Online Appendix

1 Qualitative Analysis: In-Depth Interviewing and Archival Research

The research ethics protocol was approved by the Office of Research Compliance (Protocol number 22-11-7517). Interviews and archival materials were collected across four waves of fieldwork: June-July 2021, September-November 2022, January-November 2023, and February-April 2024. In-person interviews were held in Bogotá DC, Medellín (Antioquia), Popayán and Inzá (Cauca), Cartagena and María La Baja (Bolívar), Cúcuta and Tibú (Norte de Santander), Bucaramanga (Santander), and Rio Sucio (Chocó).

1.1 Interview Sample Selection

I conducted in-depth, semi-structured interviews with government and insurgent negotiators and advisors, representatives of social movements, allied organizations such as NGOs, and staff members responsible for facilitating participatory spaces. Interviewees were selected based on their firsthand knowledge and expertise in land grievances and peace negotiations. Leveraging existing networks, I initiated contact with several interviewees, who subsequently referred me to additional participants, following a snowball sampling method. To address ethnic, racial, and gender disparities in the sample, I actively recruited participants from underrepresented groups. However, the number of women recruited was limited, reflecting gender imbalances in the Havana peace talks, where men predominantly occupied negotiation roles despite efforts to enhance women's representation on both sides to the table.

Given the localized nature of rural mobilization, I selected movement representatives from municipalities directly engaged in protests and high-level negotiations. These high-ranking interviews enabled me to trace the role of rural movements in peace negotiations. Furthermore, my sampling strategy accounted for variation in subnational mobilization strength. Hence, interviewees were primarily drawn from municipalities exhibiting different levels of direct involvement and disruptive actions during the period under study. I also included participants from movements showing diverse ideological perspectives to explore the varying collective action frames used by these actors in articulating their grievances. To ensure anonymity promised to participants, I assigned a code to interviewees. Table 1 lists interviewees' codes, profiles, and the date they were interviewed.

Code	**Interviewee Profile**	**Date**
26	FARC-EP Negotiator	05/03/2023
27	Peasant Movement Leader in Meta	05/08/2023
28	Coca-Growing Peasant Movement Leader in Putumayo	06/07/2023
29	Government Negotiation Advisor	06/20/2023
30	Government Negotiation Advisor	06/21/2023
31	National Indigenous Movement Leader	06/21/2023
32	NGO representative	06/23/2023
33	FARC-EP Negotiation Advisor	06/28/2023
34	Participatory Institutions Staff Member	06/30/2023
35	Participatory Institutions Staff Member	06/30/2023
36	Afro-descendant Movement Peasant Leader in Cauca	07/07/2023
37	Coca-Growing Movement Peasant Leader in Putumayo	07/08/2023
38	Coca-Growing Movement Leader in Putumayo	07/11/2023
39	Peasant Movement Leader in Cauca	07/12/2023
40	National Coca-Growing Peasant Movement Leader	09/08/2023
41	Coca-Growing Peasant Movement Leader in Catatumbo	09/23/2023
42	Coca-Growing Peasant Movement Leader in Catatumbo	09/23/2023
43	FARC-EP Negotiation Advisor	09/23/2023
44	National Peasant Movement Leader	09/27/2023
45	Afro-descendant Movement Leader in Chocó	11/15/2023
46	FARC-EP Negotiator	02/13/2024
47	Government Negotiation Advisor	26/03/2024
48	Foreign Diplomat Envoy	02/05/2024

I conducted semi-structured interviews, in-person or online, lasting between 30 minutes and 2 hours. I began interviews with contextual questions and follow up with more in-depth inquiries

Table 1: In-Depth Interviews List

Code	Interviewee Profile	Date
1	Peasant Movement Leader in Cauca	07/15/2021
2	Peasant Movement Leader in Nariño	07/17/2021
3	Peasant Movement Leader in Cauca	07/28/2021
4	FARC-EP Negotiator	09/05/2022
5	Government Negotiator	09/15/2022
6	Peasant Movement Leader in Cauca	11/08/2022
7	Peasant Movement Leader in Bolívar	11/10/2022
8	Participatory Institutions Staff Member	11/15/2022
9	National Indigenous Movement Leader	11/21/2022
10	National Leftist Political Movement Leader	01/20/2023
11	National Leftist Political Movement Leader	03/14/2023
12	National Peasant Movement Leader	03/01/2023
13	Peasant Movement Leader in Cauca	03/14/2023
14	National Indigenous Movement Leader	03/15/2023
15	National Peasant Movement Leader	03/22/2023
16	FARC-EP Negotiation Advisor	03/24/2023
17	FARC-EP Negotiator	03/25/2023
18	Coca-Growing Peasant Movement Leader in Catatumbo	03/30/2023
19	Coca-Growing Peasant Movement Leader in Catatumbo	03/30/2023
20	Government Negotiation Advisor	04/13/2023
21	Mid-Sized Farmer Movement Representative	04/14/2023
22	FARC-EP Negotiator	04/19/2023
23	FARC-EP Negotiator	04/21/2023
24	Coca-Growing Peasant Movement Leader in Catatumbo	04/27/2023
25	Peasant Movement Leader in Bolívar	04/27/2023

into the "behind-the-scenes" causal mechanisms relevant to my research, adopting the role of a "provocateur" (Kapiszewski et al., 2015).

1.2 Interview Analysis: Coding, Saturation, and Consistency

Coding: I promised anonymity to all participants, seeking to ensure a confidential environment where interviewees could speak freely about the influence of unarmed, marginalized actors on peace bargaining. While some elite interviewees might face minimal harm from identity disclosure, I do not reveal identifiable information for any participant, instead using unique IDs. Only interviews with public officials or public figures were recorded. Most interviewees came from marginalized backgrounds and were involved in high-risk activism within a violent context, so I primarily took written notes, which were promptly transcribed after the interviews. I transcribed in-depth interviews for comprehensive analysis. Following predefined interview categories, I manually coded excerpts that provided evidence on the theorized effects and causal sequences. I also identified segments that did not align with existing categories, organizing these into new categories as necessary.

To ensure the robustness of this coding procedure, I utilized MAXQDA to assess whether the existing categories were exhaustive. Additionally, I assigned weight scores to each segment, ranging from 0 to 100, based on the extent to which the interview excerpts related to my main research questions. Segments with scores above 60 were retained for their relevance to the research question. I then compared trends across different groups, focusing on similarities and differences in peace negotiation strategies, ideological and instrumental perspectives on land redistribution, and the influence of unarmed actors in the bargaining process. This comparative analysis was extended to social movements to explore their impact on peace negotiations, particularly regarding how and why they shaped the outcomes.

Saturation and Consistency of Responses: Although I did not prime interviewees on peace negotiation strategies, stances on land redistribution, or social movement involvement, their responses consistently aligned with the hypothesized effects. Consistency was evident both within and across different profile groups. For within-group comparisons, I assessed consistency among participants by considering their hierarchical positions within each organization. I further ensured consistency by cross-checking interview excerpts from participants holding equivalent positions across different groups. This process allowed me to evaluate the saturation and consistency of responses, thereby increasing my confidence in the findings and the reliability of my reporting.

1.3 Archival Sources

I collected diverse archival materials on peace negotiation, movements' demands, and protest agreements. Most peace negotiation archives were retrieved from the open-source digital archive `https://bapp.com.co/`, assembled by *Fundación Compaz*—a nonprofit founded by former President Santos. To address potential imbalances in data collection, I also gathered undisclosed documents shared by *Partido Comunes*—the FARC-EP successor party. Social movements' documents and protest agreements were collected onsite at movement offices during fieldwork across various municipalities and from institutional archives compiled by *Vivamos Humanos*—a nonprofit founded by former President Samper. These archives were manually coded based on pre-established categories also used for interviews. This coding procedure was then reviewed in MAXQDA to ensure consistency. I use these documents to complement interview analysis, allowing me to fact check events mentioned in interview excerpts.

2 Quantitative Analysis: Variables and Operationalization

2.1 Dependent Variable: Text Reuse in the 2016 Peace Agreement

I used an original and so far unexplored dataset collected and assembled *Fundación Ideas para la Paz* (FIP) under Santos' administration commission. Thematically, this dataset classifies citizen proposals by peace agreement topics, including themes left unaddressed at the peace table, such as extractive industries and security sector reform. Documents are relatively short, ranging from 2,694 to 34 words with a mean of 99 words. These petitions address multiple topics and are signed by several petitioners. Before calculating cosine similarity scores, I pre-processed the rural development sections of the peace agreement using conventional techniques (Grimmer et al., 2022), such as lemmatization through Stanza and standardizing frequent terms through spaCy's rule-based matcher engine. After this preprocessing procedure, I retained only those proposals containing at least 26 words, ensuring sufficient textual content for meaningful comparison.

To capture text alignment, I computed cosine similarity between citizen proposals focused on rural issues and the rural sections of the peace agreement. Cosine similarity measures how similar two texts are by comparing the angle between their vector representations in a high-dimensional spaces, in which texts with more similar content have vectors that point in similar directions. It ranges from 0 (no alignment) to 1 (identical content), and allows high-dimensional text data to be summarized as a single, comparable similarity score.

I employ two complementary approaches to represent texts as vectors and capture both semantic and lexical similarity between proposals and the agreement. Firs, I use a Sentence-BERT (SBERT) model to encode dense vector representations that capture contextual meaning instead of only word overlap (Reimers and Gurevych, 2019). Since the agreement text exceeds the model's input limit, I split it into 27 contiguous chunks of up to 512 tokens each. I represent every chunk as a numerical vector that summarizes its semantic content, and then average these vectors to obtain a single representation of the full rural agreement. I apply the same procedure to citizen proposals, yielding one vector per proposal. Thus, similarity scores are computed between the averaged proposal and agreement vectors, producing one document-level measure per proposal. This aggregation strategy captures overall alignment between texts rather than rewarding isolated local overlaps. In my dataset, SBERT similarity scores range from 0.137 to 0.769, with a mean of 0.453. Table 2 compares citizen proposals with high similarity scores and the peace agreement using the SBERT similarity algorithm.

As an alternative measure of the outcome, I implement a Bag-of-Words (BoW) model with term frequency–inverse document frequency (TF-IDF) weighting to capture lexical overlap between proposals and the agreement. To minimize estimation bias, I down-weight common language found in the agreement and proposals by excluding frequent terms when constructing word vectors for cosine similarity computation. Following the principle that text informativeness is inversely proportional to frequency (Grimmer et al., 2022), I retain more informative—or less common—terms by introducing TF-IDF weighting as a parameter. TF-IDF produces a value that reflects both the importance of a term in a document (TF) and the uniqueness of that term across the corpus (IDF). Moreover, I exclude terms occurring in fewer than 5% of the documents to mitigate noise and reduce corpus dimensionality. Rare terms often lack sufficient informational value for effective comparison and may otherwise introduce skewness. Additionally, I normalize vector lengths during word vector distance calculations to minimize document length's effect on similarity scores. Finally, I apply Latent Semantic Analysis (LSA) for dimensionality reduction, projecting high-dimensional term-document matrices into a compact semantic space. In this specification, similarity scores span from 0.028 to 0.716, with a mean of 0.453.

Table 2: Proposal-Agreement Comparison (using SBERT algorithm)

Proposal	**Agreement**
"Victims: Land Restitution and Rural Development as Reparative and Transformative Measures for Victims of Land Dispossession and/or Forced Abandonment. In order to enable victims to fully enjoy their rights within a reparative framework, a series of actions are proposed to be carried out by territorial entities and national-level institutions. These actions should take the form of specifically designed programs and measures aimed at economic reestablishment, conceived within a rural development approach, for victims of land dispossession or forced abandonment, and linked to broader return strategies. a) A diagnostic assessment and action plan should be developed to identify the needs and expectations of the victims. This process must be participatory in nature, in order to define the activities to be undertaken based on the victims' own knowledge and lived experiences. The ultimate goal is to design and implement, from the regional level, training and skills-development plans focused on productive activities, for both the victims and their families."[1]	"Amid armed conflict cessation and with the aim of strengthening and accelerating land restitution processes, we have agreed that such processes will be integrated with collective reparation efforts, territorial development programs, and the plans and programs arising from the implementation of the Final Agreement. It is also agreed that: The implementation of land restitution policy shall be guided, among other factors, by technical criteria such as the historical density of dispossession and the conditions for return. It shall also take into account the recommendations—particularly those related to territorial targeting—offered by victims' organizations and subject-matter experts. Territorial entities must actively participate in the implementation of the land restitution policy and contribute to the comprehensive attention to restitution beneficiaries through the formulation of their territorial development plans. This includes investments in infrastructure and public services. Beneficiaries of restitution processes shall receive both technical and financial support for the reconstruction of their life projects and income-generation strategies. They shall also receive support for the substitution of illicit crops, the recovery and rebuilding of the social fabric, the strengthening of community organizing processes, and the construction of historical memory aimed at reconciliation. Information resulting from entries in the Registry of Forcibly Dispossessed and Abandoned Lands, as well as from judicial rulings ordering land restitution, will be incorporated into the Unified Victims Registry (Registro Único de Víctimas) in order to harmonize existing registries and ensure access to the full range of reparative measures."[2]

Proposal	Agreement
"Guiding Principles for the Voluntary Substitution of Illicit Crops (...) 5. Inclusion of the Entire Rural Population of the Municipality or Community Council in the Economic-Productive Development Component. This is a fundamental element of the program, as it is essential to avoid sending the wrong message—that cultivating coca is a prerequisite for receiving state support and collaboration. Furthermore, one of the key design features is to leverage social pressure on those reluctant to participate; for this to be effective, it is crucial that the entire population benefits from the program. In other experiences, the selective inclusion of some beneficiaries while excluding others has led to social tensions that ultimately undermine positive outcomes. The intervention should focus on the components set forth in the Comprehensive Rural Development Plans of the Community Councils. These include: productive development, food security, comprehensive technical assistance, and the strengthening of territorial organizational capacities for socio-productive and entrepreneurial development."[3]	"4.1.1. Principles. Given that the National Comprehensive Program for the Substitution of Illicit Crops (PNIS) is part of the Comprehensive Rural Reform (RRI), it shall be governed not only by the principles established under that Reform, but also by the following additional principles: Joint, participatory, and consensual construction: The transformation of territories and the design of alternatives for communities affected by illicit crops shall be based on a process of joint and participatory construction between those communities and national, departmental, and municipal authorities. This process will aim to develop shared solutions to the problem of illicit crop cultivation and to overcome conditions of poverty. This joint construction is grounded in the autonomous decision of communities—both women and men—to abandon illicit crops and transition, through substitution, to other economic activities. Consensus-building with communities is a priority in the planning, implementation, and oversight of the Program within the territories."[4]

2.2 Independent Variable: Rural Mobilization

To identify rural movements from the universe of collective petitioners, I manually classified collective petitioners as rural movements if they were initially categorized as labor unions, indigenous *resguardos* (collective territories enjoying political autonomy), community action boards (or village- and neighborhood-level social organizations), and social organizations (or *movimientos de base*). I manually verified the type of organization and the population represented by each petitioner using secondary sources. This procedure allowed me to distinguish between collective actors endowed with political and economic power—such as political parties, business firms, and economic interest groups—and rural movements. Social movements actively engaged in participatory institutions during peace negotiation: on average, social movements submitted 5 proposals (standard deviation of ~12). At the subnational level, social movements from 299 municipalities participated in proposal-making forums and approximately 4 rural movements sent proposals per municipality (standard deviation of ~15.1).

3 Robustness Checks

3.1 OLS Analysis of Restricted Sample

As a conservative robustness check, I re-estimate the regression models on a restricted sample of citizen proposals submitted before the parties announced partial agreements on each negotiation topic. Peace negotiations unfolded along a thematic timeline, wherein the warring factions reached partial agreements sequentially across issue areas. Although these interim agreements were not formally binding until the final accord in August 2016—and remained subject to revision throughout the process—they may nonetheless have influenced how citizens articulated their demands. To address this potential concern, I restrict the sample to proposals submitted prior to the public announcement of each thematic agreement. This restriction yields a lower-bound estimate of the relationship, as it excludes proposals that may already reflect emerging consensus or alignment with the negotiation agenda. As shown in Table 3, the results remain substantively unchanged, reinforcing the robustness of the main specification.

Table 3: OLS Results (Restricted Sample)

	SBERT Similarity				BoW Similarity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rural Movement (Dummy)	0.164***		0.166***		0.060		0.067	
	(0.034)		(0.034)		(0.040)		(0.035)	
Rural Movement (Proportion)		0.077***		0.071***		0.035*		0.036*
		(0.015)		(0.015)		(0.017)		(0.016)
Number of Signatures (std)	0.000	0.013	−0.003	0.010	0.029*	0.034**	0.008	0.013
	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Proposal Length (log, std)	0.490***	0.490***	0.477***	0.477***	0.415***	0.416***	0.383***	0.383***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
Thematic Coverage	0.093***	0.095***	0.185***	0.186***	0.146***	0.147***	0.149***	0.149***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
Endowed Organizations (std)	0.023	0.019	0.026	0.018	−0.033	−0.029	−0.029	−0.027
	(0.015)	(0.014)	(0.015)	(0.014)	(0.021)	(0.019)	(0.017)	(0.015)
Observations	6220	6220	6220	6220	6219	6219	6219	6219
Mean of Dependent Variable	0.458	0.458	0.458	0.458	0.312	0.312	0.312	0.312

* p <0.05, ** p <0.01, *** p <0.001
Similarity measured via SBERT (M1–M4) and Bag-of-Words (M5–M8).

3.2 OLS Analysis of Revised Agreement

I replicated these regression models for the revised peace agreement on November 24, 2016. Table 4 reports estimates from standard OLS regression models with year-fixed effects and robust standard errors for both algorithms, using standardized variables. Table 5 shows results these models, retaining variables at their original scales. The main findings remain robust for text alignment between citizen proposals and the revised peace agreement.

Table 4: Main OLS Results (November Peace Accord)

	SBERT Similarity				**BoW Similarity**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rural Movement (Dummy)	0.183***		0.193***		0.103**		0.126***	
	(0.031)		(0.031)		(0.038)		(0.032)	
Rural Movement (Proportion)		0.089***		0.081***		0.057***		0.057***
		(0.014)		(0.014)		(0.016)		(0.014)
Number of Signatures (std)	−0.033***	−0.018*	−0.051***	−0.035***	−0.004	0.004	−0.021*	−0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Proposal Length (log, std)	0.475***	0.476***	0.449***	0.450***	0.386***	0.387***	0.342***	0.343***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
Thematic Coverage	0.072***	0.074***	0.139***	0.139***	0.112***	0.114***	0.139***	0.140***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.020)	(0.020)
Endowed Organizations (std)	0.032*	0.030*	0.044**	0.033*	−0.010	−0.007	0.002	−0.002
	(0.015)	(0.014)	(0.015)	(0.014)	(0.021)	(0.019)	(0.017)	(0.016)
Observations	8238	8238	8238	8238	8237	8237	8237	8237
Mean of Dependent Variable	0.454	0.454	0.454	0.454	0.306	0.306	0.306	0.306

* p <0.05, ** p <0.01, *** p <0.001
Similarity measured via SBERT (M1–M4) and Bag-of-Words (M5–M8).

Table 5: OLS Results (DV in Original Scale, November Peace Accord)

	SBERT Similarity				BoW Similarity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rural Movement (Dummy)	0.017***		0.018***		0.010**		0.013***	
	(0.003)		(0.003)		(0.004)		(0.003)	
Rural Movement (Proportion)		0.018***		0.016***		0.012***		0.012***
		(0.003)		(0.003)		(0.004)		(0.003)
Number of Signatures	−0.001***	0.000*	−0.001***	−0.001***	0.000	0.000	−0.001*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Proposal Length	0.088***	0.088***	0.083***	0.084***	0.079***	0.079***	0.070***	0.070***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Thematic Coverage	0.007***	0.007***	0.013***	0.013***	0.011***	0.012***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Endowed Organizations	0.005*	0.004*	0.006**	0.005*	−0.002	−0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	8238	8238	8238	8238	8237	8237	8237	8237
Mean of Dependent Variable	0.454	0.454	0.454	0.454	0.306	0.306	0.306	0.306

* p <0.05, ** p <0.01, *** p <0.001
Similarity measured via SBERT (M1–M4) and Bag-of-Words (M5–M8).

4 Placebo Test

To assess the specificity of the observed associations between rural mobilization and textual similarity, I conduct a placebo test using proposals related to security sector reform. Notably, the 2016 peace agreement did not include any commitments regarding the armed forces or security institutions. As such, there is no substantive basis to expect alignment between citizen demands in this area and the agreement text. I computed lexical and semantic similarity between these proposals and sections of the agreement thematically related to security issues (e.g., points 3 and 6). As shown in Table 6, rural mobilization is not associated with textual similarity at a statistically significant level. These results suggest that the stronger associations observed in the land domain are not merely artifacts of the similarity metric or text length, although some weak alignment in unrelated domains cannot be entirely ruled out.

Table 6: OLS Placebo Models (DV: Security Sector Reform)

	SBERT Similarity				**BoW Similarity**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rural Movement (Dummy)	0.228		0.216		0.249		0.370*	
	(0.118)		(0.123)		(0.191)		(0.179)	
Rural Movement (Proportion)		0.022		0.027		0.145		0.166*
		(0.051)		(0.051)		(0.079)		(0.075)
Number of Signatures (std)	0.040	0.057	0.047	0.064	−0.044	−0.024	−0.041	−0.009
	(0.034)	(0.033)	(0.037)	(0.036)	(0.054)	(0.053)	(0.058)	(0.057)
Proposal Length (log, std)	0.686***	0.681***	0.693***	0.691***	0.440***	0.441***	0.386***	0.386***
	(0.057)	(0.057)	(0.056)	(0.057)	(0.046)	(0.047)	(0.046)	(0.046)
Thematic Coverage	−0.043	−0.038	−0.071	−0.069	−0.052	−0.045	0.069	0.074
	(0.093)	(0.094)	(0.093)	(0.094)	(0.111)	(0.109)	(0.105)	(0.104)
Endowed Organizations (std)	0.144**	0.073	0.142*	0.079	−0.020	−0.008	0.043	0.023
	(0.053)	(0.045)	(0.058)	(0.048)	(0.098)	(0.082)	(0.093)	(0.080)
Observations	399	399	399	399	400	400	400	400
Mean of Dependent Variable	0.494	0.494	0.494	0.494	0.260	0.260	0.260	0.260

* p <0.05, ** p <0.01, *** p <0.001
Similarity measured via SBERT (M1–M4) and Bag-of-Words (M5–M8).

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