Predicting Political Violence Targeting Women Across the Globe, 2018-2021

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Abstract

While there has been active research on political violence and sexual violence, many scholars have not investigated political violence targeting women as a separate strand of study. This distinction is important since frameworks used in political violence and sexual violence do not fully explain political violence targeting women happening across the globe. In such contexts, this research contributes to the new strand of literature through finding systematic gendered patterns in political violence around the world. Specifically, this research expands the new literature by finding evidence that shows the limitations of using frameworks in political violence and sexual violence in understanding political violence targeting women. This has important implications since this distinction illuminates ways in which women have been politically oppressed but have not been properly understood.

1. Introduction

The World Health Organization defines political violence as the deliberate use of power and force to achieve political goals (Krug et al 2002). Despite many scholarly attempts to define political violence from multiple disciplines, it is widely acknowledged that political violence broadly refers to an organized activity that wields violence against individuals or groups with its distinct set of motives and goals (Aoláin 2006).[1] That is, political violence events are not random and haphazard affairs that happen spontaneously. In such contexts, it is puzzling that political violence targeting women happens across the globe and thus requires scholarly attention. Specifically, it is important to investigate why political violence targeting women happens globally when there are significant regional heterogeneities in the political motives and goals behind the violence.

Although non-governmental organizations have published a few brief reports that describe such gendered patterns, there has been little systematic analysis of political violence targeting women due to practical challenges. For instance, it is difficult to monitor and track expansive types of political violence events happening around the globe. Additionally, it is uncertain whether a political violence event targets woman or not due to lack of principled methodology in defining and categorizing political violence events. Finally, it is infeasible to conduct experiments on political violence to investigate the underlying patterns of political violence targeting women. Although there have been many more concerted efforts and innovations in collecting dating in recent periods, the nature of political violence still presents obstacles in obtaining high-quality data (Gleditsch 2014). These unfavorable circumstances have made it difficult to conduct rigorous analysis that shows whether there are gendered patterns in political violence targeting women.

[1] Armed Conflict Locations & Event Data Project (ACLED) shares this definition of political violence.

In such contexts, this study aims to conduct systematic analysis that shows whether political violence targeting women are distinguishable from other types of political violence that are not targeting women through predictive modeling. Specifically, this study attempts to answer the research question of whether there are systematic gendered patterns in political violence across the globe. To do so, this study exploits comprehensive dataset on political violence that have been collected and maintained in a principled way from the Armed Conflict Locations & Event Data Project. Using this comprehensive dataset, this study uses high performance of predictive models in classifying whether political violence events are targeting women or not as evidence to substantiate gendered patterns in political violence. Since predictive models cannot correctly classify political violence events without their distinguishable patterns, high performance of these predictive models can be used to indicate the presence of systematic gendered patterns in political violence. Afterwards, this research runs two panel fixed effects regression to provide descriptions about the gendered patterns in political violence[2].

Finally, this research has important implications with growing female political participation around the globe in the past decades. It has been widely acknowledged that women's political participation brings substantive changes to the political and economic spheres in many regions (Hessami and Fonseca 2020; Xu 2015; Beckwith 2010). With more women participating in politics more than ever, it is crucial to understand the impact of gendered political violence on gender inequality. Also, this research has practical implications considering significant amounts of resources are used to combat violence against women. This research can be used to facilitate informed decision-making for policymakers through providing information about the systematic gendered patterns in political violence.

[2] Due to many identification problems, the results from the panel fixed effects regression will be used to help discuss the main findings of this paper.

2. Literature Review

Although there are abundant amounts of literature on political violence and sexual violence, there is limited research on political violence targeting women (Bardall et al 2020). The intricate nature of gendered political violence happening across many sociocultural contexts presents challenges to separating political violence targeting women from political violence and sexual violence. For instance, it has been unclear whether sexual violence happening during wartime periods should be understood as political violence, or sexual violence, or political violence targeting women. This is an important distinction to be made since political violence targeting women is an organized activity that entails a distinct set of political interests and goals. In recent periods, scholars have started to investigate political violence targeting women as a distinct area of literature that needs to be further studied. For example, a recent report has revealed that political violence targeting women take distinct patterns where the violence is not always sexual in nature and is common in both wartime and non-wartime contexts (Kishi et al 2019). These patterns suggest that frameworks used in political violence and sexual violence are insufficient to capture the full dimensions of political violence targeting women that results in a high-risk political space for women. For instance, these frameworks do not fully explain the global prevalence of non-sexual political violence targeting women despite significant regional differences in political motives and interest. This can be problematic because improper understanding of political violence targeting women can leave ways in which women are oppressed in politics concealed and unexplained.

Despite such lack of research on political violence targeting women, there have been active areas of research that investigated the role of gender at the intersection of political violence and sexual violence. For instance, Cohen has documented that committing rape during civil wars served as a method of socialization for armed groups in many civil wars (Cohen 2013). Cohen also showed how female fighters and combatants were perceived as supporters and followers rather than fellow combatants in the Sierra Leon civil war (Cohen 2013). These studies have documented that gender plays a decisive role in how political violence is being organized, wielded, and experienced. Additionally, other scholars have studied the differential impacts of political violence on post-conflict political participation for men and women separately. Specifically, Hazdic and Tavits showed that political violence events results in less political participation for women and more political participation for men in Bosania (Hazdic and Tavits 2019). There have also been studies of gendered violence in mundane political settings. For instance, it has been documented that female politician received more criticism for political social media activities than male politicians in the United Kingdom (Farrell et al 2020). Similarly, female politicians were far more likely to experience violence and pay more penalties for visibility in Sweden (Håkansson 2021). These strands of evidence imply there are gendered patterns in political violence in various forms and contexts.

This research thus contributes to the growing area of literature that identifies political violence targeting women separately from political violence and sexual violence. Mainly, this research attempts to provide evidence that shows whether there are systematic gendered patterns in political violence across the globe. This research additionally seeks to find regional heterogeneities in political violence targeting women and to provide substantive descriptions of the patterns. These agenda can bring important contribution to the literature by reinforcing the necessity to expand the growing literature. Specifically, finding systematic gendered patterns in political violence across the globe can highlight the limitations of using framework in political violence and sexual violence for understanding political violence targeting women. This can prompt other scholars to study political violence targeting women as a distinct area of study. Furthermore, the cross-national or cross-regional characteristics of this research can encourage more subsequent research that studies regional differences in political violence targeting women.

3. Data

This study uses political violence data from the Armed Conflict Locations & Event Data Project (ACLED). The ACLED is a recent disaggregated data collection, analysis, and crisis mapping project supported by governments and universities that provides comprehensive and consistent data on political violence across the globe.

The ACLED records political violence events through its constituent events to provide a comprehensive overview on all types of political violence where the unit of observation is an event. The ACLED provides detailed definition and categorization of political violence events through using its own taxonomy that consists of 3 general categories, 6 broad event types, and 25 sub-event types. The types of political violence events included in the dataset range from non-violent events such as peace agreement to violent events such as bomb explosions for instance. Please see ACLED codebook for more information about how the ACLED defines and categorizes political violence events for all types of the events.

The ACLED uses four data sources and four sourcing strategies to provide high-quality data on political violence. The ACLED collects all reported data about political violence from four primary data sources to define and categorize political violence: (1) Traditional Media, (2) Reports, (3) Local Partner Data, (4) Verified Social Media. The ACLED uses a wide variety of data sources to increase both the accuracy and coverage of their data on political violence. Additionally, the ACLED uses four primary strategies to enhance sourcing quality control: (1) Source Control, (2) Continued Identification of New Sources, (3) Corrections, (4) Anonymization. These sourcing strategies include cross-referencing and fact-checking to ensure consistency in their data. Using these two broad data sourcing and sourcing quality strategies, the ACLED maintains a principled methodology to provide comprehensive and consistent data on political violence across the globe. For more information about their methodology, please see [ACLED Methodology].

This study uses two datasets from the ACLED that contain information about all political violence events across regions and political violence events that are classified as political violence targeting women from January 2018 to April 2021. The ACLED defines political violence targeting women when the majority of the main victims in a political violence event are female or the target of the event specifically features women such as Women's Movement or Women of Zimbabwe Arise (WOZA). Accordingly, this study follows the ACLED's definition and categorization of political violence and political violence targeting women for all types of events. The regions included in this analysis are Africa, Middle East, Latin America & the Caribbean, Central Asia & the Caucasus, East Asia, Southeast Asia, South Asia, and Europe. The United States has been excluded from the analysis due to lack of sufficient data.

This study merges these two ACLED datasets and creates the *woman* variable that is coded as 1 if it is classified as political violence targeting women and 0 otherwise based on multiple common indicators. The dependent variable is *woman* and the primary independent variable is *sub_event_type*. The *woman* variable indicates whether a political violence event has targeted woman or not. The *sub_event_type* variable contains information about the type of political violence events such as bomb explosion or peaceful demonstrations. It is important to note that the number of event types for political violence can vary depending on time and region since the dataset is a collection of event-based records of political violence events. The variable *fatality* shows the number of fatalities in an incidence. The *inter1* and *inter2* variables show the identity of the actors involved in an event such as civilians, militia, and government among many others. There are two variables, *inter1* and *inter2*, that indicate the actors involved in an event because most political violence events happen between two groups of actors. For one-sided political violence events, the *inter2* variable is coded as 0. Except for the value of 0 in the *inter2* variable, there is no inherent ordering in *inter1* and *inter2*. For example, there is no difference whether we observe militia in either *inter1* variable or *inter2* variable. This study uses this merged dataset for the entire analysis. The following variables are used in this analysis:

Table 1: The Description of Variables

Variable Name	Description
woman	The categorical variable suggesting women targeted political violence that has been coded as 1 if true and 0 otherwise.
year	The year in which an event happened
country	The country in which an event happened
sub_event_type	The sub-type of an event
fatality	The number of fatalities in an event
inter1	The identity of the actors involved in an event
inter2	The identity of the actors involved in an event

4. Methodology

This study first divides the balanced data into training data and testing data at the ratio of 80% and 20% respectively. Afterwards, this study performs minority oversampling technique

(SMOTE) to handle class imbalance in the training data[3]. This study then performs 5-fold cross-validation on the training data to evaluate its cross-validated performance across (1) logistic model, (2) LASSO model, and (3) random forest model. This study tunes the parameters for the lasso model and random forest based on the Area Under the Curve – Receiving Operator Characteristic (AUC ROC) performance metric prior to comparing across different models. This study then chooses the best model based on AUC ROC metric and fits the selected model on the entire training data and evaluates its performance on the test data. Finally, this study runs panel fixed effects regression to provide description about the gendered patterns in political violence.

4.1. SMOTE and class imbalance

SMOTE is an oversampling technique that creates new synthetic samples based on the K-nearest neighbor technique (Chawla et al 2002). Specifically, the SMOTE algorithm oversamples the minority class observations by interpolating and selecting the near minority class neighbor based on feature space in a random fashion. The SMOTE algorithm is known to be one of the most popular techniques in handling class imbalance in machine learning (Fernández et al 2018). This research utilizes the SMOTH algorithm to address the class imbalance issue in the dataset.

The data used in this research suffers from class imbalance where the majority of the events are not classified as political violence targeting women. This can be problematic because most predictive machine learning algorithms are designed for balanced class distribution and thus can provide deceivable results (Sun et al 2009). For instance, class imbalance in the dataset often results in false high accuracy rates where predictive models predict the majority class for every

[3] This technique does not address class imbalance in the test data. This technique is used to balance the training dataset such that classifiers can sufficiently learn about the characteristics of each class. The test data is used to evaluate the performance of the predictive models that have been trained on the oversampled data.

observation due to insufficient information learned about the minority class. This can be inappropriate because it is important for the model to have a well-balanced high sensitivity and specificity as in the classic example of spam detection problem. Thus, this study adopts the minority oversampling technique (SMOTE) to handle class imbalance issues by balancing the training data such that the models can sufficiently learn about the characteristics of both classes.

4.2. Logistic Regression

A Logistic regression is a standard classification algorithm used to predict one or more categorical outcomes based on the independent variables (Menard 2002). The logistic regression is used to estimate the probability of occurrence of an event using the Logit link function. The cost function that logistic regression minimizes is:

$$\boldsymbol{J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}log(h_\theta(x^{(i)})) + (1-y^{(i)})log(1-h_\theta(x^{(i)}))\ \right]}$$

This study uses logistic regression to classify whether political violence events are targeting women or not.

4.3. LASSO Regression

LASSO regression is a penalized regression model that penalizes redundant regression coefficients to improve its power (Tibshirani 1996). The LASSO regression places the L2-norm loss function on regression coefficients to shrink redundant coefficients towards zero using the λ penalty parameter. This shrinkage improves the model's power and stability. The cost function that LASSO regression minimizes is:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{Lasso} = \boldsymbol{argmin}\left\{\sum_{i=1}^{n}\left(\boldsymbol{y}_i - \boldsymbol{\beta}_0 - \sum_{j=1}^{p}\boldsymbol{\beta}_j\boldsymbol{X}_{ij}\right)^2 + \boldsymbol{\lambda}\sum_{i=1}^{p}|\boldsymbol{\beta}_j|\right\}$$

This study uses LASSO regression to classify whether political violence events are targeting women or not.

4.4. Random Forest

Random Forest is an ensemble learning method that uses multiple machine learning algorithms to improve its power. Random forest provides improved performance in both regression and classification settings by combining randomized decision tress and aggregating their predictions (Breiman 2001). In this classification setting, random forest reduces Gini index at each branch to provide the best branch split. Thus, this research minimizes the following Gini index where $\hat{p}_{mk}$ is the proportions of observations in the m^{th} region in the k^{th} class.

$$\boldsymbol{Gini}(\boldsymbol{K}) = \sum_{k=1}^{K}\widehat{\boldsymbol{p}}_{mk}(\mathbf{1} - \widehat{\boldsymbol{p}}_{mk})$$

This study uses random forest to classify whether political violent events are targeting women or not.

4.5. Cross-validation

The optimal parameters for the LASSO model and the random forest model are selected through cross-validation. In this process, the training data are randomly divided into 5-folds of equal size datasets where each subset is further divided into a training set and a testing set that comprises 80% and 20% of each fold respectively. Afterwards, each training subset is used to fit a selected model, and each test subset is used to produce predicted outcome at different levels of parameters. This research finds the optimal parameters for the LASSO model and the random forest model based on the highest AUC ROC metric. In the LASSO model, this research tunes the cost parameter λ through cross validation. In the random forest model, this research tunes *mtry*, which is the number of predictors that is randomly sampled at each split when creating the trees, and *min_n,* which is the minimum number of data points in a node that are required for the node to be split further. The maximum number of trees has been set to 1000 trees to allow for a variety of tree forms. It is typical to not tune the number of trees and set a high number of tress in tuning for random forest (Probst et als 2017). The selected parameters are the following:

Table 2: The Selected Parameters for Lasso and Random Forest

Region	**Cost Penalty (Lasso)**	**Mtry (Random Forest)**	**Min_n (Random Forest)**
Africa	0.00281	4	30
Central Asia & the Caucasus	0.00121	8	20
East Asia	0.000687	8	22
Europe	1e-05	8	20
Latin America & the Caribbean	0.00121	6	30
Middle East	0.000518	8	27
South Asia	0.0016	8	27

4.6. Panel Fixed Effects

While predictive models can be used to show evidence of gendered patterns in political violence and provide some insight about political violence targeting women (Cranmer 2017), they fail to provide substantiative descriptions about the gendered patterns in political violence. Thus, this research runs two separate panel fixed effects regression for political violence events that are targeting women and that are not targeting women to describe the gendered patterns.[4] Using the original data, this research estimates the following regression form:

$$\boldsymbol{Y_{it} = \alpha_i + \eta_t + \beta type_{it} + \Gamma X_{it} + \epsilon_i}$$

Where Y_{it} is the total number of political violence events for each year, region, and the type of the political violence event, α_i is the country fixed effects, and η_t is the calendar year fixed effects, and X_{it} controls for fatality and types of actors involved in a political violence event. The standard errors of the regression are clustered at the country level. The result of the regression is displayed in table 8-A in the Appendix section.

5. Analysis

In this section, this study presents the results in three ways: model-level accuracy rates, model-level classification accuracy, and model-level accuracy via receiver operating characteristic (ROC) curves and area under the curve (AUC) calculations.

5.1. Predictive Accuracy

In this sub-section, this study shows the mean accuracy prediction rates for each region across all three specified models in Table 2. The baseline average accuracy rates have been set to 50% since this research attempts to determine whether political violence targeting women happens in a random manner or systematic manner. Although there are differences in the mean accuracy rates across the models, all three models consistently show high accuracy rates compared to the baseline of 50% accuracy rates. Specifically, the average accuracy rates for each model are above

[4] The panel fixed effects model is not central to this research and serves as a supplementary source of information

65% and the best performing random forest model shows the average accuracy rates of 73.9%. The random forest model shows the best performance in the mean accuracy rates. There is no discernable difference between the logistic model and the LASSO model in the mean accuracy rates.

Additionally, there are regional heterogeneities in the mean accuracy for each region. The mean accuracy rates high for Africa, Central Asia & the Caucasus, Europe, Middle East, and South Asia across all three models. The mean accuracy rates are low for Latin America & the Caribbean and South Asia. The result is less clear for East Asia with the Random Forest showing significant improvements over the logistic and lasso models. Overall, the results show that most regional heterogeneities seem to be consistent across alternative forms of model specification.

Table 2: The Average Accuracy Rate by Model

Region	Logistic Regression	Lasso Regression	Random Forest
Africa	0.743	0.742	0.826
Central Asia & the Caucasus	0.88	0.876	0.915
East Asia	0.552	0.553	0.709
Europe	0.664	0.661	0.685
Latin America & the Caribbean	0.55	0.548	0.566
Middle East	0.852	0.851	0.895
South Asia	0.556	0.556	0.582
Southeast Asia	0.65	0.628	0.736
Average	0.68	0.676	0.739

Notes 1: The average accuracy rates have been calculated by summing up the average accuracy for each region and dividing by the number of regions. Mathematically, $\sum_{r=1}^{R} \frac{1}{n} Accuracy_r$, where the subscript $r = region$. Note that this average accuracy rate may differ from the accuracy rates obtained using the overall confusion matrix that does not place any weight for each region.

5.2. Classification Accuracy

In this sub-section, this study presents the overall confusion matrix for each model. The confusion matrix provides detailed information about classification accuracy such as sensitivity and specificity among many other performance metrics. In this section, this research uses sensitivity and specificity to measure the classification accuracy of the models. Sensitivity, also known as the true positive rate, measures the proportion of positives that are correctly classified as positive. Specificity, also known as true negative rates, measures the proportion of negatives that are correctly classified as negative. These two metrics are known to be highly important in an imbalanced dataset (Banerjee et al 2018). The following confusion matrices show the results for all regions by each model and thus ignore regional differences. The overall results show that all three models show high sensitivity rates and moderately high precision rates. For instance, this study witnesses 0.817, 0.821, and 0.752 sensitivity rates and 0.688, 0.685, and 0.773 precision rates for logistic, LASSO, and random forest models respectively. If you would like to see all confusion matrices for each region by each model, please see Appendix Section 8-2 through 8-4.

Table 3-1: The Average Confusion Matrix for Logistic Model

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	377135 (67.09%)	2550 (0.45%)
Targeting women	170968 (30.41%)	11418 (2.03%)

Table 3-2: The Average Confusion Matrix for Lasso Model

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	375836 (66.86%)	2502 (0.44%)
Targeting women	172267 (30.64%)	11466 (2.03%)

Table 3-3: The Average Confusion Matrix for Random Forest Model

Prediction \ Truth	Not targeting women	Targeting women
Not targeting women	333673 (75.64%)	2360 (0.53%)
Targeting women	97899 (22.19%)	7168 (1.62%)

5.3. Checking Model Accuracy: ROC Curve and Area Under the Curve

In this sub-section, this study plots the receiving operator characteristic (ROC) curve and presents the total area under the curve (AUC) for each model. The ROC curve is created by plotting the true positive rate on the y-axis and the false positive rate on the x-axis. The ROC curve shows the performance of a model at each level of threshold. The AUC indicates the probability of correctly classifying a random pair of observations.

Figure 1-1. The Average ROC Curve For Logistic Regression

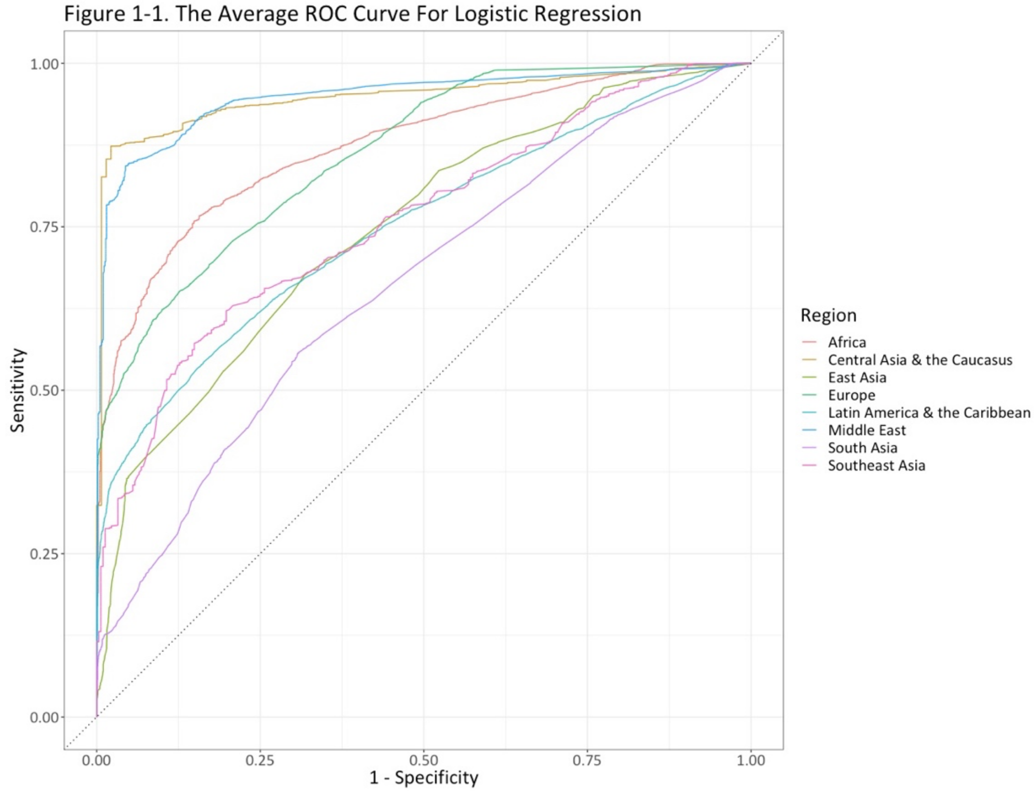


Figure 1-2. The Average ROC Curve For Lasso Regression

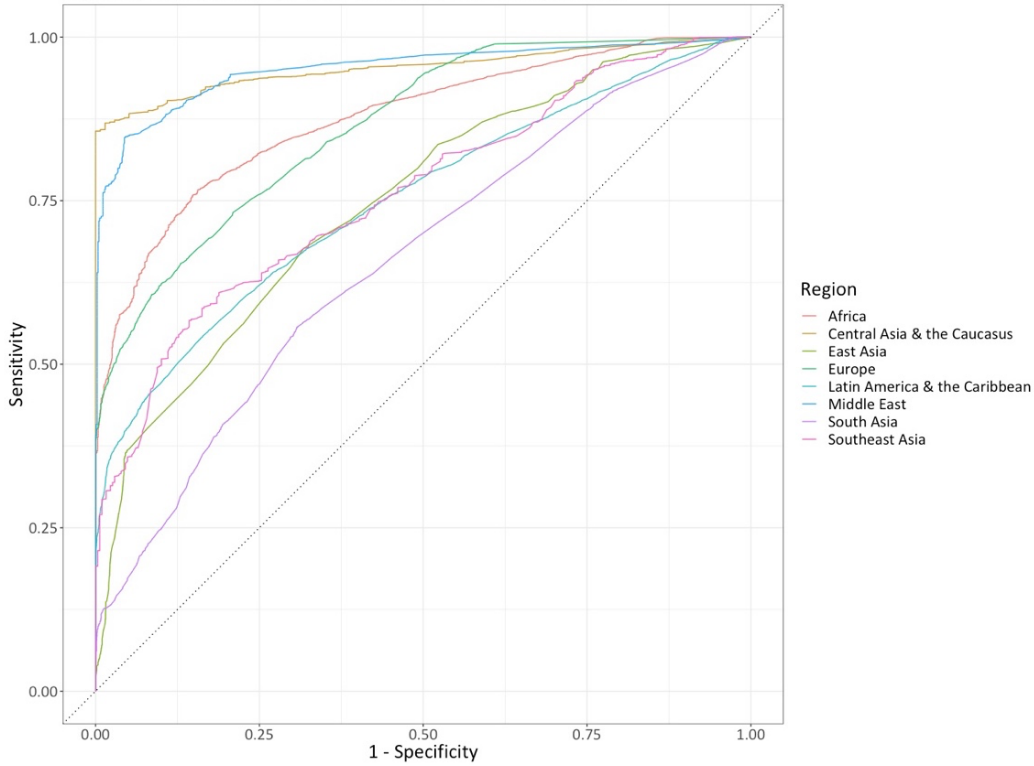
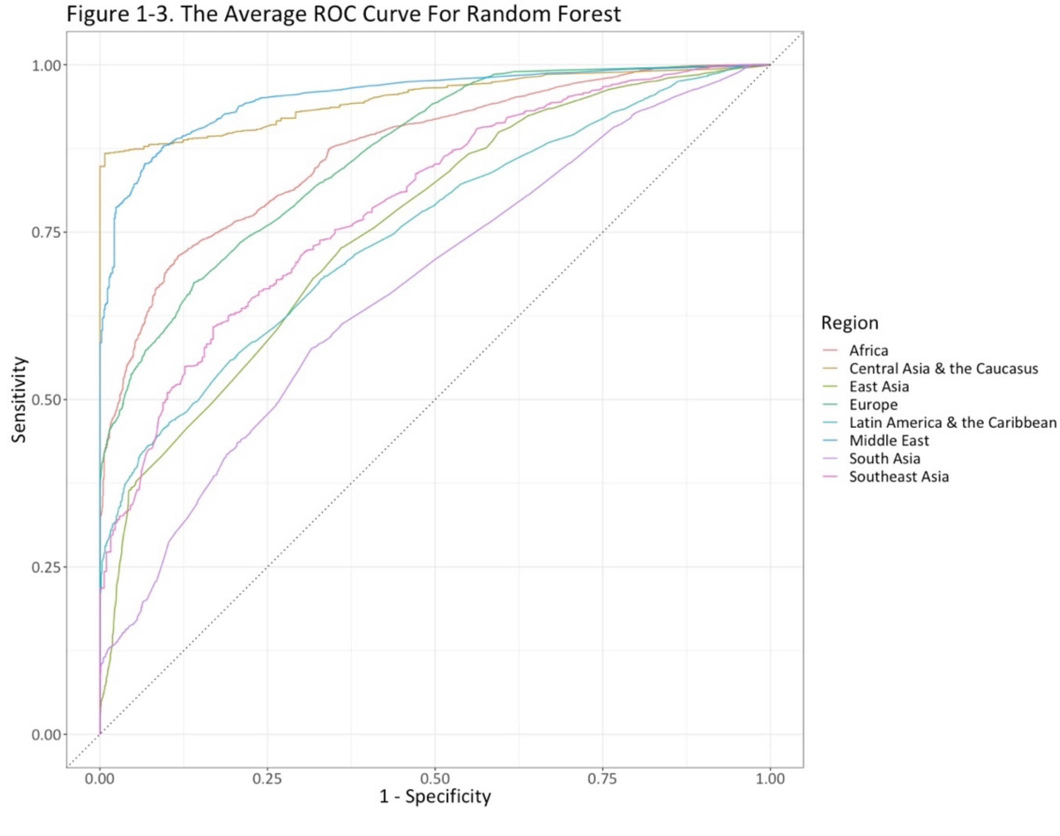


Figure 1-3. The Average ROC Curve For Random Forest



The following table shows the area under the curve in numerical from.

Table 4: The Area Under the Curve (AUC) by Model

Region	Logistic Regression	Lasso Regression	Random Forest
Africa	0.874	0.875	0.872
Central Asia & the Caucasus	0.95	0.954	0.951
East Asia	0.749	0.75	0.761
Europe	0.864	0.865	0.866
Latin America & the Caribbean	0.75	0.751	0.752
Middle East	0.95	0.952	0.954
South Asia	0.661	0.661	0.67
Southeast Asia	0.759	0.761	0.795
Average	0.819	0.821	0.827

These results show the important results that there is strong consistency and agreement across all three models. This implies that the models have learned true gendered patterns in political violence.

5.4. Final fit

In this sub-section, this study selects the random forest model as the best performing model based on the AUC ROC metric and evaluates its performance. Specifically, this study shows the performance of the selected random forest model fitted on the training data and evaluated on the testing data. The results are almost identical to the results obtained using the cross-validation with the difference of 0.004 mean accuracy rates and 0.001 area under the curve.

Table 5: The Performance of the Final Fit from the Random Forest Model

Region	**Accuracy**	**Roc_auc**
Africa	0.812	0.86
Central Asia & the Caucasus	0.895	0.94
East Asia	0.725	0.762
Europe	0.68	0.869
Latin America & the Caribbean	0.566	0.757
Middle East	0.894	0.961
South Asia	0.582	0.661
Southeast Asia	0.73	0.817
Average	0.735	0.828

6. Discussion

All of the results presented in the previous sections support that there are systematic gendered patters in political violence around the globe. Specifically, the predictive models used in this study showed high performance in classifying political violence events for the majority of the regions. Additionally, the results showed evidence of regional heterogeneities. In this section, this study analyzes the substantive implications of each result.

In the predictive accuracy section, this research has demonstrated that the best performing predictive model showed 74% accuracy rates in classifying whether political violence events are targeting women or not. This is a 24-percentage point increase from the baseline of 50% accuracy rates. This finding indicates that there is a global pattern in political violence where the majority of political violence events targeting women have distinctive characteristics. Additionally, this research has shown regional heterogeneities where the model performed particularly worse for Latin America & the Caribbean and South Asia. This finding implies that these regions may not exhibit strong gendered patterns in political violence. This is an important discovery that can encourage more research on the existence of these regional heterogeneities.

In the classification section, this research provided additional information about the classification performance of the predictive models. This research showed that all three models showed roughly 0.8 of sensitivity and 0.7 of specificity on average. This is an important finding because high and well-balanced sensitivity and specific indicate that the model did not suffer from the false high accuracy rates problems addressed earlier for imbalanced datasets. Moreover, high performance in these two metrics showed that the models had small number of false negatived and false positives. As shown in the Appendix section 8-2 through 8-4 for confusion matrices, however, these results were less clear for Latin America & the Caribbean and South Asia where sensitivity was much greater than specificity. In the checking model accuracy section. the overall accuracy was further corroborated using ROC curves and AUC. The metrics showed strong coherence and consistency of the models in classifying political violence events. These results once again verify systematic gendered patterns in political violence across the globe.

Finally, the results from the panel fixed effects model in the Appendix section 8-1 provide additional information about the overall gendered patterns in political violence. Specifically. the information about the event types suggests that there are noticeable gendered differences in arrests, attack, mob violence, other, remote explosive, and sexual violence. For instance, sexual violence is not statistically associated with the number of political violence events targeting women. However, the coefficient of -18.975 is statistically associated with the number of political violence events that are not targeting women. Additionally, arrests, attack, and other political violence types show significant relationship with the number of political violence events that are not targeting women only. These types of violence do not provide statically meaningful information about violence events that are targeting women. On the other hand, mob violence is statistically associated with the number of political violence events targeting women only. When it comes to other types of political violence events that show common support, they show similar levels of statistical confidence and same signs of relationship. These findings show that there were key types of political violence events that characterized political violence targeting women differently from those that did not target women.

7. Conclusion

In conclusion, this research has presented evidence of systematic gendered patterns in political violence around the globe. Although there were regional heterogeneities in the performance for classification, the predictive models classified the political violence events correctly for the majority of regions. Additionally, other measures such as sensitivity, specificity, and ROC AUC further corroborated evidence in favor of gendered patterns in political violence.

This research contributes to the growing literature about political violence targeting women through providing evidence that there are systematic gendered patterns in political violence. This was important considering the growing necessity to view political violence targeting women as sperate from political violence and sexual violence. This research showed that the existing frameworks in political violence and sexual violence were limited in explaining the patterns of political violence targeting women. For instance, sexual violence was not a significant indicator in explaining the total number of political violence targeting women. Also, there was a global pattern despite significant regional heterogeneities in political motive and goals. These observations indicate that political violence targeting women could have limited women's political participation in ways that have not been properly understood with frameworks in political violence and sexual violence. Thus, this research contributes to the literature by illuminating the necessity to establish the new strand of literature that distinguishes political violence targeting women from sexual violence and political violence.

Finally, this research has significant implications considering the number of women participating in politics has been increasing over the past decades. This is important because women's political participation bring substantive changes to the political and economic spheres. For instance, public policies and public spending (Hessami and Fonseca 2020). There is evidence showing that female political participation increases economy in Asia (Xu 2015). Additionally, there is evidence that female political institutions and representations (Beckwith 2010). Furthermore, there is cross-national evidence that more female political representation encourages more female political participation (Liu and Banaszak 2017). These show that political violence targeting women that creates a high-risk political space for women could have severe ramifications in exacerbating gender inequality. Thus, this research highlights the existence of political violence targeting women across the globe and prompts further research and actions to prevent the violence.

References

Aoláin, F. N. (2006). Political violence and gender during times of transition. *Colum. J. Gender & L.*, *15*, 829

Banerjee, P., Dehnbostel, F. O., & Preissner, R. (2018). Prediction is a balancing Act: importance of sampling methods to balance sensitivity and specificity of predictive models based on imbalanced chemical data sets. *Frontiers in chemistry*, *6*, 362.

Bardall, G., Bjarnegård, E., & Piscopo, J. M. (2020). How is political violence gendered? Disentangling motives, forms, and impacts. *Political Studies*, *68*(4), 916-935.

Beckwith, K. (2010). A comparative politics of gender symposium introduction: Comparative politics and the logics of a comparative politics of gender. *Perspectives on Politics*, *8*(1), 159.

Breiman, L. (2001). Random forests. *Machine learning*, *45*(1), 5-32.

Cranmer, S. J., & Desmarais, B. A. (2017). What can we learn from predictive modeling?. *Political Analysis*, *25*(2), 145-166.

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, *16*, 321-357.

Cohen, D. K. (2013). Explaining rape during civil war: Cross-national evidence (1980-2009). *American Political Science Review*, 461-477.

Cohen, D. K. (2013). Female combatants and the perpetration of violence: Wartime rape in the Sierra Leone civil war. *World Pol.*, *65*, 383.

Farrell, T., Gorrell, G., & Bontcheva, K. (2020). Vindication, virtue, and vitriol. *Journal of Computational Social Science*, *3*(2), 401-443.

Fernández, A., Garcia, S., Herrera, F., & Chawla, N. V. (2018). SMOTE for learning from imbalanced data: progress and challenges, marking the 15-year anniversary. *Journal of artificial intelligence research*, *61*, 863-905.

Gleditsch, K. S., Metternich, N. W., & Ruggeri, A. (2014). Data and progress in peace and conflict research. *Journal of Peace Research*, *51*(2), 301-314.

Hadzic, D., & Tavits, M. (2019). The gendered effects of violence on political engagement. *The Journal of Politics*, *81*(2), 676-680.

Håkansson, S. (2021). Do women pay a higher price for power? Gender bias in political violence in Sweden. *The Journal of Politics*, *83*(2), 000-000.

Kishi, Roudabeh, Melissa Pavlik, and Hilary Matfess. "Terribly and Terrifyingly Normal': Political Violence Targeting Women." *ACLED, May* (2019).

Krug, Etienne G., et al. "The world report on violence and health." *The lancet* 360.9339 (2002): 1083-1088.

Liu, S. J. S., & Banaszak, L. A. (2017). Do Government Positions Held by Women Matter? A Cross-National Examination of Female Ministers' Impacts on Women's Political Participation. *Politics & Gender*, *13*(1), 132-162.

Menard, S. (2002). *Applied logistic regression analysis* (Vol. 106). Sage.

Probst, P., & Boulesteix, A. L. (2017). To Tune or Not to Tune the Number of Trees in Random Forest. *J. Mach. Learn. Res.*, *18*(1), 6673-6690.

Sun, Y., Wong, A. K., & Kamel, M. S. (2009). Classification of imbalanced data: A review. *International journal of pattern recognition and artificial intelligence*, *23*(04), 687-719.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267-288.

Xu, Liangxue. "Effects of female political participation on economic growth: Evidence from Asian countries." (2015).

8. Appendix

8.1. Panel Fixed Effects Regression

	Dependent variable:	
	Total Events	
	Man	Woman
	(1)	(2)
Agreement	-7.340	
	(8.544)	
Air/Drone Strike	42.018***	
	(14.253)	
Armed Clash	70.922***	
	(19.355)	
Arrests	-12.688*	1.905
	(7.516)	(7.023)
Attack	56.726***	6.081
	(18.549)	(5.061)
Change To Group/Activity	-43.662***	-12.520**
	(11.386)	(4.988)
Chemical Weapon	-98.037***	
	(12.125)	
Disrupted Weapons Use	-27.821***	
	(8.636)	
Excessive Force Against Protesters	270.865***	48.945***
	(58.823)	(15.163)
Government Regains Territory	16.329	
	(12.966)	
Grenade	-34.243***	-3.398
	(8.294)	(2.494)
Headquarters Or Base Established	-74.077***	
	(17.351)	
Looting/Property Destruction	-3.581	-1.928
	(4.177)	(3.674)
Mob Violence	-2.599	19.435**

	(12.049)	(8.898)
Non-State Actor Overtakes Territory	-0.039	
	(8.696)	
Non-Violent Transfer Of Territory	-41.492***	
	(9.244)	
Other	-22.601**	11.302
	(10.557)	(7.985)
Peaceful Protest	735.091***	77.666***
	(151.856)	(21.797)
Protest With Intervention	287.841***	50.125***
	(64.864)	(15.615)
Remote Explosive/Landmine/Ied	-9.910	-7.078*
	(6.047)	(4.195)
Sexual Violence	-18.957***	-2.618
	(6.758)	(2.903)
Shelling/Artillery/Missile Attack	39.138	-2.079
	(27.253)	(5.260)
Suicide Bomb	-32.074***	
	(10.883)	
Violent Demonstration	-6.547	7.768
	(13.575)	(8.182)
Observations	15,573	1,582
R^2	0.118	0.239
Adjusted R^2	0.108	0.155
Residual Std. Error	299.849 (df = 15392)	43.726 (df = 1424)
Note:	*p**p***p<0.01	

8.2. Confusion Matrix for Each Region in Logistic Regression Model

Table 8.2-1: Confusion Matrix for Africa

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	48963	174
Targeting women	17160	1090

Table 8.2-2: Confusion Matrix for Central Asia & the Caucasus

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	46670	10
Targeting women	6356	127

Table 8.2-3: Confusion Matrix for East Asia

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	12914	408
Targeting women	11444	1681

Table 8.2-4: Confusion Matrix for Europe

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	52888	372
Targeting women	27628	2349

Table 8.2-5: Confusion Matrix for Latin America & the Caribbean

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	58038	639
Targeting women	49613	3337

Table 8.2-6: Confusion Matrix for Middle East

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	103917	49
Targeting women	18079	744

Table 8.2-7: Confusion Matrix for South Asia

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	42711	820
Targeting women	34765	1860

Table 8.2-8: Confusion Matrix for Southeast Asia

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	10934	78
Targeting women	5923	230

8.3. Confusion Matrix for Each Region in Lasso Regression Model

Table 8.3-1: Confusion Matrix for Africa

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	48895	173
Targeting women	17228	1091

Table 8.3-2: Confusion Matrix for Central Asia & the Caucasus

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	46535	6
Targeting women	6591	131

Table 8.3-3: Confusion Matrix for East Asia

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	12933	407
Targeting women	11425	1682

Table 8.3-4: Confusion Matrix for Europe

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	52679	356
Targeting women	27837	2365

Table 8.3-5: Confusion Matrix for Latin America & the Caribbean

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	57803	628
Targeting women	49848	3348

Table 8.3-6: Confusion Matrix for Middle East

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	103733	41
Targeting women	18263	752

Table 8.3-7: Confusion Matrix for South Asia

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	42709	819
Targeting women	34767	1861

Table 8.3-8: Confusion Matrix for Southeast Asia

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	10549	72
Targeting women	6308	236

8.4. Confusion Matrix for Each Region in Random Forest Model

Table 8.4-1: Confusion Matrix for Africa

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	54751	387
Targeting women	11372	877

Table 8.4-2: Confusion Matrix for Central Asia & the Caucasus

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	48656	36
Targeting women	4470	101

Table 8.4-3: Confusion Matrix for East Asia

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	13931	580
Targeting women	5571	1077

Table 8.4-4: Confusion Matrix for Europe

Truth / Prediction	Not targeting women	Targeting women
Not targeting women	43790	330
Targeting women	20622	1849

Table 8.4-5: Confusion Matrix for Latin America & the Caribbean

Prediction \ Truth	Not targeting women	Targeting women
Not targeting women	24001	306
Targeting women	19070	1275

Table 8.4-6: Confusion Matrix for Middle East

Prediction \ Truth	Not targeting women	Targeting women
Not targeting women	109220	102
Targeting women	12776	691

Table 8.4-7: Confusion Matrix for South Asia

Prediction \ Truth	Not targeting women	Targeting women
Not targeting women	26895	518
Targeting women	19590	1091

Table 8.4-8: Confusion Matrix for Southeast Asia

Prediction \ Truth	Not targeting women	Targeting women
Not targeting women	12429	101
Targeting women	4428	207