mediation Location.
Dependent variable is lagged one month.

The coefficient for the main independent variable of interest, distance, is positive and statistically significant ($\beta = 0.046, p < 0.05$).[11] This suggests that for every additional "close by" mediation event to the conflict area, the expected number of battle deaths in the following month decreases by approximately 4.7%. This finding matches with the expectation for Hypothesis 2, which posited that closer mediation events would be associated with lower conflict intensity.

This finding, when considered alongside the results of Hypothesis 1, prompts reflection for peacemakers engaged in this era of protracted conflicts regarding their priorities: the signing of peace agreements, often facilitated by greater distance, versus the immediate mitigation of conflict fatalities, which is facilitated by closer proximity. This divergence suggests a potential trade-off in mediation strategies, highlighting the complex and multifaceted goals of conflict resolution in enduring conflicts.

Several control variables significantly influence fatalities. The spatial lag shows a significant positive coefficient ($\beta = 0.654, p < 0.001$), indicating spatial clustering of violence likely due to conflict spillover or shared drivers. Conflict intensity also has a significant positive coefficient ($\beta = 0.861, p < 0.001$), highlighting the conflict magnitude in increasing fatalities. State-based conflict is positively and significantly associated with battle deaths ($\beta = 0.579, p < 0.05$), with approximately 78.4% more fatalities than non-state conflicts, likely due to states' greater military capacity and the higher stakes involved.

In conclusion, the analyses presented in this section offer nuanced insights into the spatial dynamics of conflict mediation. The implications of these findings for peacebuilding practice and future research directions are discussed in the subsequent section.

Robustness

Several robustness checks are implemented to ensure the validity and reliability of the findings. These mostly include careful attention to model specification and fit as well as variable importance and inclusion.

[11] In a negative binomial model, the exponentiated coefficient, $\exp(0.046) \approx 1.047$, represents the multiplicative change in the expected number of battle deaths for a one-unit increase in the logged distance. For a negative binomial model, $\exp(\beta)$ is the incidence rate ratio (IRR). An IRR greater than 1 indicates an increase in the expected count of the outcome variable.

For Hypothesis 1, multiple model specifications were tested to ensure robustness in the analysis (see Appendix D. The first model was a simple logistic regression with fixed effects, but without additional control variables. The second fixed effects model built on this by incorporating relevant control variables. The third model is the conditional logistic regression with controls, which accounts for stratification within the data.

To determine which model provided the best fit, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used for comparison. Comparing AIC and BIC across all four model specifications, the mixed effects logistic regression model with clustered standard errors yielded the lowest values ($AIC = 1091.65$, $BIC = 1490.34$), indicating that it best balances model fit and complexity among the alternatives.

Beyond model selection, additional robustness checks were conducted on the mixed effects logit model chosen. The Hosmer-Lemeshow goodness-of-fit test ($p = 0.62$) showed no significant discrepancy between predicted and observed values, suggesting that the mixed effects logistic regression model fits the data well. Similarly, the Pearson dispersion statistic (0.25), being less than 1, indicated that the model does not suffer from overdispersion. Together, these results confirm that the final model is not only the best choice based on AIC/BIC but also appropriately specified and well-calibrated to the data (See Appendix E for goodness-of-fit testing).

Careful attention was also paid to the variable selection. Random Forest models are employed to identify the most important predictor variables for the signing of peace agreements (see Figure 2). This helps to refine the regression models by including the most relevant covariates. In particular, we assess Mean Decrease in Gini, a measure of variable importance that reflects how much each predictor contributes to reducing impurity in the classification. Variables with higher Mean Decrease in Gini values have a stronger influence on the model's decision-making process, helping to ensure that only the most impactful predictors are retained in the final analysis.

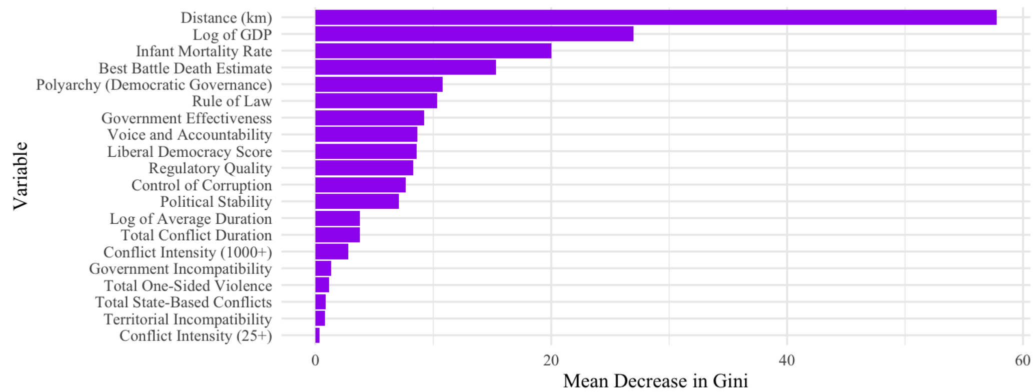

Figure 2. Random Forest Variable Importance for Prediction of Agreement Signing. This figure shows the top 20 most important variables based on Mean Decrease in Gini.

Hence, the most important predictors including distance, GDP, Infant Mortality Rate, Battle Deaths, and conflict duration are included in the final model. These variables collectively account for 95% of the model's explanatory power.[12] Notable for both robustness and substantive importance, distance between the mediation event and the conflict show as the most important feature of the model.

For Hypothesis 2, key robustness concern is the potential spatial dependence in our the dependent variable, battle deaths, which could bias estimates if not properly accounted for. To address this, I utilize a spatial weight matrix using a distance-based neighbor approach and computed a spatial lag of the dependent variable. Then, I incorporated this spatially lagged term into several model specifications, including a Poisson model, a negative binomial model, and a zero-inflated negative binomial (ZINB) model. The inclusion of the spatial lag allows for testing of whether conflict spillovers significantly affect total deaths (see Appendix F for model results). The variety of model specifications facilitates the identification of the best model fit.

Given that total deaths is a count variable, I first estimated a Poisson model (with and without control variables). However, the assumption of equidispersion (mean equals variance) was tested by checking the ratio of deviance to degrees of freedom, indicating potential overdispersion. To correct

[12]Highly collinear variables were dropped from the model, with the most important variables retained for analysis.

for overdispersion, I fitted a negative binomial model. This model provided a better fit, as evidenced by lower AIC values compared to the Poisson model. However, recognizing the presence of excess zeros in the dependent variable, I tested a ZINB model to account for the probability of observing zero deaths separately from the count process. This model performed well in distinguishing between structural and stochastic zeros.

To compare the relative fit of different models, I calculated the AIC for these key specifications. The AIC values indicated that the ZINB model was the best fit and was therefore included in the main text. Additionally, I calculated Pearson's Chi-squared values for each model, which further supported the selection of the ZINB model (see Appendix G).

Now for variable selection in Hypothesis 2, I also used Random Forest variable importance, specifically the Mean Decrease Gini score, to ensure that only the most relevant variables were included in the model. See Figure 3:

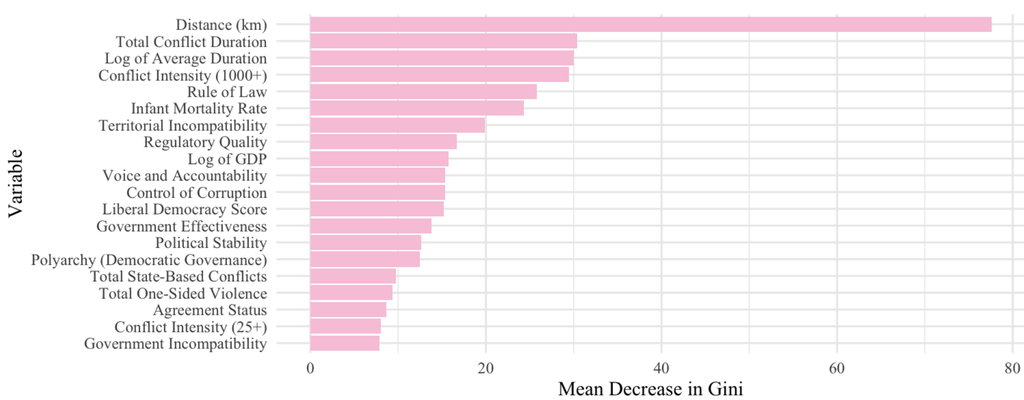

Figure 3. Random Forest Variable Importance for Prediction of Battle Deaths. This figure shows the top 20 most important variables based on Mean Decrease in Gini.

The results highlighted several key predictors with substantial importance. Notably, distance, rule of law, infant mortality rate, conflict intensity, and state-based conflict were significant contributors, indicating their strong relevance to the model. The variables selected for the main models collectively account for 90% of the model's explanatory power. Once again, the distance from the conflict location to the mediation location emerged as the most important variable in predicting changes in battle deaths. This suggests that proximity to mediation efforts plays a vital role in influencing conflict fatalities, underscoring the importance of strategic peace interventions.

In conclusion, the robustness checks conducted in this study provide strong validation for the findings. The careful attention to model specification ensures that the results are not only reliable but also reflect the complexity of the data. Additionally, the use of Random Forest variable importance helped refine the models by ensuring only the most impactful predictors were included, enhancing the precision of the analysis. The distance from conflict locations to mediation sites emerged as a key determinant in predicting both peace agreement signing and changes in battle deaths. The results underscore the relevance of strategic mediation and suggest that the geographic proximity of such efforts can significantly influence the trajectory of conflict resolution and intensity. These robust findings contribute to a deeper understanding of the factors influencing conflict dynamics and the role of international mediation in mitigating violence.

Discussion and Conclusions

The results of this study offer nuanced insights into the role of spatial dynamics in conflict mediation, specifically regarding the location of mediation events relative to conflict zones. The findings indicate that greater distance between mediation events and conflict zones is associated with a higher likelihood of peace agreements being signed, supporting the idea that spatial distance can enhance the perceived neutrality and legitimacy of the mediation process. Conversely, mediation efforts conducted closer to conflict areas are linked to greater reductions in conflict-related fatalities, suggesting that proximity may facilitate more immediate and effective violence mitigation on the ground.

These patterns raise a fundamental and difficult question for peacemakers: Where should mediation events be held—near or far from conflict zones? Two possible interpretations emerge from the findings, each carrying important implications for conflict intervention strategies.

One interpretation highlights a tension between goals. Distant mediation events appear more successful at achieving formal peace agreements, yet they may not effectively curb immediate violence. Meanwhile, mediation close to the conflict may reduce casualties but may be less successful at securing formal agreements. This suggests that peacemakers may face a trade-off, forced to prioritize either conflict resolution (formal agreements) or conflict management (reducing fatalities). From this perspective, the results underscore the need for greater clarity about what "success" means in peace processes: Is it the signing of an agreement, or the reduction of human suffering through violence prevention?

An alternative interpretation is that distant and proximate mediation efforts are not mutually exclusive but complementary. Distant mediation might establish the political frameworks necessary for durable peace, while local mediation builds the immediate trust and security needed to sustain that peace over time. Under this view, both forms of mediation are necessary components of a holistic strategy. However, even if distant and proximate efforts work together, the tension between resolution and management remains salient. Policymakers must still grapple with which goal to prioritize at different stages of the peace process and how to allocate resources accordingly.

These findings carry significant implications for policymakers and peace practitioners. They suggest that a one-size-fits-all approach to conflict mediation is unlikely to succeed. Instead, a more sophisticated, multi-layered strategy is needed—one that leverages the neutrality advantages of distant mediation for formal negotiations, while simultaneously investing in localized efforts to immediately de-escalate violence and build trust at the ground level. Future research should explore the mechanisms through which distance and proximity operate, including how they interact with issues such as trust-building, power asymmetries, and local ownership of the peace process. Moreover, further investigation into how different types of mediation—high-level diplomatic negotiations versus grassroots dialogues—might be spatially and temporally coordinated could yield important insights for designing more effective interventions.

Ultimately, recognizing the spatial complexities of mediation highlights a deeper theoretical and practical challenge: defining what constitutes success in peacemaking. By confronting the tension between conflict resolution and conflict management directly, the field can move toward interventions that are both more practical and more conscientious—aiming not only for agreements on paper but also for genuine reductions in violence on the ground.

This study contributes to the broader peace and conflict literature by systematically demonstrating that where mediation occurs is not simply a logistical detail but a meaningful factor influencing mediation outcomes. By bringing spatial considerations into the analysis of mediation effectiveness, this research opens a new line of inquiry into how geographic, symbolic, and psychological factors interact during peace processes. Future research could build on these findings by exploring additional dimensions of spatial mediation—such as the role of regional versus international locations, symbolic venues versus neutral third spaces, or even virtual mediation environments. Longitudinal analyses could also help clarify whether the spatial dynamics observed here have lasting effects on post-conflict stability, not just immediate outcomes. In doing so, scholars and practitioners alike can work toward a richer understanding of how the design of mediation efforts—including their geography—can better align with the complex realities of conflict and peacebuilding.

Replication

Replication data and code will be available on Author GitHub Repository. Link to this Repository is currently redacted for the purposes of double-blind peer review.

Acknowledgments

Currently redacted for the purposes of double-blind peer review.

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Currently redacted for the purposes of double-blind peer review.

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Biography

Currently redacted for the purposes of double-blind peer review.

Online Appendices

Appendix A Hotspot mapping methodology

The first involves the spatial clustering of mediation events and agreements. This part takes a simplistic look at the spatial relationship between mediation event locations and locations where peace agreements are signed. The Getis-Ord Gi* statistic (see Equation 8) is used to identify and visualize "hotspots" of mediation activity and "hotspots" of successful peace agreement signings.

$$G_i^* = \frac{\sum_j w_{i,j} x_j}{\sum_j x_j} \tag{8}$$

where x_j is the value of the agreement signing at location j , $w_{i,j}$ is the spatial weight between locations i and j based on k-nearest neighbor contiguity, and the summation is across all locations of mediation events.

For robustness, I applied False Discovery Rate (FDR) control to account for the risk of false positives when identifying spatial clusters of mediation events. Given the multiple spatial tests conducted, FDR control adjusts the p-values to ensure that the proportion of false positives remains within an acceptable threshold (25% in this case). This step was necessary to robustly identify true hotspots while reducing the impact of random chance. Figure A.4 presents only those locations where significant clustering remained after applying the FDR threshold, ensuring that the identified hotspots are statistically sound and meaningful.

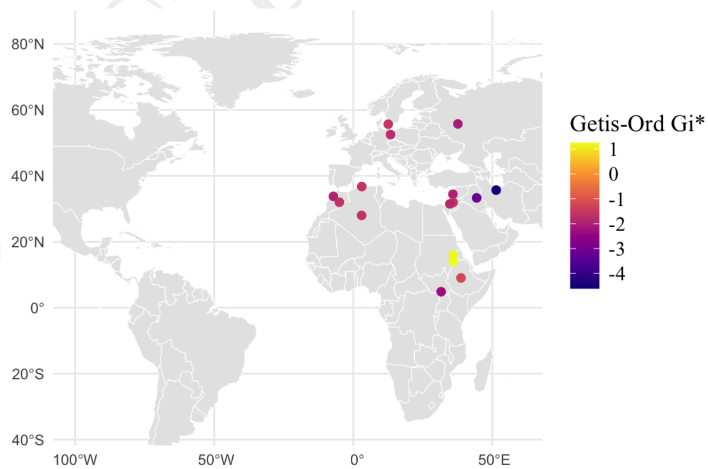

Figure A.4. FDR Controlled Hotspot Mapping of Mediation Events (2018-2024).

Appendix B Conflicts included in models

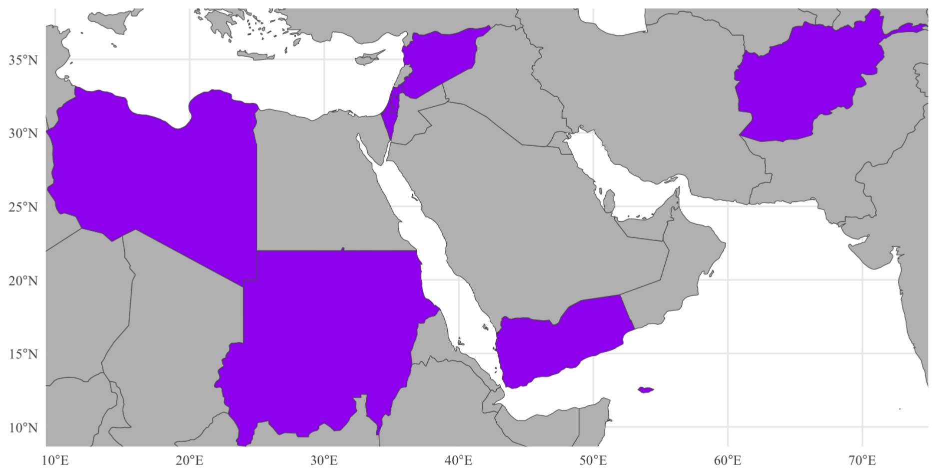

Figure B.5. Map of Highlighted Conflict Countries. Conflicts locations include in Sudan, Libya, Syria, Israel, Palestine, Yemen, and Afghanistan.

Appendix C Hypothesis 1 over-dispersion check

The deviance statistic for the chosen model is calculated as:

$$\text{Deviance} = -2\log\left(\frac{\mathcal{L}(\hat{\theta})}{\mathcal{L}(\hat{\theta}_{\text{max}})}\right)$$

where $\mathcal{L}(\hat{\theta})$ is the likelihood of the fitted model, and $\mathcal{L}(\hat{\theta}_{\text{max}})$ is the likelihood of the saturated model. The ratio of deviance to residual degrees of freedom is:

$$\frac{\text{Deviance}}{\text{df.residual}} = \frac{21.53815}{\text{df.residual}}$$

where df.residual represents the residual degrees of freedom. A lower deviance-to-residual ratio suggests better model fit.

The model with the lowest Akaike Information Criterion (AIC) was selected. AIC balances the model's goodness-of-fit with its complexity, and the non-zero binary model achieved the lowest AIC. Thus, this model was chosen as it provided the best trade-off between fit and parsimony.

Appendix D Additional model specifications for Hypothesis 1

Table D.3 below shows the results of the additional models that were run in preparation for the final model fit, including the binary fixed-effects logit, the logit model with controls, and the mixed-effects model. These models helped assess the impact of including additional covariates and different modeling approaches before selecting the condxitional logistic regression as the final specification. These models show robustness for the findings in the main text.

Table D.3. H_1 Binary, Fixed Effects, and Conditional Logistic Regression Results

	Dependent variable: Agreement		
	Binary	*Fixed-Effects*	*Conditional Logit*
	(1)	(2)	(3)
Distance (log)	-0.051^{*}	0.133^{**}	0.019
	(0.029)	(0.056)	(0.031)
GDP (log)		-4.587^{***}	-1.824^{***}
		(1.042)	(0.519)
Infant mortality rate		0.407^{***}	0.155^{***}
		(0.094)	(0.059)
Battle deaths (log)		0.0004	0.0002
		(0.0002)	(0.0002)
Conflict Duration (log)		-0.024	-0.015
		(0.016)	(0.013)
Constant	-2.554^{***}	1.244	
	(0.192)	(9,244.058)	
AIC	1913.11	1091.65	1499.16
Observations	4,585	4,585	4,585
Log Likelihood	-954.556	-483.824	-744.580
Akaike Inf. Crit.	1,913.112	1,091.649	
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix E Model fit testing for Hypothesis 1

To determine which model provided the best fit, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used for comparison. AIC and BIC are both model selection metrics that evaluate the goodness-of-fit while penalizing model complexity. AIC is given by:

$$AIC = -2 \log L + 2k$$

where L is the likelihood function and k is the number of estimated parameters. Lower AIC values indicate a better tradeoff between model fit and complexity. Similarly, BIC is defined as:

$$BIC = -2 \log L + k \log n$$

where n is the sample size. Unlike AIC, BIC imposes a stronger penalty on model complexity, favoring simpler models when sample sizes are large.

Comparing AIC and BIC across all four model specifications, the conditional logistic regression model yielded the lowest values ($AIC = 147.65$, $BIC = 157.22$), indicating that it best balances model fit and complexity among the alternatives. Lower values indicate a better balance of fit and complexity, with Model 4 (Conditional Logit) performing the best. See Table E.4:

Table E.4. H_1 Model Fit Comparison: AIC and BIC Values

Model	Model 1 (Binary)	Model 2 (FE Logit)	Model 3 (Mixed Effects)	Model 4 (Conditional Logit)
AIC	1913.112	1089.649	1091.649	1499.160
BIC	1925.974	1481.912	1490.343	1516.666

Additionally, for the final model, conducted goodness-of-fit test assess its calibration and overall suitability (see Table E.5). The Hosmer-Lemeshow test yielded a non-significant result ($p = 0.76$), indicating no evidence of poor model fit and suggesting that the predicted probabilities align well with observed outcomes. Moreover, the Pearson residual mean squared value (0.89) is close to 1, signifying that the model does not suffer from overdispersion. These results provide further support for the conditional logistic regression model as the most appropriate specification for analyzing the data.

Table E.5. H_1 Goodness of Fit Test Results

Test	Statistic	
Hosmer-Lemeshow GOF Test	6.24	0.6202
Pearson Residuals Overdispersion	0.245	–

Note: The Hosmer-Lemeshow test assesses model fit, with a high p-value ($p = 0.62$) indicating good fit. The Pearson residual ratio (0.245) suggests no overdispersion, indicating acceptable model variance.

Appendix F Additional model specifications for Hypothesis 2

Table **??** below shows the results of the additional models that were run in preparation for the final model fit, including the binary Poisson model, the Poisson model with controls, and the negative binomial model. These models helped assess the impact of different specifications before selecting the ZINB as the final specification. These models show robustness for the findings in the main text.

Table F.6. H_2 Binary, Poisson, and Negative Binomial Hypothesis Results

	Dependent variable: Battle Deaths		
	Binary	*Poisson*	*Negative Binomial*
	(1)	(2)	(3)
Conflict Distance (log)	0.039$^{\cdot}$	0.020**	0.002
	(0.026)	(0.006)	(0.010)
Rule of Law		0.319$^{\cdot}$	0.031
		(0.188)	(0.020)
Infant Mortality Rate		0.581*	0.020*
		(0.258)	(0.010)
Conflict Intensity		1.440***	0.230**
		(0.113)	(0.090)
Sum of State-Based Conflict		0.119	0.164
		(0.162)	(0.124)
Spatial Lag	0.694***	0.716***	0.141***
	(0.025)	(0.003)	(0.017)
Constant	0.387	-24.503^{*}	1.774***
	(0.254)	(10.564)	(0.372)
AIC	16761.0	145617	18401.2
Observations	2,453	2,452	2,453
Log Likelihood	-8374.5	-72808.5	-9190.6
θ	0.713		54.7
Akaike Inf. Crit.	16795.8	145617	18459.3
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Standard errors in parentheses. Factor variables are excluded.

Appendix G Model fit testing for Hypothesis 2

To assess the relative fit of the different model specifications used in this analysis, both AIC and Pearson's Chi-squared values were calculated for each model. These measures provide insights into how well each model fits the data while accounting for model complexity. The results, presented in Table G.7 below, demonstrate the comparative performance of the models, highlighting the ZINB model as the best fit based on both AIC and Pearson's Chi-squared values.

Table G.7. H_2 Model Fit Comparison: AIC and Pearson's Chi-squared Values

Model	**AIC**	**Pearson's Chi-squared**
Poisson (with controls)	145616.8	301.74
Negative binomial (with controls)	18401.24	22.77
ZINB (Binary)	16760.98	4.63
ZINB (with controls)	16700.09	4.65