Are Many Sets of Eyes Better Than One?

Evaluating Multiple Databases of Armed Actors in Colombia

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Abstract

In contrast to the pervasive scarcity of disaggregated data affecting sub-national conflict studies, Colombia concentrates a wealth of databases measuring armed actors. How comparable are these databases? What are the implications of their differences for statistical inference? This research compares seven prominent sub-national measures of armed actors in Colombia. Using the Jaccard Similarity Index, the analysis reveals low similarity between measures. At best, results show 28.7% similarity when considering aggregated actor types, but similarity drops to 14.4% when considering specific armed groups. These measures also yield diverging statistical results when used as dependent or independent variables. In addition to their conceptual and methodological differences, pervasive missing data seem to be driving estimate discrepancies. The nuances of these measurement sets make it difficult to categorically determine if this low similarity is an asset or a limitation for empirical research. Yet, the analysis provides clear prescriptions for researchers in data-abundant settings.

Keywords: Colombia; similarity; robustness test; paramilitaries; insurgents

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Introduction

The quantitative analysis of the micro-dynamics of conflict requires high-quality, disaggregated, and accurate data about the characteristics and behaviors or armed actors to enable precise description, valid inferences, and knowledge accumulation. To build confidence that the results are not artifacts driven by particular modeling strategies or data choices, researchers generally conduct robustness tests using different models and alternative measures (Neumayer and Plümper 2017; Weisber 2006). In contrast to the robustness tests firmly rooted in country-year conflict research (Sambanis 2004; Hegre and Sambanis 2006), sub-national analyses are often limited to a single database or variable, thus hindering the possibility of conducting robustness tests. Despite efforts to enrich sub-national conflict data repositories (Zhukov et al. 2019), data scarcity remains a considerable obstacle to study the micro-dynamics of violence (Eck 2012). Lack of sub-national data prevents knowledge accumulation based on robust findings, thus leaving researchers with the uneasiness of accepting results based on limited data or convincing robustness tests.

In contrast to the scarcity of sub-national data in many research environments, the wealth of conflict data on Colombia offers a unique opportunity to assess different sub-national databases. How comparable are these measures? What are the consequences of their differences for statistical analyses? This research evaluates the Colombian conflict data environment by comparing seven different databases and provides four main contributions. First, it evaluates substantive differences between measures and discusses their limitations. Second, it focuses on armed actor presence as a commensurable indicator to compare their similarity using the Jaccard Index. Third, to prevent missing data from distorting similarity scores, the study presents a dimensionality-reduction algorithm to accurately estimate Jaccard similarity. Finally, it evaluates the implications of using different databases for statistical inference.

The study compares measures of guerrilla and paramilitaries as two generic types of actors, and further disaggregates them into specific organizations: the Revolutionary Armed Forces of Colombia (*Fuerzas Armadas Revolucionarias de Colombia*, FARC), the National

Liberation Army (*Ejército de Liberación Nacional*, ELN), and the United Self-defense Forces of Colombia (*Autodefensas Unidas de Colombia*, AUC). The study compares the substantive and methodological characteristics of seven databases. The pairwise and aggregate comparisons indicate that the proliferation of databases is not a panacea as results reveal considerable discrepancies between databases. At best, the Jaccard Index reports 28.7% similarity for guerrillas and 27.5% similarity for paramilitaries. Agreement is even lower for specific groups such as ELN, with only 14.4% similarity, followed by FARC with 15.3%, and AUC with 23.9% similarity. Moreover, the statistical analysis reveals that these distinct databases yield varying statistical results.

A nuanced interpretation of the low similarity across databases makes it difficult to categorically determine if these differences are an asset that help analyzing different conflict dimensions or a shortcoming that prevents conducting meaningful robustness tests. In any case, the analysis shows the importance of researchers systematically assessing the similarity between measures to advance their research, replicate findings, or collect new data.

Measuring in the Midst of Conflict

Advancing quantitative research on the micro-dynamics of violence relies on the availability of high-quality data collection efforts at the sub-national or individual level. As researchers depart from country-year studies and analyze conflict in a disaggregated manner (Kalyvas et al. 2008), micro-level studies of conflict often face the problem of lack of available data (Eck 2012). With the gradual progression of the field, scholars have been producing temporally and geographically disaggregated databases to analyze the micro-dynamics of conflict.

Developing databases in the midst of conflict is not a trivial endeavor. Violence may distort, suppress, destroy, or limit access to sources, documents, or testimonies (Weidmann 2016; Bell-Martin and Marston 2019; Osorio 2013). Coding data may be subject to coder bias, or methodological and logistical challenges (Baumgartner et al. 1998), and investigators

may suffer psychological and ethical burdens (Loyle and Simoni 2017). Research on data quality has identified problems of geo-location, lax actor attribution, over or under-reporting, coding ambiguity or rigidity, and challenges with multi-label categories (Donnay et al. 2019; Eck 2012; Ward et al. 2013; Douglass and Harkness 2018; Hammond and Weidmann 2014; Weidmann 2016). These problems are more acute when databases rely on a single information source (Davenport and Ball 2002; Earl et al. 2004).

To address some of these concerns, the standard recommendation is to use multiple information sources (Davenport and Ball 2002). Just as a database benefits from integrating several information streams, a field of study benefits from having multiple databases. In line with this idea, conflict scholars have produced subnational-level databases using dedicated coders (Salehyan et al. 2012; Raleigh et al. 2010; Hegre et al. 2018; Sundberg and Melander 2013) or computerized approaches (Schrodt 2006; Schrodt and Van Brackel 2013; Osorio et al. 2019). Some scholars favor one database over another (Eck 2012), while others develop large repositories of sub-national data for replication and robustness checks (Zhukov et al. 2019). Some prefer integrating data streams (Donnay et al. 2019) while others use multiple systems estimation (Lum et al. 2013). Unfortunately, different databases could yield mixed results. Although adversarial arguments are fundamental to knowledge accumulation (Kuhn 1962), the lack of robust results leaves open questions and unconfirmed theories.

Measurement Sets

Taking advantage of the wealth of data on the Colombian conflict, this study compares seven prestigious databases often used to analyze armed actor presence or violent behavior. These databases include: (i) paramilitary presence by Rutas del Conflicto (2019), RC; (ii) paramilitary and guerrilla presence by Claudia López (2010), CL; (iii) reports of narcoparamilitary presence by Indepaz (2019), IN; (iv) paramilitary and guerrilla attacks by the Centro de Estudios Sobre Desarrollo Económico (2019), CD; (v) paramilitary and guerrilla violent presence

from Violent Presence of Armed Actors, ViPAA (Osorio et al. 2019), VI; (vi) paramilitary and guerrilla attacks by Restrepo et al. (2004), RE; and (vii) paramilitary and guerrilla violent events from UCDP (Sundberg and Melander 2013), UC. Some measurements are produced by local researchers (RC, CL, IN, CD) and others by international scholars (UC and VI). See Appendix A1 and A7 for details.

Figure 1 compares these data along seven categories including the type of variable (dichotomous or count), information gathered from news agencies, NGOs, government, and testimonies, as well as their internal quality controls, and replicability. The analysis reveals considerable differences (see Appendix A1). RC presents dichotomous data on paramilitary presence using local and national newspapers, NGOs, and victims. CL data comes from a prestigious conflict study (López 2010) coding paramilitary and guerrilla presence (dichotomously) using local and national newspapers, and interviews. IN provides dichotomous data on paramilitary presence using local and national newspapers, local NGOs, and government records. CD presents count data on paramilitary and guerrilla attacks exclusively relying on government statistics from the Police, Army, and the Colombian census authority. VI provides count data on paramilitary and guerrilla violent presence using computerized coding (Osorio et al. 2019) based on *Noche y Niebla*, a collection of political violence and human rights narratives gathered from local and national news, NGOs, and victims, produced by CINEP (2016). RE presents count data on paramilitary and guerrilla attacks manually coded from CINEP's *Noche y Niebla* using their own codebook. Finally, UC provides count data on organized violence events involving paramilitary and guerrilla based on international news and NGOs. The top row of Figure 1 presents the databases measuring armed actor presence and the bottom row are the databases measuring attacks.

[Figure 1 around here]

Although generally focused on the Colombian conflict, these databases have considerable conceptual and operationalization differences, and vary in the armed groups they include. There is only partial substantive overlap on their objects of study as some databases analyze

different actors or behaviors than others. This could constitute an advantage as it may enable studying distinct conflict dimensions. However, partial overlap could also limit the feasibility of robustness tests. Despite their conceptual differences, databases seem to overlap on their information sources. With the exception of CD, all other databases use a combination of news and NGO reports; however, few rely on testimonies. Unfortunately, there are noticeable discrepancies in internal quality control and replicability. See Appendix A1.

These measures also have commensurability problems that hinder comparison. While IN, CL, and RC use dummy variables, VI, RE, UC, and CD use count data. To address this incommensurability, the similarity analysis in this study transforms count variables into dichotomous measures taking the value of 1 whenever count data reports non-zero values. Although this minimalist approach reduces the data variation, it enables the comparison across databases. The transformed dummy variables could be interpreted as indicators of armed actor's *violent presence*. However, since violence is a limited proxy of armed actor presence (Arjona 2011), particularly for groups holding monopolistic control, measures of violent presence of armed actors require careful interpretation.

Figure 2 reveals pervasive missing data affecting some measurement sets. Panel (a) shows that VI is the most complete database by covering the entire 1988-2017 period, followed closely by UC, with one year less. All other measures have truncated or sporadic coverage. Unfortunately, there is not a single year in which all databases overlap, which prevents comparing all metrics in a concurrent period. The exploration also reveals missing municipalities in some databases. Panel (b) shows the extent of overall missingness by type of actor per measurement set. VI is the least affected by missingness while RC's guerrilla suffers from the most missing data. Assessing the reasons for missing data is beyond the objectives of this study (Fariss 2014), but missingness posts considerable difficulties for data analysis.

[Figure 2 around here]

Similarity Assessment

To assess the consistency between measures, the study relies on the Jaccard Similarity Index (Jaccard 1901, 1912), a score often used in ecology to evaluate the similarity of measures tracking species in a study site (Ricotta and Pavoine 2015). Although Jaccard is gaining popularity as an evaluation metric (Niwattanakul et al. 2013; Fletcher and Isla 2018), its use in political science still is limited (e.g. Sanger and Warin 2019). The intuition behind Jaccard Similarity considers a measurement set, M, as a vector recording the presence of an entity (e) in location i at time t, such that $M = \{e_{it}, \ldots, e_{NT}\}$, where e takes the value of 1 if the entity is present, and 0 otherwise. If there is no measurement effort in a location-time, then the observation is recorded as missing, $e_{it} = \text{NA}$, since it is not possible to determine the entity's presence or absence. Now, consider a comparison set, C, containing multiple measurement sets, $C = \{M_1, M_2, \ldots, M_{\overline{N}}\}$.

The Jaccard Similarity Index (J) evaluates the similarity between two measurement sets, $M_1 = (e_{1it}, \ldots, e_{1NT})$ and $M_2 = (e_{2it}, \ldots, e_{2NT})$ by ranging from 0 to 1, where 0 indicates total dissimilarity and 1 perfect similarity. For a single time point t, the local Jaccard Similarity of two vectors is:

$$\text{J}_t(M_1, M_2) = \frac{M_1 \cdot M_2}{M_1^2 + M_2^2 - (M_1 \cdot M_2)} = \frac{\sum_{i=1}^{n} e_{1i} e_{2i}}{\sum_{i=1}^{n} e_{1i}^2 + \sum_{i=1}^{n} e_{2i}^2 - \sum_{i=1}^{n} e_{1i} e_{2i}} \tag{1}$$

More intuitively, Jaccard Similarity is the ratio of the intersection between observations and their union:

$$\text{J}_t(M_1, M_2) = \frac{|M_1 \cap M_2|}{|M_1 \cup M_2|} \tag{2}$$

Based on equation 2, it is possible to generate an Average Jaccard Index for two measurement sets across an entire time frame:

$$\overline{\mathrm{J}} = \frac{\sum_t^T \mathrm{J}_t(M_1, M_2)}{T} \tag{3}$$

The Jaccard Similarity Index can be extended to compare any number of measures in a given comparison set, C, which includes $C = \{\text{RC, IN, CL, CD, VI, RE, UC}\}$ in this study. However, as Figure 2 shows, missingness is a pervasive problem in some measures. Imputing missing data with $e_{it} = 0$ would erroneously assume that a measurement took place but the entity was not detected, thus distorting the similarity score. Zero-imputation could inflate similarity if other observations already have zeros or if the imputed zeros fill in multiple measurement sets. Zero-imputation could also reduce similarity if the zero-imputed values contradict observations marked with 1.

Rather than making about the missing data generation process, the study proposes a dimensionality-reduction algorithm to calculate Jaccard Similarity in the presence of missingness. The algorithm (detailed in Appendix A2) considers time (t), location (i), and measurement sets (M) as relevant dimensions to calculate the Jaccard similarity. The algorithm uses the available M and i in a given t to generate data subsets (s) and calculate their local Jaccard scores (J_{ts}). If missing data alters the subsets' dimensions in a given year, the algorithm calculates the weighted average local Jaccard using the proportion of observations in each subset ($w_s = n_s/N$), such that $J_{tw} = (\sum_s^S J_{ts} w_s)(1/S)$. If there are no subsets in a given year, the algorithm directly calculates the local Jaccard (J_t). After computing the local Jaccard scores for each t, the algorithm generates an aggregated Jaccard ($\overline{\mathrm{J}}$) averaging local similarity scores over time ($t = 1, ..., T$). In this way, the algorithm only uses data overlapping at common points in time without being affected by missing data.

Pairwise Similarity Assessment

The similarity assessment applies the Jaccard dimentionality-reduction algorithm on two levels. First, the type-level analysis focuses on *Paramilitaries* or *Guerrilla*, including all the groups classified in each database as paramilitaries or insurgents. The type-level comparison

is largely forgiving as it only requires identifying the actor type without agreeing on the specific group. The second level analyzes three specific armed actors: the FARC and ELN guerrilla groups, and the AUC paramilitaries. The group-level assessment is more stringent as it requires detecting the same armed organization per municipality-year.

Figure 3 presents the Average Jaccard Similarity by actor type and specific groups for each measurement pair. The solid square groups databases measuring attacks, while the dashed square clusters databases measuring presence. Overall, the pairwise matrices reveal low similarity between measures. Across panels, similarity is considerably lower between data measuring presence (dashed clusters) than between data measuring violence (solid clusters). At the type-level, the highest similarity of paramilitary and insurgent groups is between VI and CD, each with 34% similarity (Panels a and b). At the actor-level, similarity is even lower. The highest FARC similarity is between CD and RE with only 26% (Panel c). Similarity of ELN reaches only 21% agreement between VI and CD (Panel d). Finally, VI and CD are the most similar measures of AUC with 34% similarity (Panel e).

[Figure 3 around here]

Databases CD and VI report the highest level of similarity in four out of five comparisons, yet they only agree in about three out of ten observations. The ontological and methodological differences between CD and VI could explain these differences (see Figure 1). On one hand, CD reports armed attacks by paramilitary or guerrilla groups based on government records. In contrast, VI reports violent presence of armed actors based on CINEP narratives of political violence and human rights violations coming from national and local news, and testimonies. Substantively, violent attacks measured in CD could be considered a subset within VI's broader conceptualization of violent presence that includes many other behaviors such as threats, kidnapping, rape, displacement, etc.

Similarity Across Measures

This section analyses Average Jaccard Similarity across measures rather than by pairs. The type-level assessment in Panel (a) of Figure 4 shows low similarity across databases with 28.7% for guerrillas and 27.5% for paramilitaries. The actor-level analysis in Panel (b) reveals even lower similarity across measures. The Average Jaccard Similarity for AUC is 23.9%, for ELN is 14.4%, and for FARC is 15.3%. Despite the decades-long centrality of these armed groups in the Colombian conflict, there is little agreement about these actors.

[Figure 4 around here]

Figure 5 reports Local Jaccard scores over time by actor type and group, with darker color indicating low similarity and abbreviations for the databases included in each year. Panel (a) shows variation in guerrilla similarity with a minimum of 11.4% in 1989 and a maximum of 44.3% in 2000. In contrast, the paramilitary similarity is generally lower but fluctuates more markedly with a minimum of 6.4% in 2006 and a 56.1% peak in 2013. Panel (b) in Figure 5 shows even lower similarity at the group level. AUC similarity shows broad variation, ranging from 0% similarity between 1988 and 1992, up to 52.9% in 2015. ELN similarity is the lowest, ranging from 0% in 1988 to 52.4% in 2012. Finally, FARC similarity is also lower than AUC but slightly better than ELN, ranging from 3.3% in 1989 and 33.9% in 2002. Overall, measures tracking the presence of Colombian armed groups have low levels of agreement. These discrepancies make it difficult to determine patterns of territorial presence or behavioral trends for different groups.

[Figure 5 around here]

Overall, the descriptive analysis reveals low similarity across measures. These discrepancies are not necessarily problematic nor surprising if we consider the relatively different objects of study, operationalization, and information sources used in these databases. This

measurement diversity can help enrich our understanding of the Colombian conflict by analyzing distinct aspects of it. However, the lack of comparable data makes it difficult to implement robustness tests to corroborate trends across databases.

Empirical Implications

This section evaluates the statistical consequences of using different measures of armed actors in two ways. First, it replicates the Dube and Vargas (2013) causal inference model using each database as the dependent variable. The second assessment uses these measures as independent variables to explain homicides in a correlational model. In addition to the seven measurement sets discussed above, this section includes an integrative variable labeled *All*, taking the value of 1 when any other databases detect an armed actor (by type or group), and 0 otherwise. In contrast to more sophisticated data aggregation methods (Donnay et al. 2019; Lum et al. 2013), this integrative approach represents the simplest and most straight-forward amalgamation of individual measures.

Armed Actors as Dependent Variable

Dube and Vargas (2013) estimate the effects of oil and coffee price shocks on armed conflict using instrumental variables. Their paper analyzes paramilitary and guerrilla attacks as count data, but this study uses the dichotomous measures of actor presence mentioned above. Based on their study, oil shocks should increase armed actor presence by promoting predatory behavior. In contrast, coffee shocks should reduce armed actor presence through a labor substitution process diverting combatants away from fighting and into coffee production. This analysis replicates the Dube and Vargas (2013) model by substituting each measure of armed actor presence as the dependent variable using the following second-stage specification:

$$y_{irt} = \lambda(Oil_{rt} \times OP_t) + \rho(\widehat{Cof_{it} \times CP_t}) + \gamma Coca_{irt} + \phi X_{irt} + \alpha_i + \beta_t + \delta_{rt} + \epsilon_{irt} \qquad (4)$$

where y indicates armed actor presence by type or group from each database in municipality i, region r, and year t; oil shocks are defined as oil production Oil_{rt} interacted with international oil prices OP_t; coffee shocks come from municipal coffee cultivation Cof_{it} interacted with domestic coffee prices CP_t as derived from the first stage; $Coca_{irt}$ indicates coca cultivation; X_{irt} represents controls; and the model includes several fixed effects. See Appendix A4.

The top row of Figure 6 presents the second-stage coefficients of oil and coffee shocks on armed actor types (Panels a and b) and specific organizations (Panels c-e), with the marker representing the sample size. Results indicate some variations with respect to oil shocks. Most paramilitary measures (Panel a) and all AUC indicators (Panel e) present the expected positive sign of oil shocks, but with different point estimates and only half of the models reaching significance. Contrary to the expectation, most guerrilla measures (Panel b) present negative effects of coffee shocks and half of them are statistically significant, while FARC and ELN (Panels c and d) show mixed coefficient signs with varying significance. Regarding the coffee substitution mechanism, coffee shocks have consistently negative effects on armed actor presence (Panels a-e), but coefficient magnitudes and their significance vary considerably.

[Figure 6 around here]

The pairwise comparison above indicates that CD and VI are the most similar databases. A closer inspection of these data sets in Figure 6 shows that the coefficients associated with CD and VI present some inconsistencies. The negative sing of the coffee shock coefficients in VI and CD remain largely consistent across Panels a-e. In contrast, the oil shock coefficient of VI is positive and statistically significant in most cases in Panels a-e; however, the CD oil coefficients flip sings across Panels a-e and only reach significance in two out of five models. These varying results indicate that event the most similar pair of databases could lead to statistically inconsistent results. See Appendix A4 for details.

Armed Actors as Independent Variable

This section evaluates different measures of armed actor presence as independent variables used to explain homicide rates. The model uses the following specification:

$$y_{it} = \alpha_i + \beta A_{it} + \delta X_{it} + \epsilon_{it} \tag{5}$$

where y_{it} is the homicide rate reported by the Colombian Police (Moreno 2014); A_{it} refers to the actor type or group by measurement; X_{it} are the controls described in Appendix A5; α_i are municipal fixed effects, and ϵ_{it} the disturbances.

The bottom of Figure 6 reports the effects of different measures of armed actor presence on homicide rates with the marker size representing the sample size. See Appendix A5 for details. In general, Panels f-j consistently show that armed actors' presence increases violence. However, coefficient magnitudes vary broadly. Panel (f) shows that the UC paramilitary measure is associated with the highest homicide rate of 52.1, while IN attributes paramilitaries a homicide rate of only 2.6. Similarly, Panel (g) shows broad discrepancies for guerrillas. Again, UC reports the strongest effect of guerrilla with a homicide rate of 25.1, while CL reports a homicide rate of 10.4. Coefficient discrepancies are even sharper for specific group estimates. Panel (h) shows that UC attributes AUC a coefficient of 52.1 homicides, while the variable All is associated with a 5.01 homicide rate. According to Panel (i), RC has the strongest effect of ELN with a homicide rate of 86.3, however it has the smallest sample size and widest confidence intervals. In contrast, All has the smallest effect of ELN on violence with 10.4. Finally, Panel (j) associates RC's measure of FARC with the strongest effect on homicides and All with the smallest effect, 45.2 and 14.7, respectively.

A closer look at CD and VI, the pair of databases with the highest similarity score, reveals that the sign and statistical significance of their coefficients is consistent across Panels f-j in Figure 6. However, the magnitude of the VI estimates is always larger than CD's coefficients. See Appendix A5 for details.

In general, different measures of armed actor presence yield distinct results. Using different metrics as the dependent variable to replicate the Dube and Vargas (2013) study fails to support the expected positive effect of oil shocks and offers limited confirmation of the negative effect of coffee shocks. Similarly, using different measures as independent variable provides limited agreement for the positive effect of armed actors on homicides due to wide-varying coefficients. The conceptualization and measurement differences of these databases could be driving result discrepancies. Moreover, given the pervasiveness of missing data in some measures, gaps in the data coverage are probably a key reason for the disparities in the statistical results.

The logic of territorial control outlined by Kalyvas (2006) could offer a potential substantive interpretation of the diverging statistical results between measures of presence and measures of violence used either as dependent or independent variables. According to this expectation, armed actors are likely to display distinct patterns of violence depending on the degree of control they hold on a territory. In this way, estimate discrepancies could be expected between measures of violence and those of armed presence. Unfortunately, the Colombian data on armed actor presence is not measured categorically to capture degrees of territorial control. Without the right kind of empirical support, the above-mentioned interpretation could be no different than mere speculation.

Conclusion

Contrary to the data scarcity pervasive in the micro-dynamics of conflict research, the long duration of the Colombian conflict enabled the production of multiple databases on non-state armed actors, thus providing a rich data environment to study conflict. This study compares seven different measurement sets of armed actors in Colombia at the municipality-year level between 1988 and 2017. The study provides five main lessons.

First, the descriptive analysis reveals some ontological and methodological differences across measures, as well as a pervasive problem of missing data. S Second, the study advances a novel algorithm for calculating Jaccard similarity that prevents distortions from missing data. This similarity assessment generally shows low agreement across databases. Third, the analysis compares the of similarity between each pair of databases.Pairwise comparisons indicate that VI and CD are the most similar databases; however, they only overlap in about 3 out of 10 cases. Fourth, moving from pairwise to aggregate comparisons across databases shows that, at best, there is 28.7% of similarity for measures of guerrilla presence and 27.5% for paramilitary groups. Similarity is even lower when considering specific armed groups: similarity across AUC measures is 23.9%, for the ELN insurgency is 14.4%, and for FARC is 15.3%. It is remarkable that despite the centrality of these three armed organizations in the Colombian conflict, different databases display such low levels of similarity. Finally, the analysis also shows that using distinct measures as dependent or independent variables is consequential for statistical inference. The regression results show limited statistical consistency across database with frequent instances of flipping coefficient signs, different estimate magnitudes, and varying confidence intervals when using the different measures of armed actors.

A careful and nuanced analysis of the data makes it difficult to make a definite interpretation of the similarity across databases as an asset or a shortcoming for quantitative analysis. If we consider that these databases measure inherently distinct phenomena with minor overlap, then the low similarity and statistical consistency should not be surprising nor concerning. The descriptive and inferential differences could be the results of distinct databases measuring different behaviors. In such case, the ontological and operationalization discrepancies of these databases could be an asset that helps researchers analyze different questions. In contrast, if we consider that these measures capture substantively interrelated phenomena, then the low data similarity and lack of robust statistical results would be prob-

lematic. In consequence, lessons derived from disparate data would hardly lead to meaningful robustness tests and knowledge accumulation.

This study shows that despite the wealth of data in some settings, the availability of sub-national databases is not a panacea. Researchers studying conflict in data-abundant settings would benefit from evaluating the similarity of the databases. This research advances methodological guidelines on how to assess data similarity in a systematic way. Researchers in low-similarity data environments should be particularly careful in assessing and using different measures to conduct robustness tests. Swapping one database for another one is not a sound decision without a proper assessment of their substantive, methodological, and coverage characteristics. Similarity assessments could also guide future data collection efforts while trying to maximize the overlap between existing databases and new ones. Given the pervasive problem of missingness, researchers could also focus on filling historical gaps of existing databases and updating truncated ones while keeping in mind substantive and methodological similarities.

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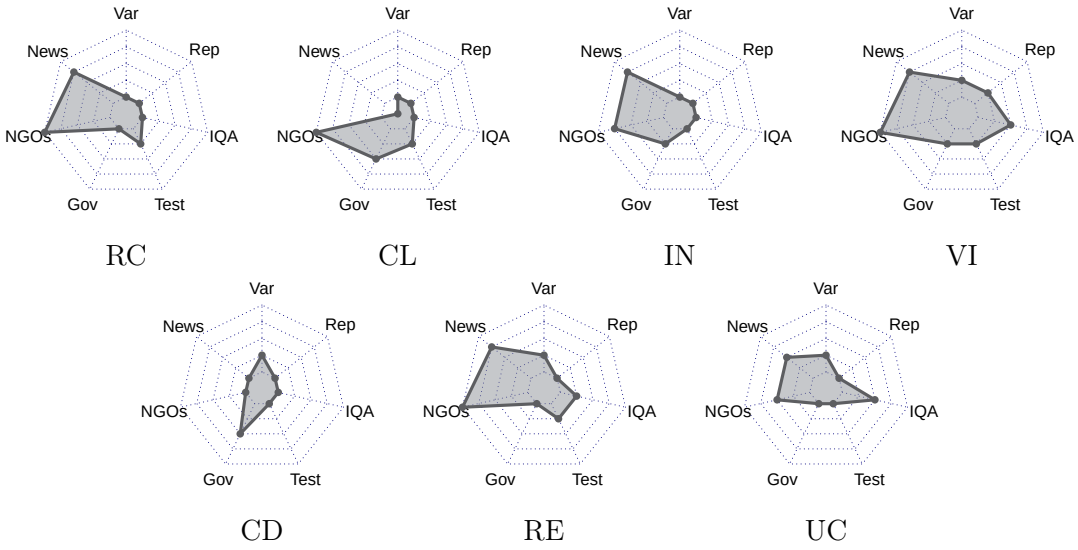
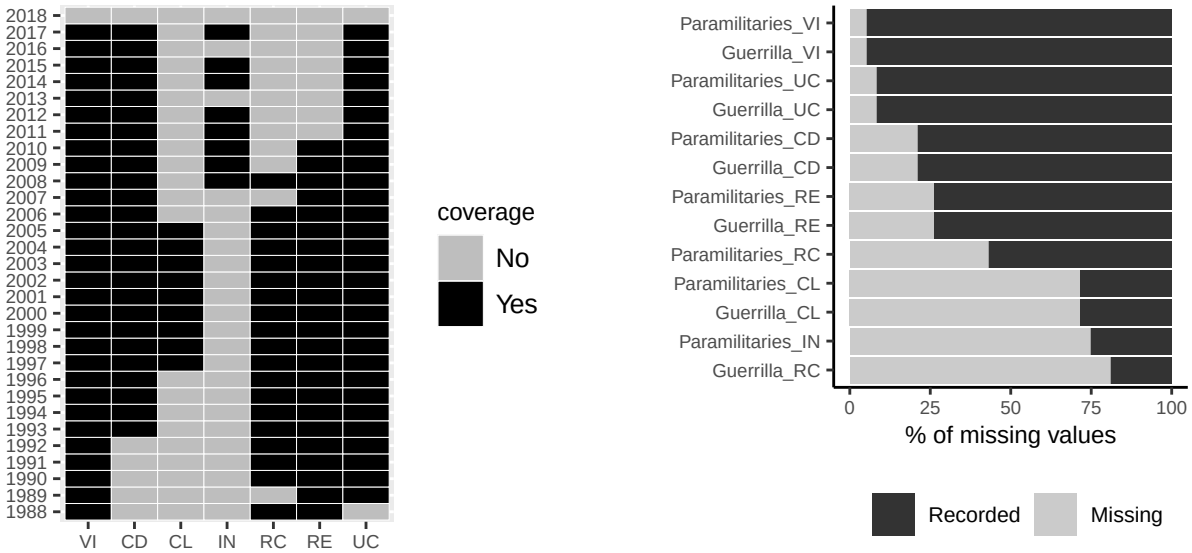


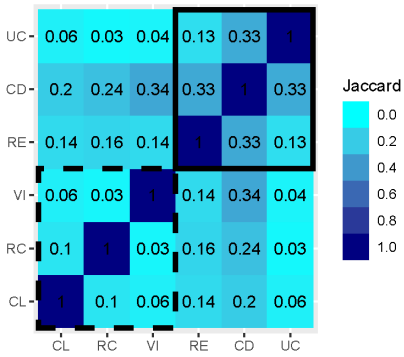
Figure 1: Measurement set characteristics



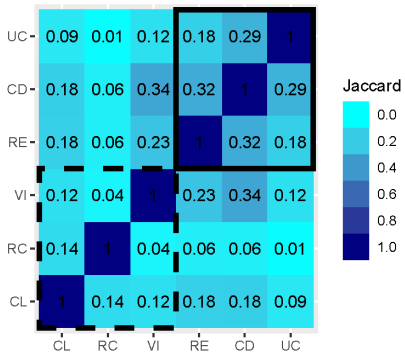
(a) Temporal Coverage

(b) Missing Data

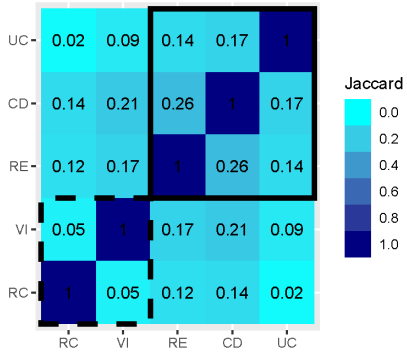
Figure 2: Coverage and Missingness



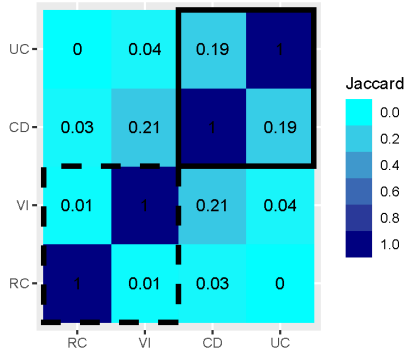
(a) Paramilitaries



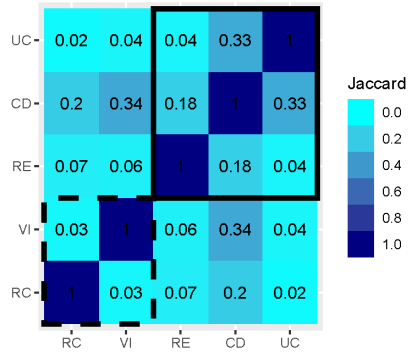
(b) Guerrilla



(c) FARC

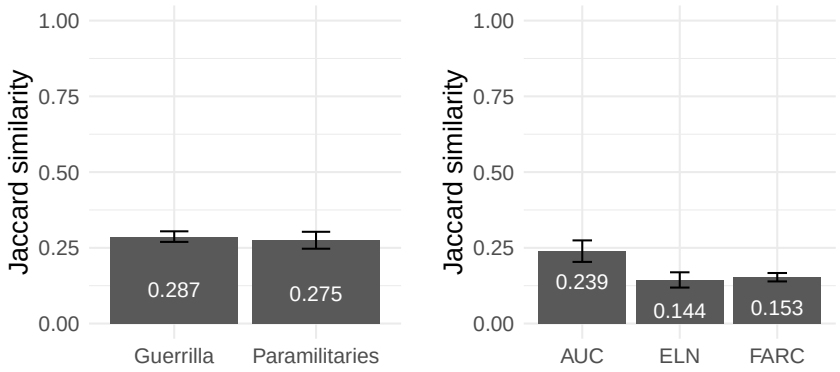


(d) ELN



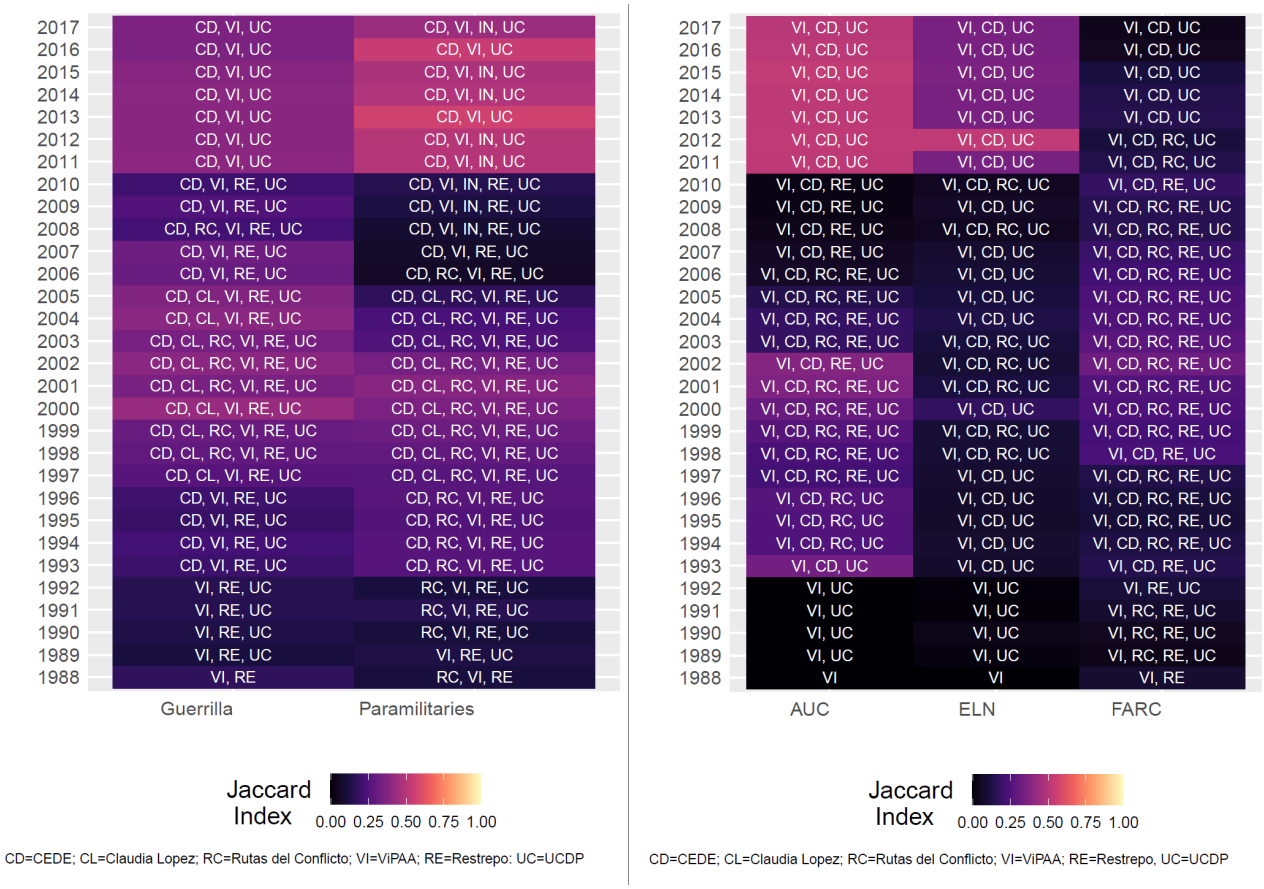
(e) AUC

Figure 3: Pairwise Jaccard Similarity



(a) Actor Type (b) Armed Group

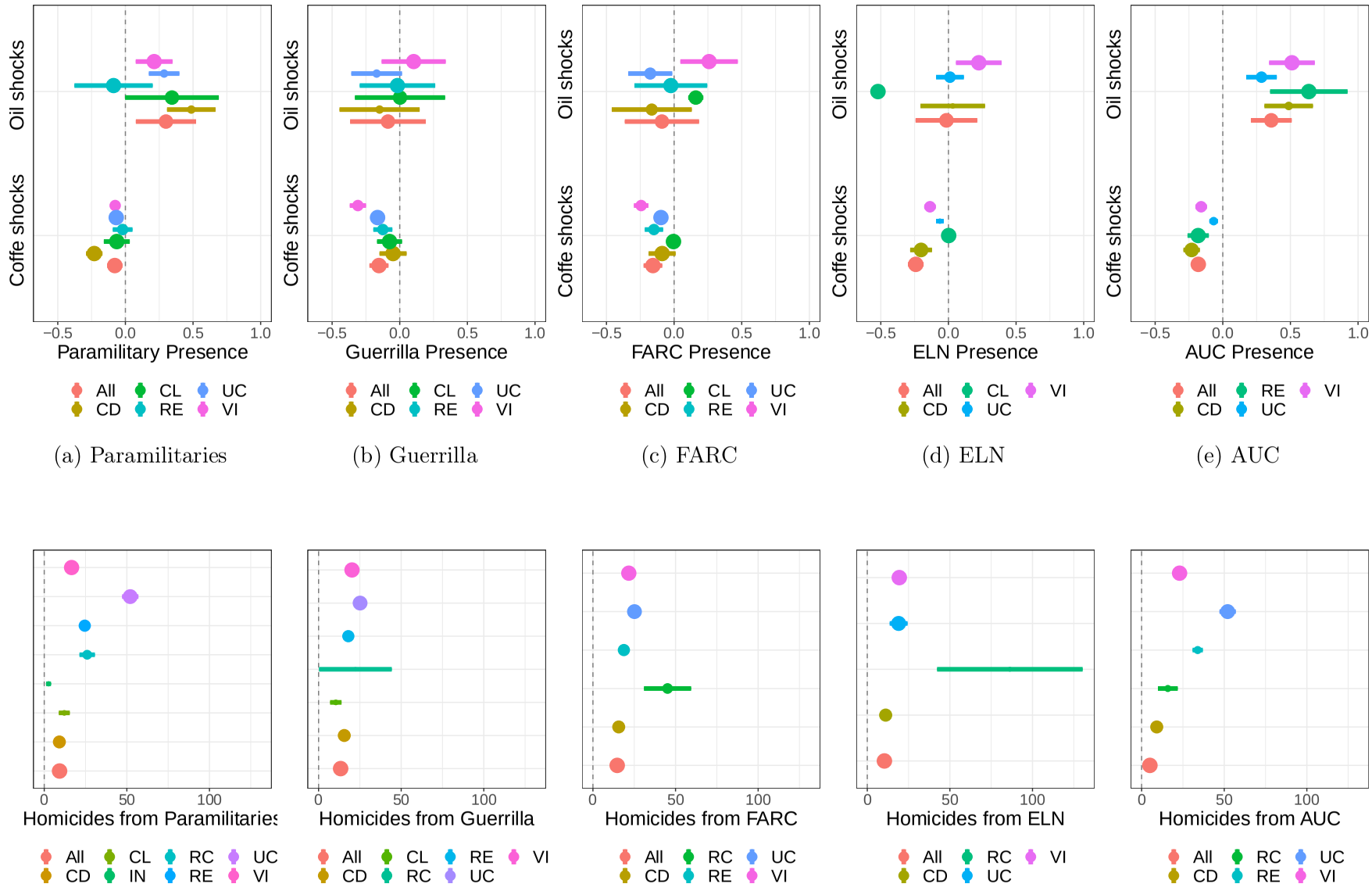
Figure 4: Average Jaccard Similarity



(a) Actor type

(b) Armed groups

Figure 5: Local Jaccard Similarity



(a) Paramilitaries (b) Guerrilla (c) FARC (d) ELN (e) AUC

(f) Paramilitaries (g) Guerrilla (h) FARC (i) ELN (j) AUC

Figure 6: Predicted Effects Using Different Measures

Appendix

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A1. Data Set Characteristics

This section presents in detail the different characteristics of the seven databases analyzed in this study. These data bases are:

- **RC**: Paramilitary presence from Rutas del Conflicto (2019).
- **CL**: Paramilitary and guerrilla groups from Claudia López (2010).
- **IN**: Narcoparamilitary group activity from Indepaz (2019).
- **CD**: Paramilitary and guerrilla attacks from Centro de Estudios Sobre Desarrollo Económico (2019).
- **VI**: Paramilitary and guerrilla violent presence from ViPAA (Osorio et al. 2019).
- **RE**: Paramilitary and guerrilla attacks from Restrepo et al. (2004).
- **UC**: Paramilitary and guerrilla violent events from the UCDP (Sundberg and Melander 2013).

Definitions

Table 1 below presents the definitions of the dependent variables used in each database.

Table 1: Definitions

Database	Object of study	Definition
INDEPAZ	Narcopraramilitary presence.	"Narcoparamilitaies "are defined as illegal armed organizations primarily focused on maximizing profit for their leaders and members. To foster their presence and expansion, [these groups] engage in pubic order and subversive activities, as long as they are related to their business" (Gonzalez Posso and Espitia 2017, p. 3). Narcoparamilitary activity "is defined as the group activity mentioned in a news article that indicates the presence of the group in a given date." [...] "This type of record indicates the presence of transit of the armed group." [. . .] "The type of activity indicates the characteristics of their presence" (Gonzalez Posso and Espitia 2017, p. 3)."
UCDP	Event of organized violence by paramilitaries or guerrilla groups.	"Event of organized violence is defined as "an individual incident (phenomenon) of lethal violence occurring at a given time and place" (Högbladh 2021, p. 4). An event is defined as "an incidente where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date" (Högbladh 2021, p. 4).
Restrepo	Bellicose actions perpetrated by paramilitaries or insurgent groups.	"Political violence is defined as violent acts exerted as a means of political-social fighting aimed at maintaining, modifying, substituting, or destroying a model of state or society, or directed to the destruction or repression of a human group, organized or not, identified by social, political, occupation, ethnic, racial, religious, cultural or ideological traits" (Restrepo et al. 2004, p. 404). "In building our database, we included only those actions that, given the descriptions found in the publication, we considered as bellicose by following the criteria of motivation and group action" (Restrepo et al. 2004, p. 404). "We also believe that this classification procedure is more objective [...] as it is based on a clear characterization of 'warfare actions' as defined by the Geneva Convention as bellicose actions. It follows that there is a wide range of events including not only clashes, but also incursions, shootings, attacks on military targets, ambushes, attacks on pipelines and energy and communication infrastructure, etc." (Restrepo et al. 2004, p. 405). "For each event we include general descriptors: date and location [...] whether or not there was a clash and, if so, the groups involved, whether or not there was an attack and, if so, the type of attack and the group(s) responsible, finally killings and injuries, the intensity measures." (Restrepo et al. 2004, p. 405).
Claudia Lopez	Paramilitary or guerrilla presence.	Presence of guerrilla or paramilitary groups at the municipal level. The source does not provide specific definitions. See López (2010).
ViPAA	Violent presence of paramilitary or guerrilla groups involved in events of political violence.	"Political violence is defined as violence used as mean of socio-political struggle with the objective of maintaining, modifying, substituting, or destroying the State or a society, or with the objective to destroy or repress a human group on the basis of their social, political, group, ethnic, racial, religious, cultural or ideological identity, whether they are organized or not" (Centro de Investigación y Educación Popular 2017, p. 14). Political violence includes: human rights violations when the State is the perpetrator, and bellicous actions when perpetrated by insurgents or non-state armed actors such as paramilitaries or criminal groups."
Rutas del Conflicto	Paramilitary presence.	Paramilitary presence at the municipal level. The source does not provide a specific definition. See Rutas del Conflicto (2019).
CEDE	Paramilitary and guerrilla attacks.	Offensive activities by armed groups. The source does not provide a specific definition. See Acevedo and Bornacelly (2014)

Measurement Set Characteristics

Table 2 presents in detail the characteristics of the different measurement sets analyzed in this study. The assessment considers the characteristics indicated below. These features are associated with a ranking that informs visualizations in Figure 1 in the body of the paper. The categories used to describe the measurement sets are:

- **Variable type**: Indicates whether the variables in each measurement set are dichotomous or count data. The ranking considers the variation in count data about the frequency of incidents more informative that dichotomous variables only indicating the presence of armed actors. Denoted as "Var" in Figure 1, this dimension considers the following categories and their respective values.
  - Dichotomous (1)
  - Count data (2)
- **Newspapers**: Indicates whether each measurement set relies on newspaper articles or not. If they do, it indicates whether the sources are international or local and whether it provides a specific list of sources or not. The assumption is that local sources are more reliable and specific than international ones. Denoted as "News" in Figure 1, this dimension includes the following levels:
  - No news (1)
  - International news - not specific (2)
  - International news - specific (3)
  - Local news - not specific (4)
  - Local news - specific (5)
- **NGOs**: Indicates whether each measurement set relies on information from NGOs or not. If they do, the values reflect if those are international or local NGOs, and whether it presents a detailed list of organizations or not. The assumption is that local NGOs are more reliable and specific than international organizations. Denoted as "NGOs" in Figure 1, this dimension includes the following levels:

  - No NGOs (1)
  - International NGOs - not specific (2)
  - International NGOs - specific (3)
  - Local NGOs - not specific (4)
  - Local NGOs - specific (5)

- **Government agencies**: Indicates whether each measurement set relies on information from government agencies or not. If they do, the values reflect if the names of those agencies are listed specifically or not. The assumption is that using information from government agencies contributes to the content of the database. Denoted as "Gov" in Figure 1, this dimension includes the following levels:
  - No government (1)
  - Government - not specific (2)
  - Government - specific (3)
- **Testimonies**: Indicates whether a measurement set relies on testimonies or interviews as part of the information sources. The assumption is that testimonies and interviews provide rich information that contributes to the content of the database. Denoted as "Test" in Figure 1, this dimension includes the following levels:
  - Does not rely on testimonies (1)
  - Relies on testimonies (2)
- **Internal Quality Assessment (IQA)**: Indicates whether or not the methodology describes the procedures put in place to internally assess the validity and quality of the data produced in each measurement set. The assumption is that a mix of manual and automated procedures yield a higher data quality and validity than only manual protocols or no IQA procedures at all. Denoted as "IQA" in Figure 1, this dimension includes the following levels:
  - No explicit IQA (1)
  - Manual IQA (2)

  - Manual and automated IQA (3)

- **External Replicability**: Indicates whether or not it is possible to replicate the output of the data independently from the researchers. The assumption is that data that allows replicabillity is more transparent. Denoted as "Rep" in Figure 1, this dimension includes the following levels:
  - No replicability (1)
  - Replicability (2)

Table 2: Measurement Set Characteristics

Measurement set	Variable type	International news agencies	International NGOs	National newspapers	Local newspapers	Local NGOs	Local HR NGOs	Government agencies	Internal quality assessment	External replicability
INDEPAZ	Dichotomous	No	No	Yes Not specific	Yes Not specific	Yes Not specific	Yes Not specific	Yes Not specific	No	No
UCDP	Count	Yes Specific list	Yes Specific list	No	No	No	No	No	Yes Manual & automated	No
Restrepo	Count	No	No	Yes Not specific	Yes Not specific	Yes Specific list	Yes Not specific	No	Yes Manual	No
Claudia Lopez	Dichotomous	No	No	No	No	Yes Specific list	Yes Specific list	Yes Specific list	No	No
ViPAA	Count	No	No	Yes Not specific	Yes Not specific	Yes Not specific	Yes Not specific	Yes Not specific	Yes Manual & automated	Yes
Rutas del Conflicto	Dichotomous	No	No	Yes Not specific	Yes Not specific	No	No	No	No	No
CEDE	Count		No	No	No	No	No	Yes Specific list	No	No

Table 3: Detail of Actors Considered by each Measurement Set

Source	Type of actor	Num. groups	Armed Groups
CEDE	Guerrilla	3	National Liberation Army (ELN), People's Revolutionary Army (ERP), Revolutionary ArmedForces of Colombia (FARC)
	Paramilitaries	1	United Self-defense forces of Colombia (AUC)
Lopez	Guerrilla	1	Generic
	Paramilitaries	1	Generic
Indepaz	Guerrilla	0	NA
	Paramilitaries	22	Aguilas Negras, Autodefensas Campesinas de Tolima, Bloque Meta, Clan del Golfo, Cordillera, EPL Los Pelusos, FIAC, La Constru, La empresa, Libertadores del Vichada, Llaneros, Los Botalones, Los del ejido, Los Pacheca, Los Policarpa, Los Rastrojos, Los Soto, Narcoparamilitar, Otros , Puntilleros, Renacer, Urabeños
Rutas del Conflicto	Guerrilla	5	Disidencia de las FARC - Columna Ricardo Franco, ELN, FARC, Grupo Guerrillero no identificado, Movimiento Armado Quintin Lame
	Paramilitaries	36	Autodefensas de Cordoba y Uraba, Autodefensas de Meta y Vichada, Carranceros, Autodefensas de Ortega, Autodefensas del Casanare, Autodefensas del Magdalena Medio, Autodefensas del Sur del Cesar, Autodefensas de Los Rojas o el Palmor, Autodefensas de Puerto Boyaca, Autodefensas de Puerto Boyaca, Autodefensas de Santander y del Sur del Cesar, Grupo Paramilitar Andaquies Caqueta, Grupo Paramilitar no identificado , Masetos, Narcoparamilitar, Paramilitares Bananero, Paramilitares Cacique Nutibara, Paramilitares Calima, Paramilitares Catatumbo, Paramilitares Centauros, Paramilitares de Hernan Giraldo, Paramilitares del Bloque, Paramilitares del Fidel Castaño, Paramilitares del Norte del Valle, Paramilitares Elmer Cardenas, Paramilitares Heroes de Granada, Paramilitares Heroes de Tolova, Paramilitares Libertadores del Sur, Paramilitares Metro, Paramilitares Mineros, Paramilitares Montes de Maria, Paramilitares Noroccidente Antioqueño, Paramilitares Norte, Paramilitares Pacifico, Paramilitares Suroeste Antioqueño, Paramilitares Tolima, Paramilitares Vencedres de Arauca
ViPPA	Guerrilla	8	19th of April Movement (M-19), Ernesto Rojas Commandos (CER), Generic mentions of insurgents, National Liberation Army (ELN), People's Revolutionary Army (ERP), Popular Liberation Army (EPL), Revolutionary Armed Forces of Colombia (FARC), Simon Bolivar Guerrilla Coordinating Board (CGSB)
	Paramilitaries	7	Generic mentions of paramilitaries , Independent paramilitary groups, Peasant Self-defense forces of Cordoba and Uraba (ACCU), Popular Revolutionary Anti-Terrorist Army of Colombia (ERPAC), Social Cleansing, United Gaitan Self-defense forces (AGU), United Self-defense forces of Colombia (AUC)
UCDP	Guerrilla	2	National Liberation Army (ELN), Revolutionary Armed Forces of Colombia (FARC)
	Paramilitaries	1	United Self-defense forces of Colombia (AUC)

A2. Dimensionality-reduction Jaccard Similarity Algorithm

Calculating Jaccard similarity in the presence of missing data can distort the similarity assessment. As discussed in the body of the article, missing data is a considerable problem in many measurement sets considered in the study, thus representing a challenge for assessing their similarity. To address this challenge, the analysis proposes a dimensionality-reduction algorithm to calculate Jaccard Similarity in the presence of missingness.

Algorithm 1 considers time (t), location (i), and measurement sets (M) as relevant dimensions to calculate the Jaccard similarity. The algorithm uses the available M and i in a given t to generate vectors as data subsets (s) and calculates their local Jaccard scores (J_{ts}) as indicated in equation 1 in the body of the manuscript.

If the data comprises subsets of different dimensions in a given year, the algorithm calculates the weighted average of the local Jaccard using the proportion of observations in each subset ($w_s = n_s/N$), such that $J_{tw} = (\sum_s^S J_{ts} w_s)(1/S)$. If there are no subsets in a given year, the algorithm directly calculates the local Jaccard (J_t) as in equation 1. After computing local Jaccard scores for each t, the algorithm generates an aggregated Jaccard score ($\overline{\mathrm{J}}$) averaging local similarity scores over time ($t = 1, ..., T$) as expressed in equation 3 in the manuscript. In this way, the algorithm only uses measures overlapping at different points in time without being affected by missing data.

Algorithm 1 Dimensionality-Reduction Jaccard Calculator

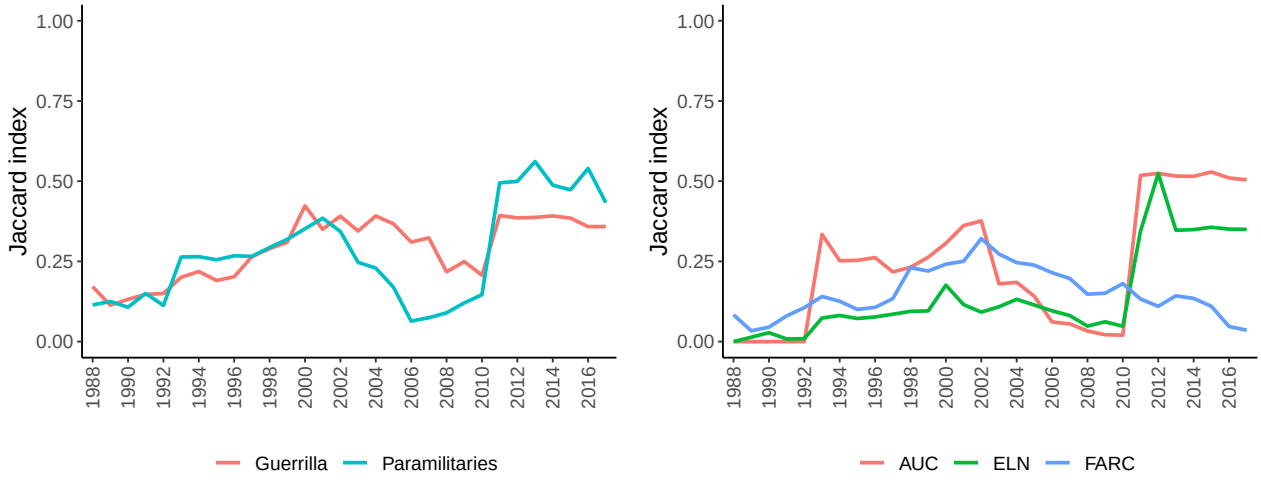
Input: Comparison set $C = \{M_1, M_2, \ldots, M_{\overline{N}}\}$

for each actor e in C **do**
  for each t in year **do**
    Subset data by t and keep all locations i
    Eliminate empty measurement sets M (columns with all NAs)
    Consider each M as a data vector
    if any available M has missing cells **then**
      Create data subsets (s) using available dimensions of i and M.
      for each s **do**
        Assign $x \leftarrow \mathbb{Z}$ as the number of measurement sets M available
        Calculate the weight w_s of each s
        if $x > 1$ **then**
          Calculate local Jaccard Index J_t for each s in time t using available M
        else
          Assign $\mathrm{J}_t = 0$ as there is no other M
        end if
      end for
      For all data subsets that exist in a given year, $\forall\ s$, $\exists\ t$,
      calculate the weighted average of Local Jaccard scores of $\forall\ s$
    else
      There are no missing cells in M
      Assign $x \leftarrow \mathbb{Z}$ as the number of measurement sets M available
      if $x > 1$ **then**
        Calculate the Local Jaccard J_t in time t using available M
      else
        Assign $\mathrm{J}_t = 0$ since there is no other M to compare to
      end if
    end if
    if Local Jaccard Index by t **then**
      Save similarity scores and plot J_t for $\forall\ t$, $\exists\ T$
    else
      For all measurement sets that exist in the comparison set, $\forall\ m$, $\exists\ C$,
      Calculate the average Jaccard $\overline{\mathrm{J}}$
      Save similarity scores and plot $\overline{\mathrm{J}}$
    end if
  end for
end for

A3. Jaccard Similarity Over Time

Figure 7 reports the temporal variation of Local Jaccard scores by actor type (Panel a) and at the group level (Panel b). Temporal oscillations in Panel (a) show that guerrilla and paramilitary similarity steadily increases until reaching an inflection point around 2000; then both series decline with paramilitaries experiencing a sharper drop; finally their similarity increases around 2010.

The time series in Panel (d) display a plateau of AUC similarity between 1993 and 2002, after which the level of agreement sharply drops, just to bounce up in 2011. The temporal fluctuation of ELN similarity follows a similar pattern, but at a lower level of agreement. Finally, FARC displays an inverse U shape reaching a similarity peak around 2002 and then experiencing a sustained decline.



(a) Actor type

(b) Armed groups

Figure 7: Local Jaccard Similarity Over Time

A4. Armed Actors ad Dependent Variable - full results

Model Specification and Control Variables in Statistical Analysis

Dube and Vargas (2013) use an two-stages least squares (2SLS) model to estimate the differential effects of oil and coffee price shocks on armed actors in Colombia. According to their study, oil shocks are expected to increase armed actor presence by promoting predatory behavior. In contrast, coffee shocks are expected to reduce armed actor presence through a labor substitution effect diverting combatants away from fighting and into legal coffee production.

The first stage of the 2SLS model considers three plausibly exogenous instruments consisting on the coffee export volume of the other three leading coffee exporting countries Brazil, Vietnam, and Indonesia, labeled here as *Top3* variable, interacted with local weather conditions of *rainfall*, *temperature* in Colombia, and the product of those two (*rainfall*×*temperature*). For simplicity, let's label rainfall as (R) and temperature as (T). The intuition is that the exogenous international shock prices of the Top 3 coffee producers interacted with local environmental conditions are likely to generate a plausibly exogenous coffee shocks measures as the variation on local coffee production (Cof_{it}) in Colombia given local coffee prices in the domestic market (CP_t). Together, Cof_{it} and CP_t constitute the internal coffee production index as coffee shocks.

Based on this intuition, the first stage of the model has the following specification:

$$\begin{aligned}(Cof_{it} \times CP_t) = \omega_1(Top3 \times R) + \omega_1(Top3 \times T) + \omega_1(Top3 \times R \times T) + \\ \lambda(Oil_{rt} \times OP_t) + \gamma Coca_{irt} + \phi X_{irt} + \alpha_i + \beta_t + \delta_{rt} + \epsilon_{irt}\end{aligned} \tag{6}$$

where $(Cof_{it} \times CP_t)$ is the endogenous coffee shock measures as the internal coffee index comprising the interaction of local coffee production (Cof_{it}) with domestic coffee prices (CP_t) in a given municipality i and year t; the instruments are the interaction of international

coffee production from Brazil, Vietnam, and Indonesia interacted with rain ($Top3 \times R$), with temperature ($Top3 \times T$), and with the product of rain and temperature ($Top3 \times R \times T$); Oil_{rt} indicates municipal oil production interacted with international oil prices OP_t; Cof_{it} represents municipal hectares of coffee cultivation interacted with domestic coffee prices CP_t derived from the first stage; $Coca_{irt}$ indicates coca cultivation as a dummy variable; X_{irt} represents time-varying controls including: municipal population (logged) and region-year (δ_{rt}); the model also includes fixed effects by municipality (α_i) and year (β_t), and the error terms (ϵ_{irt}).

The second-stage model specification has the following functional form:

$$y_{irt} = \lambda(Oil_{rt} \times OP_t) + \rho(\widehat{Cof_{it} \times CP_t}) + \gamma Coca_{irt} + \phi X_{irt} + \alpha_i + \beta_t + \delta_{rt} + \epsilon_{irt} \qquad (7)$$

where y indicates the presence of armed actor type or specific group reported in each measurement in municipality i, region r, and year t. Oil_{rt} indicates municipal oil production interacted with international oil prices OP_t; Cof_{it} represents predicted Coffee shocks as the variation of municipal hectares of coffee cultivation interacted with domestic coffee prices CP_t derived from the exogenous instruments in the first stage; $Coca_{irt}$ indicates coca cultivation as a dummy variable; X_{irt} represents time-varying controls including: municipal population (logged) and region-year (δ_{rt}); the model also includes fixed effects by municipality (α_i) and year (β_t), and the error terms (ϵ_{irt}).

For further details about the model, variables, operationalization, and sources, see Dube and Vargas (2013).

Descriptive Statistics

Table 4: Descriptive statistics

	Mean	SD	Min	Max	N
Paramilitaries(VI)	0.04	0.20	0.00	1.00	17,532
Paramilitaries(CD)	0.85	0.36	0.00	1.00	12,662
Paramilitaries(CL)	0.30	0.46	0.00	1.00	8,766
Paramilitaries(RE)	0.38	0.48	0.00	1.00	17,712
Paramilitaries(UC)	0.03	0.16	0.00	1.00	16,558
Paramilitaries(All)	0.75	0.43	0.00	1.00	17,784
Guerrilla(VI)	0.19	0.40	0.00	1.00	17,532
Guerrilla(CD)	0.47	0.50	0.00	1.00	12,662
Guerrilla(CL)	0.47	0.50	0.00	1.00	8,766
Guerrilla(RE)	0.41	0.49	0.00	1.00	17,712
Guerrilla(UC)	0.08	0.27	0.00	1.00	16,558
Guerrilla(All)	0.50	0.50	0.00	1.00	17,784
FARC(VI)	0.14	0.34	0.00	1.00	17,532
FARC(CD)	0.39	0.49	0.00	1.00	12,662
FARC(RC)	0.00	0.06	0.00	1.00	13,636
FARC(RE)	0.30	0.46	0.00	1.00	17,712
FARC(UC)	0.06	0.24	0.00	1.00	16,558
FARC(All)	0.34	0.47	0.00	1.00	17,820
ELN(VI)	0.07	0.26	0.00	1.00	17,532
ELN(CD)	0.21	0.41	0.00	1.00	12,662
ELN(RC)	0.00	0.04	0.00	1.00	4,870
ELN(UC)	0.02	0.14	0.00	1.00	16,558
ELN(All)	0.18	0.38	0.00	1.00	17,558
AUC(VI)	0.07	0.25	0.00	1.00	17,532
AUC(CD)	0.85	0.36	0.00	1.00	12,662
AUC(RC)	0.05	0.21	0.00	1.00	10,714
AUC(RE)	0.18	0.38	0.00	1.00	8,856
AUC(UC)	0.03	0.16	0.00	1.00	16,558
AUC(All)	0.62	0.49	0.00	1.00	17,666
Coffee shocks	0.53	1.08	0.00	10.43	17,604
Oil shocks	0.01	0.22	0.00	7.83	17,964
Rainfall x T3CP	6,482.27	3,486.83	493.87	35,372.03	17,964
Temperature x T3CP	73.43	17.94	12.04	111.11	17,964
Rainfall x Temperature x T3CP	142,888.15	93,272.56	11,676.94	944,433.31	17,964
Coca 94 x year	100.03	435.55	0.00	2,005.00	17,964
Population, (log)	-4.35	0.96	-8.83	-1.36	17,964
year 1989	0.06	0.23	0.00	1.00	17,964
year 1990	0.06	0.23	0.00	1.00	17,964
year 1991	0.06	0.23	0.00	1.00	17,964
year 1992	0.06	0.23	0.00	1.00	17,964
year 1993	0.06	0.23	0.00	1.00	17,964
year 1994	0.06	0.23	0.00	1.00	17,964
year 1995	0.06	0.23	0.00	1.00	17,964
year 1996	0.06	0.23	0.00	1.00	17,964
year 1997	0.06	0.23	0.00	1.00	17,964
year 1998	0.06	0.23	0.00	1.00	17,964
year 1999	0.06	0.23	0.00	1.00	17,964
year 2000	0.06	0.23	0.00	1.00	17,964
year 2001	0.06	0.23	0.00	1.00	17,964
year 2002	0.06	0.23	0.00	1.00	17,964
year 2003	0.06	0.23	0.00	1.00	17,964
year 2004	0.06	0.23	0.00	1.00	17,964
year 2005	0.06	0.23	0.00	1.00	17,964
region 2	0.15	0.35	0.00	1.00	17,964
region 3	0.10	0.30	0.00	1.00	17,964
region 4	0.15	0.35	0.00	1.00	17,964
(region 2)*year	294.07	707.58	0.00	2,005.00	17,964
(region 3)*year	202.05	602.16	0.00	2,005.00	17,964
(region 4)*year	292.07	705.58	0.00	2,005.00	17,964

Note: T3CP = Top coffee producers (log), which includes Brazil, Vietnam, and Indonesia.

Regression Results for Paramilitary Groups

Table 5 presents the results of the First-stage of the Dube and Vargas (2013) replication using coffee shocks as the endogenous variable and the three different instruments of Top 3 coffee producing countries interacted with rain, temperature, and the interaction of rain and temperature. In line with the expectations, all three different instruments are statistically significant. The models show different sample sizes because they are estimated based on the available data from the measurement sets under study. Despite the different sample sizes, the F-statistic is above the instrument validity threshold of F-stat = 10 proposed by Angrist and Pischke (2009), but all of them are below the recent F-stat = 104.7 instrument validity threshold of Lee, David et al. (2020).

Table 5: First Stage - Paramilitaries

DV: Coffee shocks	(1)	(2)	(3)	(4)	(5)	(6)
Top3 × rain	-0.002***	-0.001***	-0.003***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × temp	-0.135***	-0.107***	-0.208***	-0.135***	-0.128***	-0.135***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × rain × temp	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Oil shocks	0.072	0.099	0.020	0.075	0.070	0.076
	(0.127)	(0.118)	(0.761)	(0.106)	(0.099)	(0.098)
Coca	-0.010	-0.011	-0.020	-0.010	-0.010	-0.010
	(0.342)	(0.289)	(0.291)	(0.355)	(0.341)	(0.360)
Population	0.100	0.080	0.210	0.095	0.101	0.091
	(0.604)	(0.591)	(0.494)	(0.615)	(0.580)	(0.626)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
AP-F-statistic	15.60	15.74	15.48	15.64	15.53	15.75
AP-p-value	0.000	0.000	0.000	0.000	0.000	0.000
J-statistic	3.76	8.30	0.64	1.93	3.35	2.90
J-p-value	0.152	0.015	0.726	0.381	0.187	0.234
Observations	17190	12415	8595	17370	16235	17442
Note: *p<0.1; **p<0.05; ***p<0.01.						

However, results of the Sargan's J test in Model (2) of the First-stage cast doubt about the validity of the instruments. The J test is used to assess the over-identifying restrictions in a statistical model where the null hypothesis considers that the over-identifying restrictions

are valid. However, if the J-statistic is statistically significant and rejects the null hypothesis, then the instruments are weak and therefore cannot be trusted as valid.

Table 6 presents the results of the second-stage model for paramilitary groups using the different measurement sets as the dependent variable. The analysis shows limited support for the expectations of Dube and Vargas (2013). Although the coefficients of coffee shocks show a consistent negative direction, the CL and RE estimates fail to reach statistical significance in Models (3) and (4). Results also provide limited support for the positive effect of oil shocks on the violent presence of armed groups. Oil shocks present the expected positive relationship for VI in Model (1), CL in Model (3), and UC in Model (3). However, oil shocks do not reach statistical significance for CD in Model (2) and All in Model (6), and the oil estimate reports a negative coefficient for RE in Model (4) without reaching statistical significance.

Table 6: Second Stage - Paramilitaries

	(1)	(2)	(3)	(4)	(5)	(6)
DV: Paramilitaries	VI	CD	CL	RE	UC	All
Coffee shocks	-0.103**	-0.297**	-0.084	-0.052	-0.082**	-0.102*
	(0.002)	(0.002)	(0.125)	(0.220)	(0.002)	(0.032)
Oil shocks	0.205**	0.357	0.294*	-0.107	0.280***	0.284
	(0.003)	(0.061)	(0.030)	(0.347)	(0.000)	(0.087)
Population	0.079**	0.179*	0.086	-0.042	0.019	-0.124*
	(0.007)	(0.050)	(0.346)	(0.421)	(0.315)	(0.014)
Coca	-0.000	0.012	-0.001	0.006	0.003	0.005
	(0.863)	(0.089)	(0.924)	(0.348)	(0.147)	(0.280)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,190	12,415	8,595	17,370	16,235	17,442

Note: *p<0.1; **p<0.05; ***p<0.01.
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA;
UC=UCDP; RE=Restrepo

In general, the replication analysis provides limited support to the findings presented by Dube and Vargas (2013) when using a variety of measurement sets of paramilitary groups. As the J-statistic in Table 6 indicates, the instruments can be considered valid in most models, with the exception of Model (2). However, the expected negative effect of coffee shocks and the positive effect of oil shocks only find support when using the VI and UC measures of paramilitaries in Models (1) and (5), respectively.

Regression Results for Guerrilla Groups

Table 7 presents the results of the First-stage of the Dube and Vargas (2013) replication for guerrilla groups at the actor-type level using coffee shocks as the endogenous variable and the three instruments mentioned in the previous model. In line with the expectations, all three different instruments are statistically significant. The models show different sample sizes because they are estimated based on the available data from the measurement sets under study. Despite the different sample sizes, the F-statistic is above the instrument validity threshold of F-stat = 10 proposed by Angrist and Pischke (2009), but all of them are below the recent F-stat = 104.7 instrument validity threshold of Lee, David et al. (2020). The p-values of the Sargan J tests across models fail to reject the null hypothesis for the over-identifying assumptions, thus suggesting that the instruments are valid.

Table 7: First Stage - Guerrilla

DV: Coffee shocks	(1)	(2)	(3)	(4)	(5)	(6)
Top3 × rain	-0.002***	-0.001***	-0.003***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × temp	-0.135***	-0.107***	-0.208***	-0.135***	-0.128***	-0.135***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × rain × temp	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Oil shocks	0.072	0.099	0.020	0.075	0.070	0.076
	(0.127)	(0.118)	(0.761)	(0.106)	(0.099)	(0.098)
Coca	-0.010	-0.011	-0.020	-0.010	-0.010	-0.010
	(0.342)	(0.289)	(0.291)	(0.355)	(0.341)	(0.360)
Population	0.100	0.080	0.210	0.095	0.101	0.091
	(0.604)	(0.591)	(0.494)	(0.615)	(0.580)	(0.626)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
AP-F-statistic	15.60	15.74	15.48	15.64	15.53	15.75
AP-p-value	0.000	0.000	0.000	0.000	0.000	0.000
J-statistic	4.42	0.08	2.78	0.95	2.42	0.13
J-p-value	0.109	0.958	0.249	0.621	0.298	0.937
Observations	17190	12415	8595	17370	16235	17442

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 8 shows the results of the second-stage model for guerrilla organizations across the different measurement sets. The analysis shows limited support for the expectations of Dube and Vargas (2013). Although the coefficients of coffee shocks show a consistent negative

direction, estimates from the CD, CL, and RE regressions fail to reach statistical significance in Models (2), (3), and (4). In contrast to the expectation of a positive effect of oil shocks on the violent presence of armed groups, results of the second-stage largely contradict this expectation. The coefficient of Oil shocks only presents the expected positive relationship for VI in Model (1), but it is not statistically significant. All the other coefficients of oil shocks present a negative effect, which reaches statistical significance for CD in Model (2), UC in Model (5), and All in Model (6). The other two models (3 and 4) present a negative sign but do not reach statistical significance.

Table 8: Second Stage - Guerrilla

	(1)	(2)	(3)	(4)	(5)	(6)
DV: Guerrilla	VI	CD	CL	RE	UC	All
Coffee shocks	-0.336***	-0.051	-0.031	-0.093	-0.143**	-0.145*
	(0.000)	(0.520)	(0.579)	(0.123)	(0.002)	(0.017)
Oil shocks	0.080	-0.175*	-0.022	-0.039	-0.185***	-0.098*
	(0.282)	(0.036)	(0.576)	(0.331)	(0.000)	(0.035)
Population	0.136	-0.091	0.029	-0.138*	-0.004	-0.048
	(0.087)	(0.313)	(0.799)	(0.022)	(0.930)	(0.376)
Coca	0.015**	0.015	-0.004	0.017**	0.012***	0.009
	(0.008)	(0.068)	(0.557)	(0.002)	(0.000)	(0.086)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,190	12,415	8,595	17,370	16,235	17,442

Note: *p<0.1; **p<0.05; ***p<0.01.
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA;
UC=UCDP; RE=Restrepo

Overall, the statistical assessment largely fails to provide support to the argument advanced by Dube and Vargas (2013) when analyzing guerrilla organizations at the actor-type level. Despite the validity of the instruments in the first stage (see J-stat in Table 8), estimates of coffee and oil shocks present contradictory or uncertain estimates.

Regression Results for FARC

Table 9 presents the results of the First-stage of the Dube and Vargas (2013) replication for the FARC insurgency using coffee shocks as the endogenous variable and the three different instruments. In line with the expectations, all three different instruments are statistically significant. The models show different sample sizes because they are estimated based on the available data from the measurement sets under study. Despite the different sample sizes, the F-statistic is above the instrument validity threshold of F-stat = 10 proposed by Angrist and Pischke (2009), but all of them are below the recent F-stat = 104.7 instrument validity threshold of Lee, David et al. (2020). However, the Sargan's J test for the over-identifying restrictions of the First-stage reject the null hypothesis in Models (1) and (3), which raises concerns about the validity of the instruments.

Table 9: First Stage - FARC

DV: Coffee shocks	(1)	(2)	(3)	(4)	(5)	(6)
Top3 × rain	-0.002***	-0.001***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × temp	-0.135***	-0.107***	-0.151***	-0.135***	-0.128***	-0.135***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × rain × temp	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Oil shocks	0.072	0.099	0.070	0.075	0.070	0.077
	(0.127)	(0.118)	(0.238)	(0.106)	(0.099)	(0.096)
Coca	-0.010	-0.011	-0.012	-0.010	-0.010	-0.009
	(0.342)	(0.289)	(0.343)	(0.355)	(0.341)	(0.362)
Population	0.100	0.080	0.131	0.095	0.101	0.092
	(0.604)	(0.591)	(0.565)	(0.615)	(0.580)	(0.623)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
AP-F-statistic	15.60	15.74	15.41	15.64	15.53	15.74
AP-p-value	0.000	0.000	0.000	0.000	0.000	0.000
J-statistic	5.15	0.44	6.59	1.56	2.06	0.59
J-p-value	0.076	0.802	0.037	0.457	0.357	0.746
Observations	17190	12415	13370	17370	16235	17478

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 10 reports the results of the second-stage model for the FARC insurgency. The analysis fails to find support for the Dube and Vargas (2013) study. Although the coffee shocks estimates show a consistent negative sign across models, estimates from the CD, RC,

and RE analysis do not reach statistical significance in Models (2), (3), and (4). In contrast to the expectation of a positive effect of oil shocks on the violent presence of armed groups, results of the second-stage largely contradict this expectation. The expected positive effect of Oil shocks on the violent presence of armed actors only reports a positive sign with statistical significance for VI in Model (1) and RC in Model (3). In contrast, estimates from CD, UC, and All present a negative effect and reach statistical significance, thus contradicting the expectation. Model (4) also presents a negative sign for FARC insurgents measured by RE, but if fails to reach statistical significance.

Table 10: Second Stage - FARC

	(1)	(2)	(3)	(4)	(5)	(6)
DV: FARC	VI	CD	RC	RE	UC	All
Coffee shocks	-0.263***	-0.093	-0.005	-0.107	-0.091**	-0.132*
	(0.000)	(0.126)	(0.252)	(0.141)	(0.003)	(0.049)
Oil shocks	0.228**	-0.197*	0.157***	-0.045	-0.191***	-0.105*
	(0.006)	(0.012)	(0.000)	(0.248)	(0.000)	(0.036)
Population	0.115	-0.067	-0.006	-0.104	0.004	-0.039
	(0.086)	(0.399)	(0.451)	(0.051)	(0.888)	(0.489)
Coca	0.012*	0.017*	0.001	0.018***	0.010*	0.013*
	(0.016)	(0.019)	(0.340)	(0.001)	(0.012)	(0.014)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,190	12,415	13,370	17,370	16,235	17,478

Note: *p<0.1; **p<0.05; ***p<0.01.
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA;
UC=UCDP; RE=Restrepo

The overall assessment fails to support the argument of Dube and Vargas (2013) when analyzing different measures of the FARC insurgency. As indicated in the J-test in the first-stage Table 9, the proposed instruments are valid in Models (2), (4), (5), and (6). However, none of these models support the expectations from Dube and Vargas (2013) as they present contradictory or uncertain results in the second stage.

Regression Results for ELN

Table 11 presents the results of the First-stage of the Dube and Vargas (2013) replication using coffee shocks as the endogenous variable and the three different instruments of Top 3 coffee producing countries interacted with rain, temperature, and the interaction of rain and temperature. In line with the expectations, all three different instruments are statistically significant. The models show different sample sizes because they are estimated based on the available data from the measurement sets under study. Despite the different sample sizes, the F-statistic is above the instrument validity threshold of F-stat = 10 proposed by Angrist and Pischke (2009), but all of them are below the recent F-stat = 104.7 instrument validity threshold of Lee, David et al. (2020). However, results of the Sargan's J test cast doubt about the validity of the instruments in Models (2) and (5).

Table 11: First Stage - ELN

DV: Coffee shocks	(1)	(2)	(3)	(4)	(5)
Top3 × rain	-0.002***	-0.001***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × temp	-0.135***	-0.107***	-0.253***	-0.128***	-0.135***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × rain × temp	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Oil shocks	0.072	0.099	0.040	0.070	0.072
	(0.127)	(0.118)	(0.641)	(0.099)	(0.127)
Coca	-0.010	-0.011	-0.030	-0.010	-0.010
	(0.342)	(0.289)	(0.337)	(0.341)	(0.340)
Population	0.100	0.080	0.294	0.101	0.100
	(0.604)	(0.591)	(0.509)	(0.580)	(0.605)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes
AP-F-statistic	15.60	15.74	15.72	15.53	15.61
AP-p-value	0.000	0.000	0.000	0.000	0.000
J-statistic	4.24	5.65	0.98	2.42	4.86
J-p-value	0.120	0.059	0.612	0.298	0.088
Observations	17190	12415	4775	16235	17216
Note: *p<0.1; **p<0.05; ***p<0.01.					

Table 12 presents the results of the second-stage model for the ELN guerrilla organization. The analysis finds limited support for the Dube and Vargas (2013) study. Although coffee shocks show a consistent negative sign across models, estimates from RC fail to reach

statistical significance in Model (3). The expectation related to the positive association between oil shocks and the violent presence of armed actors only finds support for the ELN measure by VI data in Model (1). The coefficients Models (2), (4) and (5) present a positive sign for the CD, UC, and All measures of the ELN insurgency, but do not reach statistical significance. In contrast, Model (3) presents a negative sign with high statistical significance for the RC measure.

Table 12: Second Stage - ELN

	(1)	(2)	(3)	(4)	(5)
DV: ELN	VI	CD	RC	UC	All
Coffee shocks	-0.139*	-0.139*	-0.000	-0.049*	-0.188*
	(0.024)	(0.022)	(0.937)	(0.031)	(0.013)
Oil shocks	0.226**	0.039	-0.529***	0.013	-0.013
	(0.007)	(0.487)	(0.000)	(0.613)	(0.790)
Population	0.060	-0.029	0.023*	-0.009	0.077
	(0.173)	(0.721)	(0.045)	(0.690)	(0.244)
Coca	0.003	0.012*	-0.002	0.002	0.008
	(0.177)	(0.023)	(0.287)	(0.246)	(0.125)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	17,190	12,415	4,775	16,235	17,216

Note: *p<0.1; **p<0.05; ***p<0.01.
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; UC=UCDP; RE=Restrepo

Overall, the results provide limited support for the Dube and Vargas (2013) argument when analyzing the ELN guerrilla organization. As indicated in the first-stage post-estimation assessment in Table 11, the instruments are valid only in Models (1), (3), and (5), but only the second-stage results of Model (1) support the Dube and Vargas (2013) argument for for VI, while RC and All provide contradictory or uncertain estimates.

Regression Results for AUC

Table 13 presents the results of the First-stage of the Dube and Vargas (2013) replication using coffee shocks as the endogenous variable and the three different instruments of Top 3 coffee producing countries interacted with rain, temperature, and the interaction of rain and temperature. In line with the expectations, all three different instruments are statistically significant in the First-stage analysis. The models show different sample sizes because they are estimated based on the available data from the measurement sets under study. Despite the different sample sizes, the F-statistic is above the instrument validity threshold of F-statistic = 10 proposed by Angrist and Pischke (2009), but all of them are below the instrument validity threshold of F-stat = 104.7 by Lee, David et al. (2020). However, results of the Sargan's J test reject the null hypothesis for all models with the exception of Model (5), thus casting doubt about the validity of the instruments.

Table 13: First Stage - AUC

DV: Coffee shocks	(1)	(2)	(3)	(4)	(5)	(6)
Top3 × rain	-0.002***	-0.001***	-0.002***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × temp	-0.135***	-0.107***	-0.121***	-0.208***	-0.128***	-0.135***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top3 × rain × temp	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Oil shocks	0.072	0.099	0.063	0.026	0.070	0.069
	(0.127)	(0.118)	(0.334)	(0.671)	(0.099)	(0.133)
Coca	-0.010	-0.011	-0.013	-0.019	-0.010	-0.011
	(0.342)	(0.289)	(0.316)	(0.306)	(0.341)	(0.331)
Population	0.100	0.080	0.137	0.205	0.101	0.100
	(0.604)	(0.591)	(0.492)	(0.497)	(0.580)	(0.602)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
AP-F-statistic	15.60	15.74	15.52	15.51	15.53	15.62
AP-p-value	0.000	0.000	0.000	0.000	0.000	0.000
J-statistic	9.14	8.30	8.07	9.13	3.35	10.94
J-p-value	0.010	0.015	0.017	0.010	0.187	0.004
Observations	17190	12415	10505	8685	16235	17324
Note: *p<0.1; **p<0.05; ***p<0.01.						

Table 14 presents the results of the second-stage model for the AUC paramilitary organization. In general, the analysis finds moderate support for the Dube and Vargas (2013)

study. All the coffee shocks coefficients report negative effect across models, but the point estimate from RC in Model (3) fails to reach statistical significance. In line with the expected positive sing of oil shocks on the violent presence of the AUC, the second-stage results report a positive effect across Table 14. With the exception of the CD measure of AUC paramilitaries in Model (2), the coefficient of oil shocks reach statistical significance across all models. However, as indicated in the first-stage results of the J-test in Table 13, only the results of Model (5) can be trusted, since all other models have flawed instruments. Therefore, the results originally presented by Dube and Vargas (2013) only find support when analyzing AUC paramilitaries with the UC measure.

Table 14: Second Stage - AUC

	(1)	(2)	(3)	(4)	(5)	(6)
DV: AUC	VI	CD	RC	RE	UC	All
Coffee shocks	-0.220***	-0.297**	-0.026	-0.235***	-0.082**	-0.261***
	(0.000)	(0.002)	(0.489)	(0.000)	(0.002)	(0.001)
Oil shocks	0.500***	0.357	0.081***	0.540*	0.280***	0.308*
	(0.000)	(0.061)	(0.001)	(0.019)	(0.000)	(0.024)
Population	0.108	0.179*	0.070	0.105	0.019	0.127
	(0.094)	(0.050)	(0.118)	(0.305)	(0.315)	(0.111)
Coca	0.008*	0.012	0.011*	0.025**	0.003	0.007*
	(0.016)	(0.089)	(0.021)	(0.009)	(0.147)	(0.036)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,190	12,415	10,505	8,685	16,235	17,324

Note: *p<0.1; **p<0.05; ***p<0.01.
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA;
UC=UCDP; RE=Restrepo

A5. Armed Actors as Independent Variable - full results

Model Specification and Control Variables in Statistical Analysis

The statistical analysis reported in the lower row of Figure 6 in the manuscript evaluates the effect of using different measures of armed actor presence as independent variables. This statistical analysis uses the following model specification:

$$y_{it} = \alpha_i + \beta A_{it} + \delta X_{it} + \epsilon_{it} \tag{8}$$

where y_{it} is the homicide rate reported by the Colombian Police (Moreno 2014). The term A_{it} refers to the type of actor or specific groups reported in each measurement; X_{it} is a matrix of controls described below; α_i are municipal fixed effects, and ϵ_{it} represents the error terms.

This section presents the list of control variables used in the empirical evaluations conducted in this analysis. All the statistical models in the analysis include a rich set of control variables captured in the matrix X of the model specification in equation 8. The set of controls includes the following variables:

- The Gross Domestic Product per capita (*GDP pc*) at the department level as reported by DANE (2016). GDP is deflated to express real prices in 2005 (The World Bank 2016). This variable helps to take into account the relations between poverty and violence which could be interpreted as a measure of greed by Collier and Hoeffler (2004) or as state weakness by Fearon and Laitin (2003).
- The control variables also include data about *coca cultivation* and *oil production* with data from (Centro de Estudios Sobre Desarrollo Económico 2019). These variables account for the relationship between natural resources and conflict (Collier and Hoeffler 2004; Ross 2006; Fearon 2005, 2004).
- The model also uses the size of the municipal *population* and is its quadratic form *Population sqr.* with data from (Centro de Estudios Sobre Desarrollo Económico 2019).

This curvilienar relationship helps to model the difference between rural areas and large urban centers as they may provide distinct mechanism for violence.

- To account for the effect of Plan Colombia on the dynamics of conflict, the model uses the log of *Plan Colombia Military* funds provided by the U.S. as well as the log of *Plan Colombia Economic* aid for development.
- The controls also include a set of cross-sectional invariant dummy variables *Barco Negotiations* and *Pastrana Negotiations* taking the value of 1 for the years during which the government held peace talks with guerrilla groups in the administration of President Virgilio Barco (1990-91) and President Manuel Pastrana (1998-1999), and 0 otherwise.
- To account for the aggressive military campaign launched by the administration of President Alvaro Uribe (2002-2006), the model includes a dummy variable called *Plan Patriota*, which was the name of this military operation, and takes the value of 1 during his administration, and 0 otherwise.
- The analysis also includes a dummy variable for presidential *elections* that may offer political opportunities for guerrilla attacks or paramilitary assassinations. This variable takes the value of 1 for years when presidential elections took place in Colombia, and 0 otherwise.
- In addition, the model includes dummy variables for the municipalities that report *land mines* in any given year with data from (Centro de Estudios Sobre Desarrollo Económico 2019).
- The variable *Medellin Offensive* accounts for the confrontation period between the state and the Medellin cartel that affected Colombia between 1989 and 1993. This is a cross-sectional invariant variable taking the value of 1 for the 1989-1993 period, and 0 otherwise. Although the Medellin Cartel was located in municipality of Medellín, Antioquia, the cartel conducted violent attacks against the state and civilian targets in different parts of the country. For this reason, this variable only considers temporal variation.

- The model also includes a dummy variable for *reservations* that refer to areas designated as national parks.
- Finally, the statistical analysis includes municipality and year Fixed Effects in all its specifications. This helps to control for unit and time specific unobserved factors.

Descriptive statistics

Table 15: Descriptive statistics

	Mean	St. Dev.	Min	Max	N
Homicide rate	46.4	67.5	0.0	1,327.9	34,782
Paramilitaries (VI)	0.1	0.3	0.0	1.0	33,000
Paramilitaries (CD)	0.7	0.4	0.0	1.0	27,500
Paramilitaries (CL)	0.3	0.5	0.0	1.0	9,900
Paramilitaries (IN)	0.3	0.5	0.0	1.0	8,800
Paramilitaries (RE)	0.3	0.5	0.0	1.0	26,312
Paramilitaries (UC)	0.01	0.1	0.0	1.0	31,900
Paramilitaries (All)	0.7	0.5	0.0	1.0	34,118
Guerrilla (VI)	0.2	0.4	0.0	1.0	33,000
Guerrilla (CD)	0.6	0.5	0.0	1.0	27,500
Guerrilla (CL)	0.5	0.5	0.0	1.0	9,900
Guerrilla (RE)	0.4	0.5	0.0	1.0	26,312
Guerrilla (UC)	0.1	0.2	0.0	1.0	31,900
Guerrilla (All)	0.6	0.5	0.0	1.0	34,118
FARC (VI)	0.1	0.3	0.0	1.0	33,000
FARC (CD)	0.3	0.5	0.0	1.0	27,500
FARC (RC)	0.003	0.1	0.0	1.0	22,000
FARC (RE)	0.3	0.5	0.0	1.0	26,312
FARC (UC)	0.05	0.2	0.0	1.0	31,900
FARC (All)	0.3	0.5	0.0	1.0	34,118
ELN (VI)	0.1	0.2	0.0	1.0	33,000
ELN (CD)	0.4	0.5	0.0	1.0	27,500
ELN (RC)	0.001	0.03	0.0	1.0	7,700
ELN (UC)	0.01	0.1	0.0	1.0	31,900
ELN (All)	0.4	0.5	0.0	1.0	33,050
AUC (VI)	0.1	0.2	0.0	1.0	33,000
AUC (CD)	0.7	0.4	0.0	1.0	27,500
AUC (RC)	0.05	0.2	0.0	1.0	13,200
AUC (RE)	0.1	0.3	0.0	1.0	16,016
AUC (UC)	0.01	0.1	0.0	1.0	31,900
AUC (All)	0.6	0.5	0.0	1.0	33,694
Coca plantations	0.7	1.8	0.000	9.7	34,782
Oil	52.5	31.1	15.9	98.1	34,782
Mines	0.7	4.9	0.0	232.0	34,782
Elections	0.4	0.5	0.0	1.0	34,782
Population	9.5	1.1	5.1	15.9	34,782
Population sqr.	91.8	21.9	25.6	251.3	34,782
Plan Colombia military	4.2	2.6	0.0	6.7	34,782
Plan Colombia economic	3.1	2.4	0.0	5.5	34,782
Pastrana peace	0.2	0.4	0.0	1.0	34,782
Barco peace	0.1	0.2	0.0	1.0	34,782
Plan Patriota	0.1	0.3	0.0	1.0	34,782
Medellin offensive	0.02	0.1	0.0	1.0	34,782
GDP pc	1,708.4	2,715.1	4.1	38,546.1	34,782
National Parks	0.1	0.3	0.0	1.0	34,782

CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo

Summary of Results

The tables below present the summary of statistical results as well as the full regression tables for the analysis using the different measures of armed actor violent presence as the independent variable. In particular, Table 16 presents the summary of relevant coefficients for paramilitary groups at the actor-type level in Panel (a) and for guerrilla organizations in Panel (b). In addition, Table 17 presents the summary of the organization-level analysis for the FARC insurgency in Panel (a), the ELN guerrilla in Panel (b), and the AUC paramilitary organization in Panel (c). In addition, Tables 18-22 present the full regression results for each correspondent level of analysis using the different measurement sets considered in the study.

Table 16: Summary of Regression Results by Type of Armed Actor

	Dependent variable: Homicide rate							
Panel (a) Paramilitaries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Paramilitaries (VI)	16.55***							
	(1.34)							
Paramilitaries (CD)		9.16***						
		(0.92)						
Paramilitaries (RE)			24.53***					
			(0.99)					
Paramilitaries_CL				12.14***				
				(1.70)				
Paramilitaries_IN					2.61***			
					(0.75)			
Paramilitaries (RC)						26.00***		
						(2.38)		
Paramilitaries (UC)							52.06***	
							(2.52)	
Paramilitaries (All)								9.28***
								(0.78)
Controls included	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controls dropped	0	1	0	2	4	0	0	0
Observations	33,000	27,500	25,668	9,900	8,800	19,800	31,900	33,474

	Dependent variable: Homicide rate						
Panel (b) Guerrilla	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Guerrilla (VI)	20.21***						
	(0.99)						
Guerrilla (CD)		15.55***					
		(0.80)					
Guerrilla (RE)			18.00***				
			(0.97)				
Guerrilla_CL				10.42***			
				(1.77)			
Guerrilla (RC)					22.30**		
					(11.23)		
Guerrilla (UC)						25.12***	
						(1.43)	
Guerrilla (All)							13.35***
							(0.79)
Controls included	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controls dropped	0	1	0	2	3	0	0
Observations	33,000	27,500	25,668	9,900	6,600	31,900	33,474

Note: *p<0.1; **p<0.05; ***p<0.01.
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo.

Table 17: Summary of Regression Results by Specific Armed Group

	Dependent variable: Homicide rate					
Panel (a) FARC	(1)	(2)	(3)	(4)	(5)	(6)
FARC (VI)	21.71***					
	(1.10)					
FARC (CD)		15.61***				
		(0.84)				
FARC (RC)			45.17***			
			(7.29)			
FARC (RE)				18.73***		
				(1.04)		
FARC (UC)					25.14***	
					(1.61)	
FARC (All)						14.69***
						(0.81)
Controls included	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controls dropped	0	1	0	0	0	0
Observations	33,000	27,500	22,000	25,668	31,900	33,474

	Dependent variable: Homicide rate					
Panel (b) ELN	(1)	(2)	(3)	(4)	(5)	
ELN (VI)	19.37***					
	(1.42)					
ELN (CD)		11.13***				
		(0.86)				
ELN (RC)			86.30***			
			(22.48)			
ELN (UC)				18.97***		
				(2.76)		
ELN (All)					10.37***	
					(0.86)	
Controls included	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	
Controls dropped	0	1	3	0	0	
Observations	33,000	27,500	7,700	31,900	33,050	

	Dependent variable: Homicide rate					
Panel (c) AUC	(1)	(2)	(3)	(4)	(5)	(6)
AUC (VI)	22.97***					
	(1.40)					
AUC (CD)		9.16***				
		(0.92)				
AUC (RC)			15.87***			
			(3.06)			
AUC (RE)				33.93***		
				(1.59)		
AUC (UC)					52.06***	
					(2.52)	
AUC (All)						5.01***
						(0.77)
Controls included	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controls dropped	0	1	2	2	0	0
Observations	33,000	27,500	13,200	15,624	31,900	33,302

Note: *p<0.1; **p<0.05; ***p<0.01

CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo.

Regression Results for Paramilitary Groups

Table 18: Regression Results for Paramilitary Groups

	Dependent variable: Homicide rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Paramilitaries (VI)	16.55***							
	(1.34)							
Paramilitaries (CD)		9.16***						
		(0.92)						
Paramilitaries (RE)			24.53***					
			(0.99)					
Paramilitaries_CL				12.14***				
				(1.70)				
Paramilitaries_IN					2.61***			
					(0.75)			
Paramilitaries (RC)						26.00***		
						(2.38)		
Paramilitaries (UC)							52.06***	
							(2.52)	
Paramilitaries (All)								9.28***
								(0.78)
Coca	2.01***	2.05***	1.59***	1.81**	0.16	0.71	2.12***	2.19***
	(0.39)	(0.40)	(0.47)	(0.81)	(0.51)	(0.62)	(0.39)	(0.38)
Oil	−0.38***	−0.44***	−0.18***	0.13	0.03	−0.06	−0.39***	−0.39***
	(0.02)	(0.02)	(0.03)	(0.12)	(0.03)	(0.08)	(0.02)	(0.02)
Mines	1.03***	1.02***	1.58***	2.51***	0.25***	2.91***	1.09***	1.07***
	(0.07)	(0.06)	(0.09)	(0.21)	(0.04)	(0.16)	(0.07)	(0.07)
Elections	0.03	−0.01	−0.85	2.76	1.08	0.34	0.54	−1.14*
	(0.69)	(0.70)	(0.89)	(3.56)	(0.86)	(1.08)	(0.69)	(0.69)
Population	78.03***	9.79	78.53***	−221.65*	156.65*	148.65***	45.57**	62.06***
	(21.44)	(26.06)	(27.13)	(120.17)	(81.76)	(44.34)	(22.03)	(19.63)
Population sqr.	−4.86***	−1.15	−5.41***	8.66	−10.02**	−9.69***	−3.08***	−4.02***
	(1.10)	(1.34)	(1.40)	(6.15)	(4.18)	(2.26)	(1.13)	(1.01)
Plan Colombia military $	0.23	1.02***	0.27	−2.58	−11.67	−0.03	0.01	−0.01
	(0.29)	(0.32)	(0.31)	(5.84)	(7.76)	(0.36)	(0.30)	(0.29)
Plan Colombia economic $	−0.17	0.74**	−0.85**	0.24	26.86*	0.30	0.55	0.61*
	(0.35)	(0.34)	(0.38)	(1.85)	(14.09)	(0.43)	(0.35)	(0.35)
Pastrana peace	4.09***	0.07	3.97***	−0.64		1.52	1.66	2.61**
	(1.26)	(1.28)	(1.38)	(2.82)		(1.55)	(1.25)	(1.25)
Barco peace	1.95		−0.69			−0.19	2.07	5.23***
	(1.37)		(1.46)			(1.65)	(1.38)	(1.37)
Plan Patriota	−0.36	0.50	−1.93	−17.05***		−16.37***	−1.43	1.49
	(1.18)	(1.12)	(1.27)	(2.96)		(2.60)	(1.17)	(1.18)
Medellin Offensive	53.27***	36.01***	48.30***			42.44***	57.32***	52.66***
	(2.51)	(4.75)	(2.74)			(3.25)	(2.50)	(2.49)
GDP pc	−0.003***	−0.004***	−0.01***	−0.01***	0.001**	−0.004***	−0.003***	−0.003***
	(0.0003)	(0.0003)	(0.001)	(0.003)	(0.0005)	(0.001)	(0.0003)	(0.0003)
National park	11.52**	5.77	16.52***	−7.28	3.80	21.01**	6.64	12.29***
	(4.68)	(5.15)	(5.75)	(15.97)	(13.33)	(8.83)	(4.92)	(4.43)
Observations	33,000	27,500	25,668	9,900	8,800	19,800	31,900	33,474

Note: *p<0.1; **p<0.05; ***p<0.01

CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo

Regression Results for Guerrilla Groups

Table 19: Regression Results for Guerrilla Groups

	Dependent variable: Homicide rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Guerrilla (VI)	20.21***						
	(0.99)						
Guerrilla (CD)		15.55***					
		(0.80)					
Guerrilla (RE)			18.00***				
			(0.97)				
Guerrilla_CL				10.42***			
				(1.77)			
Guerrilla (RC)					22.30**		
					(11.23)		
Guerrilla (UC)						25.12***	
						(1.43)	
Guerrilla (All)							13.35***
							(0.79)
Coca	1.96***	1.93***	1.81***	1.80**	1.33	2.17***	2.20***
	(0.39)	(0.40)	(0.47)	(0.82)	(1.08)	(0.39)	(0.38)
Oil	−0.34***	−0.48***	−0.37***	0.15	0.20**	−0.35***	−0.45***
	(0.02)	(0.02)	(0.03)	(0.12)	(0.10)	(0.02)	(0.02)
Mines	0.94***	0.98***	1.49***	2.43***	3.75***	0.97***	1.07***
	(0.07)	(0.06)	(0.09)	(0.21)	(0.32)	(0.07)	(0.07)
Elections	0.04	−0.59	−0.60	3.26	36.94***	0.37	−0.66
	(0.69)	(0.69)	(0.90)	(3.56)	(6.41)	(0.69)	(0.68)
Population	71.84***	−4.57	95.68***	−255.23**	−265.01**	49.87**	55.47***
	(21.28)	(25.93)	(27.27)	(120.17)	(130.58)	(22.07)	(19.60)
Population sqr.	−4.58***	−0.44	−6.34***	10.43*	12.48*	−3.33***	−3.68***
	(1.09)	(1.33)	(1.40)	(6.15)	(6.69)	(1.13)	(1.01)
Plan Colombia military $	−0.03	0.62**	0.32	−0.86	63.03***	0.21	0.16
	(0.29)	(0.31)	(0.32)	(5.84)	(9.77)	(0.30)	(0.29)
Plan Colombia economic $	−0.54	−0.02	−0.25	−0.28	−17.01***	−0.14	0.03
	(0.35)	(0.33)	(0.38)	(1.85)	(3.07)	(0.35)	(0.35)
Pastrana peace	−0.31	3.14***	3.89***	−0.91	−0.31	3.90***	2.71**
	(1.28)	(1.18)	(1.39)	(2.82)	(3.64)	(1.25)	(1.24)
Barco peace	1.19		2.60*			1.87	3.25**
	(1.36)		(1.46)			(1.38)	(1.34)
Plan Patriota	−2.00*	−0.53	−0.82	−17.58***		−3.32***	−0.22
	(1.18)	(1.10)	(1.28)	(2.96)		(1.18)	(1.16)
Medellin Offensive	53.65***	34.75***	50.88***			56.10***	52.67***
	(2.50)	(4.73)	(2.75)			(2.51)	(2.48)
GDP pc	−0.003***	−0.004***	−0.01***	−0.01***	−0.004*	−0.003***	−0.004***
	(0.0003)	(0.0003)	(0.001)	(0.003)	(0.002)	(0.00)	(0.00)
National park	12.07***	6.04	15.81***	−7.74	−0.85	6.68	13.22***
	(4.66)	(5.13)	(5.78)	(15.99)	(17.07)	(4.93)	(4.42)
Observations	33,000	27,500	25,668	9,900	6,600	31,900	33,474

Note: *p<0.1; **p<0.05; ***p<0.01
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo

Regression Results for FARC

Table 20: Regression Results for FARC

	Dependent variable: Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
FARC (VI)	21.71***					
	(1.10)					
FARC (CD)		15.61***				
		(0.84)				
FARC (RC)			45.17***			
			(7.29)			
FARC (RE)				18.73***		
				(1.04)		
FARC (UC)					25.14***	
					(1.61)	
FARC (All)						14.69***
						(0.81)
Coca	2.04***	1.73***	1.93***	1.88***	2.11***	2.02***
	(0.39)	(0.40)	(0.50)	(0.47)	(0.39)	(0.38)
Oil	−0.34***	−0.33***	−0.37***	−0.33***	−0.36***	−0.32***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Mines	0.94***	0.92***	1.11***	1.44***	0.98***	1.00***
	(0.07)	(0.06)	(0.08)	(0.09)	(0.07)	(0.07)
Elections	0.07	0.90	5.15***	−1.50*	0.24	0.32
	(0.69)	(0.69)	(1.12)	(0.90)	(0.69)	(0.68)
Population	70.48***	17.24	69.85**	96.14***	52.11**	73.93***
	(21.29)	(25.94)	(32.12)	(27.28)	(22.09)	(19.58)
Population sqr.	−4.51***	−1.54	−4.65***	−6.37***	−3.45***	−4.64***
	(1.09)	(1.33)	(1.64)	(1.41)	(1.13)	(1.01)
Plan Colombia military $	0.09	0.11	1.99***	0.20	0.27	−0.08
	(0.29)	(0.31)	(0.37)	(0.32)	(0.30)	(0.29)
Plan Colombia economic $	−0.64*	−0.62*	−0.96**	−0.36	−0.13	−0.54
	(0.35)	(0.33)	(0.40)	(0.38)	(0.35)	(0.35)
Pastrana peace	0.73	4.77***	3.94***	4.28***	4.00***	4.14***
	(1.27)	(1.17)	(1.42)	(1.39)	(1.25)	(1.23)
Barco peace	1.53		2.76*	2.75*	1.99	1.62
	(1.36)		(1.62)	(1.46)	(1.38)	(1.34)
Plan Patriota	−1.71	−2.37**	−3.63***	−1.84	−2.67**	−2.08*
	(1.18)	(1.11)	(1.35)	(1.28)	(1.18)	(1.16)
Medellin Offensive	53.45***	35.29***	66.13***	50.80***	55.76***	53.67***
	(2.50)	(4.73)	(3.42)	(2.75)	(2.51)	(2.48)
GDP pc	−0.003***	−0.003***	−0.004***	−0.01***	−0.003***	−0.003***
	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.0003)
National park	11.41**	4.83	6.34	14.88**	6.15	11.78***
	(4.67)	(5.13)	(6.76)	(5.78)	(4.93)	(4.41)
Observations	33,000	27,500	22,000	25,668	31,900	33,474
R^2	0.10	0.10	0.08	0.08	0.10	0.10
Adjusted R^2	0.07	0.06	0.03	0.03	0.07	0.07

Note: *p<0.1; **p<0.05; ***p<0.01
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo

Regression Results for ELN

Table 21: Regression Results for ELN

	Dependent variable: Homicide rate				
	(1)	(2)	(3)	(4)	(5)
ELN (VI)	19.37***				
	(1.42)				
ELN (CD)		11.13***			
		(0.86)			
ELN (RC)			86.30***		
			(22.48)		
ELN (UC)				18.97***	
				(2.76)	
ELN (All)					10.37***
					(0.86)
Coca	2.09***	2.11***	2.09**	2.20***	2.28***
	(0.39)	(0.40)	(0.95)	(0.39)	(0.39)
Oil	−0.36***	−0.50***	−0.40***	−0.37***	−0.48***
	(0.02)	(0.02)	(0.06)	(0.02)	(0.03)
Mines	1.05***	0.98***	1.64***	1.06***	1.06***
	(0.07)	(0.06)	(0.19)	(0.07)	(0.07)
Elections	−0.13	−0.49	−7.81***	−0.08	−1.03
	(0.69)	(0.70)	(2.55)	(0.69)	(0.70)
Population	64.73***	1.44	−283.07***	46.94**	57.34***
	(21.35)	(26.03)	(96.20)	(22.16)	(21.23)
Population sqr.	−4.16***	−0.74	13.82***	−3.17***	−3.82***
	(1.09)	(1.33)	(4.93)	(1.13)	(1.09)
Plan Colombia military $	0.18	0.69**	0.33	0.34	0.32
	(0.29)	(0.31)	(5.07)	(0.30)	(0.29)
Plan Colombia economic $	−0.19	0.32	3.31**	−0.09	0.36
	(0.35)	(0.33)	(1.55)	(0.35)	(0.35)
Pastrana peace	2.78**	3.44***	15.36***	5.11***	3.57***
	(1.27)	(1.18)	(2.86)	(1.25)	(1.26)
Barco peace	1.63			2.23	4.06***
	(1.37)			(1.38)	(1.37)
Plan Patriota	−1.06	0.22		−1.44	0.27
	(1.18)	(1.11)		(1.18)	(1.19)
Medellin Offensive	53.64***	34.70***		56.41***	53.76***
	(2.51)	(4.75)		(2.52)	(2.51)
GDP pc	−0.003***	−0.004***	−0.01***	−0.003***	−0.003***
	(0.00)	(0.00)	(0.001)	(0.00)	(0.00)
National park	11.75**	6.40	2.35	6.04	12.27***
	(4.68)	(5.15)	(13.40)	(4.95)	(4.65)
Observations	33,000	27,500	7,700	31,900	33,050
R^2	0.10	0.09	0.07	0.10	0.10
Adjusted R^2	0.07	0.06	-0.09	0.07	0.07

Note: *p<0.1; **p<0.05; ***p<0.01
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo

Regression Results for AUC

Table 22: Regression Results for AUC

	Dependent variable: Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
AUC (VI)	22.97***					
	(1.40)					
AUC (CD)		9.16***				
		(0.92)				
AUC (RC)			15.87***			
			(3.06)			
AUC (RE)				33.93***		
				(1.59)		
AUC (UC)					52.06***	
					(2.52)	
AUC (All)						5.01***
						(0.77)
Coca	2.11***	2.05***	1.29**	1.77***	2.12***	2.27***
	(0.39)	(0.40)	(0.65)	(0.56)	(0.39)	(0.38)
Oil	−0.35***	−0.44***	−0.07	−0.24***	−0.39***	−0.40***
	(0.02)	(0.02)	(0.08)	(0.03)	(0.02)	(0.02)
Mines	1.04***	1.02***	2.63***	1.19***	1.09***	1.08***
	(0.07)	(0.06)	(0.16)	(0.10)	(0.07)	(0.07)
Elections	0.43	−0.01	−0.16	0.76	0.54	−0.95
	(0.69)	(0.70)	(1.33)	(1.27)	(0.69)	(0.70)
Population	74.62***	9.79	73.78	−131.99**	45.57**	65.36***
	(21.35)	(26.06)	(64.46)	(55.68)	(22.03)	(20.98)
Population sqr.	−4.67***	−1.15	−5.74*	6.23**	−3.08***	−4.19***
	(1.09)	(1.34)	(3.30)	(2.87)	(1.13)	(1.07)
Plan Colombia military $	0.18	1.02***	1.54***	1.73	0.01	0.002
	(0.29)	(0.32)	(0.43)	(2.39)	(0.30)	(0.29)
Plan Colombia economic $	−0.39	0.74**	−1.02**	−1.43*	0.55	0.54
	(0.35)	(0.34)	(0.43)	(0.80)	(0.35)	(0.36)
Pastrana peace	2.61**	0.07	−1.17	2.11	1.66	3.11**
	(1.26)	(1.28)	(1.49)	(1.61)	(1.25)	(1.28)
Barco peace	1.59				2.07	5.12***
	(1.36)				(1.38)	(1.44)
Plan Patriota	−2.10*	0.50	−13.73***	−5.21***	−1.43	0.23
	(1.18)	(1.12)	(2.48)	(1.50)	(1.17)	(1.18)
Medellin Offensive	54.01***	36.01***			57.32***	53.67***
	(2.50)	(4.75)			(2.50)	(2.50)
GDP pc	−0.003***	−0.004***	−0.01***	−0.01***	−0.003***	−0.003***
	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.00)	(0.00)
National park	12.08***	5.77	−0.02	4.68	6.64	11.85***
	(4.67)	(5.15)	(11.44)	(7.66)	(4.92)	(4.56)
Observations	33,000	27,500	13,200	15,624	31,900	33,302
R^2	0.10	0.09	0.04	0.09	0.11	0.09
Adjusted R^2	0.07	0.05	-0.05	0.02	0.08	0.06

Note: *p<0.1; **p<0.05; ***p<0.01
CD=CEDE; CL=Claudia Lopez; RC=Rutas del Conflicto; VI=ViPAA; RE=Restrepo

A6. Model Assessment

The empirical evaluation of using a variety of armed actor measures as independent variables in the previous section reveals the diverging estimates stemming from different measures of armed actors in relation to violence in Colombia. However, since this research is agnostic about the essential superiority or proximity to the "ground truth" of one measure over the other ones, it is necessary to rely on basic methodological prescriptions to assess the quality of the different models. It is not enough to state that the regression estimates are different simply because the they come from different measures of armed actors. Instead, this section relies on three methodological dimensions to evaluate the quality of the models derived from different measurement sets: (i) information loss; (ii) the Akaike Information Criterion (AIC) (Akaike 1974), and (iii) the Bayesian Information Criterion (BIC) (Stone 1979). Table 23 reports these three dimensions for the generic type of actors (paramilitaries and guerrilla) under Panel (a) and for the specific armed groups (FARC, ELN, and AUC) under Panel (b).

[Table 23 around here]

First, given the pervasiveness of missing data in some of the measurement sets, the loss of information is a central criteria for assessing the quality of the data and the statistical inferences derived from them. Departing from the assumption that researchers look for generalizable conclusions that are valid to explain a broad scope of cases considered under a given theoretical framework, a high rate of missing data would prevent generalizing the inferences from the model outside the sample, particularly if the missing data is generated through a non random process (Honaker and King 2010). To evaluate this concern, Table 23 reports the percentage of missing data related to each model with respect to the panel of all municipalities of Colombia between 1988 and 2017. According to the calculations, the integrative measure *All* and VI are the measurement sets with the least loss of information, with only 5.51% and 6.85% of missing data respectively. The other measurement sets generate a considerable amount of missing data ranging from 22.37% to 75.16%, thus severely undermining the completeness of the data and the prospects of generalizing results. Researchers seeking

to generate generalizable conclusions would benefit from using the *All* and VI measurement sets over alternative indicators of armed actors. Substantially, data from *All* is the most complete as it integrates the observations of armed actors from all other measurements.

Based on the initial analysis of missing data, the following evaluation of the AIC and BIC metrics focuses exclusively on comparing the performance of *All* and VI models. Panel (a) in Table 23 reports the performance of the AIC and BIC statistics for the type of actor (paramilitaries and guerrilla) and Panel (b) reports those metrics for specific armed groups (FARC, ELN, and AUC). The AIC statistic (Akaike 1974) evaluates the relative quality of the model based on the goodness of fit and its parsimony. In this way, a smaller AIC score indicates a better model than an alternative specification with a larger AIC score. In addition, the BIC statistic (Stone 1979) evaluates the relative quality of a model based on the likelihood function, the number of observations, and the parsimony of the model. A smaller BIC score also indicates a preferable specification when compared to a larger BIC score.

When comparing the integrative measure *All* and VI for paramilitary organizations and guerrilla groups in Panel (a) of Table 23, the AIC and BIC provide inconclusive results. For Paramilitary actors, the AIC favors the integrative measure *All* while the BIC favors VI. The model assessment scores alternate in a similar manner when assessing *All* and VI models for guerrilla groups. The differences between the AIC and BIC scores for *All* and VI is so small, that the alternance in favor of one model over the other is not surprising. This ambivalence at the margin suggests that the fit of the models is very similar. Therefore, it is plausible to consider *All* and VI as the two best measurement sets to track the presence of paramilitary and guerrilla groups in Colombia.[1]

Panel (b) in Table 23 yields to similar conclusions for the specific measurements of the FARC, ELN, and AUC gorups. Both the AIC and BIC criteria alternate their favor of the

[1]The AIC and BIC scores are indeed smaller for CD, CL, IN, RC, and RE than for the integrative measure *All* and VI. However, those AIC and BIC scores are smaller because they contain fewer observations than the more complete *All* and VI models.

integrative *All* metric or the VI database for each of the armed groups. This ambivalence at the margin is consistent with the assessment for paramilitary and guerrilla type of actors.

In general, conducting statistical analyses with the integrative *All* measure or the VI data is preferable than using alternative measurement sets. The specific differences between *All* and VI models are marginal when considering the percentage of missing values, as well as the AIC and BIC performance statistics. This is applicable for both the type of armed actors as well as the specific armed groups evaluated in the study. Therefore, researchers can consider both metrics as better options for conducting statistical analyses on the dynamics of conflict without incurring in severe problems of missing data that could yield bias inferences and limit the generalizability of their conclusions.

However, despite the similarity of the model fit assessment derived from the AIC and BIC measures, the integrative *All* measure and VI do not yield the same coefficients from the statistical analysis. As indicated in Tables 16 and 17, as well as in the coefficient plots in the lower row of Figure 6, VI tends to generate larger estimates than those derived from the integrative *All* measurement set for both the type of armed actors (paramilitaries and guerrillas) as well as for specific armed groups (FARC, ENL, and AUC).

Table 23: AIC and BIC Criteria

			Panel (a) Type of Actor				Panel (b) Armed Group					
			Paramilitaries		Guerrilla		FARC		ELN		AUC	
	Model	% Missing	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
1	All	5.51	11.383	361,479	11.383	361,339	11.389	374,529	11.399	357,301	11.386	359,893
2	ViPAA (VI)	6.85	11.400	356,799	11.392	356,530	11.393	356,557	11.399	356,764	11.397	356,679
3	CEDE (CD)	22.37	11.072	293,299	11.061	293,014	11.063	293,049	11.069	293,229	11.072	293,299
4	Restrepo (RE)	27.54	11.236	280,178	11.236	336,511	11.248	280,470			10.599	359,893
5	Rutas del Conflicto (RC)	59.63	11.093	218,173	11.093	72,575	11.094	240,084	10.091	84,430	10.507	143,066
6	Claudia Lopez (CL)	72.05	10.358	108,704	10.360	108,723						
7	Indepaz (IN)	75.16	8.165	78,342								

AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion.

A7. Relevance of Measurement Sets

Table 24 presents a summary of Google Scholar citations of each different database. Although these citation counts may not accurately reflect the use of these databases outside academia (e.g. policy, journalism, or civil society sectors), they provide some indication about their relevance in the research community.

Table 24: Citations of Measurement Sets in Google Scholar

Database	Publication year	Source	Number of Citations	Google Scholar links
RE	2004	Restrepo et al. (2004)	238	https://scholar.google.com/scholar?hl=en&as_sdt=807&as_ylo=2010&as_yhi=2022&q=%22The+Dynamics+of+the+Colombian+Civil+Conflict%22+%2B+Restrepo&btnG= https://scholar.google.com/scholar?hl=en&as_sdt=0%2C3&q=%22Special+Data+Feature%3B+The+Severity+of+the+Colombian+Conflict%3A+Cross-Country+Datasets+Versus+New+Micro-Data%22&btnG=
CL	2010	López (2010)	443	https://scholar.google.com/scholar?cites=13116620271918594088&as_sdt=805&sciodt=0,3&hl=en
UC	2013	(Sundberg and Melander 2013)	877	https://scholar.google.com/scholar?hl=en&as_sdt=807&as_ylo=2010&as_yhi=2022&q=%22Introducing+the+UCDP+georeferenced+event+dataset%22&btnG=
CD	2014	Acevedo and Bornacelly (2014)	193	https://scholar.google.com/scholar?hl=en&as_sdt=0%2C3&q=%22Panel+Municipal+del+CEDE%22&btnG=
RC	2019	Rutas del Conflicto (2019)	18	https://scholar.google.com/scholar?hl=en&as_sdt=807&as_ylo=2010&as_yhi=2022&q=%22Geograf%C3%ADa+del+Paramilitarismo%22+en+Colombia+%2B+Rutas+del+Conflicto&btnG= https://scholar.google.com/scholar?hl=en&as_sdt=807&q=Verdad+Abierta+%22Geograf%C3%ADa+del+Paramilitarismo%22&btnG=
VI	2019	(Osorio et al. 2019)	27	https://scholar.google.com/scholar?cites=4593544114437560797&as_sdt=805&sciodt=807&hl=en https://scholar.google.com/scholar?hl=en&as_sdt=807&q=Osorio+%22ViPAA%22&btnG=
IN	2019	Indepaz (2019)	68	https://scholar.google.com/scholar?hl=en&as_sdt=805&sciodt=807&cites=4593544114437560797&scipsc=&q=%22Informe+sobre+presencia+de+grupos+Narcoparamilitares%22&btnG=

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