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Morbi-Mortality of the Victims of Internal Conflict and Poor Population in The Risaralda Province, Colombia

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Abstract: Health differences across socioeconomic strata have always pointed out that poorer and minorities have higher mortality and morbidity than richer and majorities. This difference is exacerbated for particular populations such as the victims of ongoing armed conflicts, who are also much harder to quantify due to the conflict itself. This study applies network analysis to a combination of three large administrative records for the health system and mortality records in the province of Risaralda (Colombia) between 2011 and 2016. It produces the most common causes of morbi-mortality for both victims of violence and the poorest inhabitants of Risaralda, defined as those who qualify as recipients of subsidies from the Colombian welfare program called SISBEN in the categories of highest need. Both populations show high morbidity frequencies for non-communicable diseases such as Type II diabetes, hypertension, and hyperglyceridaemia, mostly associated with exposure to unhealthy lifestyles. Additionally, the mortality outcomes reflect the different lifestyles and medical treatments of both subpopulations. While the poorest replicate the same causes identified for morbidity, the victims of armed conflict die of additional causes including Type II diabetes, which reflects the even worse conditions they face.

Keywords: Morbidity; Mortality; Network Analysis; Victims of internal conflict.

1. Introduction

Refugees and internally displaced populations (IDPs) have much higher morbidity and mortality rates than the rest of the population for all observed conflicts in the world, as recorded from their experiences in refugee and IDP settlements [1]. These results are not surprising, as both populations are exposed to harsh physical, emotional, and economic conditions due to violence that has both direct effects on mortality [2-4] as well as indirect effects, as measured by higher infant mortality rates [5-6]. Indeed, the disruption that conflicts impose leads to extreme inequality in socioeconomic conditions between victims and the rest of the population, which in turn may be the underlying cause of those large differentials in morbidity and mortality, as this affects healthy lifestyles and all the other determinants of health [7].

This study aims to show the differences between the morbidity and mortality of Colombian victims of internal conflict and those of a comparable subpopulation, namely an economically depressed population targeted by government subsidy programs in Colombia. We propose that the living standards of victims of internal conflict are so extreme that they lead to worse physical and psychological conditions than those of the poorest population. For that purpose, this study uses micro data from the province of Risaralda, one of the highest ranked provinces in Colombia in terms of socioeconomic conditions. Risaralda has almost universal coverage of public services (roads, water, electricity, gas, and sewage), and health services access, but it is in the midst of regions that have suffered persistent and intense armed conflict, attracting victims fleeing from high violence levels zones, as Chocó, Urabá, and the southwest provinces of Colombia. From all victims registered in the official Colombian records, 80% of them are IDPs. Hence, this study presents the results for all victims in Risaralda, knowing that in this province the majority are IDPs [8].

This study adds to the increasing amount of literature on the application of network analysis and the relation between health and lifestyle disruption in three ways. First, we portray the different patterns between victims of violence and other subpopulations in an extreme case of endemic conflict, such as the Colombian one, where most victims of conflict are not living in settlements or safe havens, in contrast to other more intense but shorter conflicts in the world. Second, we take advantage of the new possibility of crossing individual administrative records that allowed us to combine information on access to the health system, individual medical records, vital statistics and the status of victims of the internal conflict in Colombia, a hard-to-reach subpopulation that is difficult or impossible to track with traditional surveys. We successfully crossed three official databases, all linked by the identification number of individuals, between 2011 and 2016: Base de Datos Única de Afiliados (BDUA, Unique Database of Affiliated [to the health system]), Registros Individuales de Prestación de Servicios de Salud (RIPS, Individual Records of Health Services) and Registro Unificado de Afiliación (RUAF, Unified Record of Affiliation). Yet, as with all big data, this novel dataset comes with its challenges for which the proposed methodology is the best solution we came up with. Network analyses allowed us to identify the patterns of morbidity and mortality for both victims of internal conflict and the proposed control group (i.e., target populations for subsidy programs). The differences among these subpopulations lead us to identify different causes of death and predominant diseases, confirming the hypothesis of this study. Third, an abrupt disruption in lifestyles leads to different observed health outcomes, and an example is the victims of internal conflict in Colombia.

The data and methods used herein include a detailed characterization of diseases, for both mortality and morbidity, of subpopulations living under the extreme conditions due to displacement. To put these results into context, we compare them with those obtained for other poor populations, namely those that participate in subsidized governmental welfare programs.

We are aware that official records, as the count of victims of the internal conflict, have several limitations. To begin with, the individuals registered in this dataset correspond to those that self-identify as victims of internal conflict and are looking for governmental support programs of any kind, which imposes a bias from the total population of victims. However, the results presented here could be considered as a lower bound of a larger issue. That is, we encourage readers to think of the population included here as the most vulnerable of all victims to the extent that despite putting their anonymity in danger, they still look for social welfare help from the State in order to survive. The total number of victims is larger; yet, there may also be larger heterogeneity in their socioeconomic conditions, even though they are below the national average [9-10].

The remainder of this paper is organized as follows. The next section includes the motivation and literature review. Section 3 describes the data and methods used, the following section presents the results and the final section contains the discussion and conclusions.

1.1. Motivation

Armed conflicts have several negative effects on human health and development, as recent literature has presented (for a review, see [11]). Among all, the populations affected by these conflicts, IDPs and refugees, report the worst morbidity and mortality conditions. Byarugaba in [12] presents low health results, both physical and psychological, for children and their mothers in IDP settlements in South Africa, driven by having access to limited health services. For instance, most of the causes of death for children under five years have preventable causes, including nutritional deficiencies, gastroenteritis, and dehydration. The World Health Organization [13] shows three examples of increased infant mortality during conflicts due to communicable diseases: (1) measles, tetanus, and diphtheria became epidemics in Uganda during the mid-1980s, producing infant mortality rates twice as large as the total national; (2) in Zepa, during the Bosnia and Herzegovina conflict, perinatal and childhood mortality rates doubled during the conflict; and (3) in Sarajevo, average birthweight fell by 20% in 1993 as a consequence of the doubling rates of premature births.

It is undeniable that the disruption created by violent conflicts affects socioeconomic conditions, which in turn shift lifestyles for all people, and it translates into worse health and mortality conditions. However, in a long and persistent conflict, such as the Colombian case, some skepticism remains about the lower life quality of the victims of the internal conflict. On the one hand, the conflict has persisted for over five decades, with a shift in the purposes of parties involved. On the other hand, the center of the conflict was itinerant around the country, which prevented enclaves of IDPs or safe havens of victims, as has occurred in other similar situations, thereby scattering victims across the country.

The Colombian conflict erupted in the 1940s with the confrontation of followers from the two main political parties, Conservatives and Liberals, in an era named “La Violencia” (The Violence), which systematically turned against unarmed civilians. By the 1960s, this conflict had evolved into a social class struggle with the eruption of communist guerrillas, as happened in many Latin American countries. By the 1980s, paramilitary groups arose as a force against leftist guerillas, and by the 1990s, armed groups found profitable violent ways for political and economic purposes, including the systematical displacement of populations to steal the land, drug production and trafficking, weapons trafficking, kidnapping, and extortion. Indeed, the most violent decade in Colombian history during the past century was the 1990s [10]. By the turn of the century, the president in place had counteracted a full military attack by guerilla groups and led a demobilization process of paramilitary groups. Afterwards, the next administration signed in November 2016 a peace agreement between the Colombian government and the largest guerrilla group, FARC (Fuerzas Armadas Revolucionarias de

Colombia), currently there is an ongoing negotiation process between the government and the next largest and eldest guerrilla group, ELN (Ejército de Liberación Nacional). The agreement began to be implemented in 2017, with the hope of ending the armed internal conflict [6].

Colombia has the second largest IDP in the world, with over six million people; many of them are also forced to dispossession [13]. As a result, when IDPs arrive at their destination, they live in poverty despite the social welfare programs implemented. Indeed, in Colombia for the past two decades they have had much lower socioeconomic, housing and employment conditions than before the displacement [10,13,14,9] reflected in lower sanitary conditions, lower access to health facilities and services and in turn worse health. However, no current studies have linked their health outcomes with their lifestyles, as we propose in this study. More importantly, IDPs and refugees may become a group that delays the epidemiological transition and even a focus of diminished communicable diseases that could spread to the rest of the population, as shown in the Jordanian case [16], mostly due to the lack of access to public health policies, leading to good habits, lower education, and bad nutrition [17].

Moreover, the measurement of victims of ongoing conflict is challenging. Brunborg and Urdal [3] explain the measurement complications of any conflict-related variable, and indeed the 2005 Colombian Population Census shows this particular issue with its measurement of IDPs. Under the question “reason for migrating” asked to recent migrants, for those who moved within the previous five years the Census added the category “due to violence.”. The results could not be more disappointing: they produced the lowest number of IDPs among all available sources at the time, which included official registers of IDPs, data from NGOs and data from the Catholic Church. The reason is simple: in an ongoing conflict, any direct question will lead to under-registration because victims of conflict feel the need for anonymity for their own protection.

The empirical results in other contexts support the hypothesis proposed herein. Audet [18] shows the negative effects of habits or lifestyle on vulnerable populations, particularly on women, linked to obesity and chronic diseases. Brown [19] used the complex network analysis perspective to associate socioeconomic and environmental variables to nutritional lifestyle in Los Angeles, they studied the restriction imposed on fast food and its implications on illness related to obesity, finding that unhealthy cheap food and poverty are structurally related.

2. Materials and Methods

We linked the records for the province of Risaralda from three independent administrative databases, for all the years between 2011 and 2016, by using a unique identification number. Since data for a sole year may record a mortality shock or bust for exogenous reasons, then we use the six years pooled together.

The first dataset is *Base de Datos Única de Afiliados* (BDUA, Unique Database of Affiliated [to the health system]), which contains individual records of the affiliated users to the health system in Colombia. There are two possible ways of being part of this dataset: making payments to the system

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(contributive regime) or being subsidized by the government (subsidize regime). Altogether, 96.6% of the population in Risaralda belong to either category. Both the victims of internal armed conflict and populations targeted for health subsidies belong to the subsidize regime; 52.2% of the population is in the contributive regime and 44.4% in the subsidize regime. Targeted populations include those who are unemployed, with no labor income and with no direct family member who could pay any contribution to the health system for them. Victims of internal armed conflict are recognized in BDUA as a distinct group number nine (9), for which the government has an obligation to provide health services as well as other health-related secondary goods. BDUA has relevant information on demographics such as age, sex and ethnicity.

The second dataset, *Registros Individuales de Prestación de Servicios de Salud* (RIPS, Individual Records of Health Services) holds the full medical records of all patients who are part of BDUA and who attended a regular medical visit, urgency care, and the follow-up of medical exams and treatments. The information holds symptoms, diagnosis and prognosis, as recorded by medical doctors. This information is essential for the morbidity profiles.

Finally, *Registro Unificado de Afiliación* (RUAF, Unified Record of Affiliation) contain vital records, including birth and death certificates that aim to be universal. One of the advantages of the vital registration system in Colombia is that death records include the main cause of death as well as the underlying causes of death, recorded under the International Diseases Classification in its 10th version (ICD-X).

The dataset built from the BDUA, RIPS and RUAF databases contains 970.000 people (96.7% of the inhabitants of the province of Risaralda), with 48'422.050 diagnoses confirmed in 242'211.050 procedures (used as a metric to eliminate disease suspicions) and 23.648 mortality records for the specific cause of the diagnoses. This information was obtained from 9'684.410 medical visits (general, emergency, and follow-up) of the inhabitants of Risaralda who used the medical system the years between 2011 and 2016.

This study uses the complex network perspective following the definitions in [20-23] . A network represents a system through its constituents and the relations between them. The network can be mapped into a graph $G(V, E)$, with V the set of vertices $v \in V$, and E the set of edges or links between vertices. This methodology has been widely used to investigate natural, social and artificial systems, as for example vector spread diseases [24-26], the link between mobility and diseases spreading [24,27], the spread of epidemics [28], and lifestyles and health [25]. In particular, studies linking mobility and epidemics are relevant for the aim of this study. Victims fleeing an armed conflict, mostly IDPs, may introduce diseases to populations in the arrival places; however, if the conflict had not existed, then this would never have occurred [16-17]. Further, their low living standards and their associated lifestyles, such as low nutritional intake, limited access to healthcare and services, exclusion from the public health system, and low sanitary conditions, lead to a particular morbidity profile [29-30].

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2 .1 *Morbidity Network of Diagnoses*

We begin with the aggregate information of the complex network, namely all diagnoses in the province of Risaralda, for both populations under study. The population who qualify for subsidy programs in Colombia are ranked in the Identification System of Potential Beneficiaries for Welfare Programs (*Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales*, SISBEN), classified at levels I and II. We define the diagnoses (ICD-X) as the nodes of the network. The edges are defined as the coupling of two diagnoses given by their co-occurrence in the records of a medical events, for every individual in the RIPS, including the main and up to three secondary medical diagnoses, in all kinds of medical events: regular, emergency consultations, treatments and follow-ups, as shown in Figure 1.

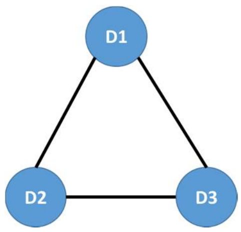

Figure 1. Structure of the Morbidity Network.

Nodes or vertexes represent diagnoses (International Diseases Classification in its 10th version, ICD-X), D_1 is the main diagnosis, while D_2 and D_3 are secondary ones. Edges or links represent the co-occurrences of primary and secondary diagnoses for every individual in any medical event: regular, emergency consultations, treatments and follow-ups.

Source: Authors' scheme.

In Figure 1, D_1 is the main diagnosis, D_2 and D_3 are the secondary diagnoses. The weight of links W_{ij} is defined as:

$$W_{ij} = \sum_k D_{ik}.D_{jk}, \qquad (1)$$

where, $D_{ik} = 1$ if diagnosis D_i was recorded at RIPS in the medical event k, and $D_{ik} = 0$ otherwise.

The graph of the network obtained by applying the methodology described above is shown in Figure 2.

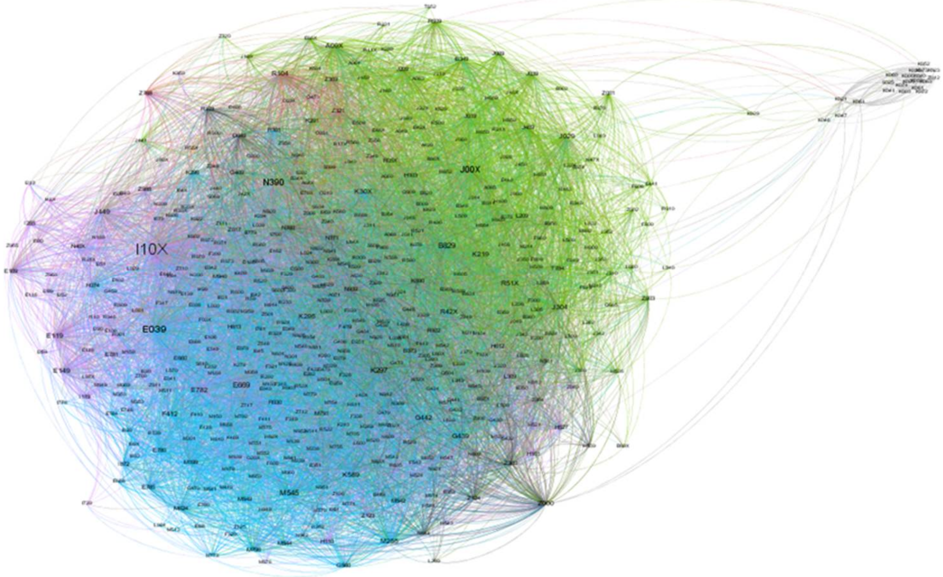

Figure 2. Graph of the Morbidity Network of Diagnoses for all medical records of residents in the province of Risaralda, years 2011 to 2016.

Nodes are diagnoses (International Diseases Classification in its 10th version, ICD-X) and links correspond to pairs of diagnoses present in medical records from all kinds of medical events: regular, emergency consultations, treatments and follow-ups. Source: Authors' own calculations.

The degree of node i, K_i, is the number of adjacent nodes to i, ; the strength of nodes i is defined as $F_i = \sum_j w_{ij}$. The diagnosis I10X, which is essential (primary) hypertension, has the largest degree and strength, 1259 connections for 9918 medical events, followed by urinary tract infection (N390), acute nasopharyngitis [common cold] (J00X), gastritis unspecified (K297), hypothyroidism unspecified (E039), intestinal parasitism unspecified (B829) and low back pain (M545).

The degree and strength probability distributions of the network, $p(k)$ and $p(f)$ respectively, can be represented using the complementary cumulative distribution function, defined in equation (2), which produces Figure 3:

$$P_K = \int_k^{\infty} p(k')\, dk' \; ; \; F_K = \int_k^{\infty} p(f')\, df' \qquad (2)$$

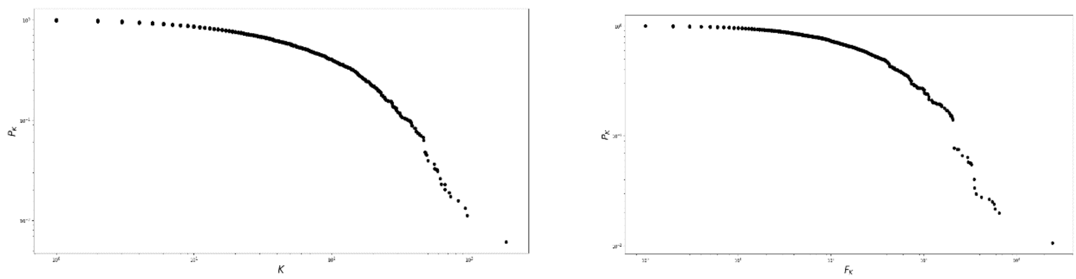

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Figure 3. Nodal degree and nodal strength for the population resident in the province of Risaralda. Complementary cumulative distribution functions for the nodal degree probability distribution (left) the nodal strength (right) for the Morbidity Network of Diagnoses for the total population resident in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

Figure 3 shows the existence of three regions. First, for P_K in the interval $[10^0, 10^{-1}]$, several nodes have few connections and small weight. Second, between 10^{-1} and 10^{-2} the links strengthen. Third, for $P_K < 10^{-2}$, in the fat tails few nodes are highly connected, neither in degree nor in strength.

We cut the network by selecting nodes with strength $F_k > 10^1$. This allows us to reduce the size of the network as well as to control spurious data from erroneous diagnoses.

The network reduction provides a better understanding of the morbidity patterns in Risaralda for both subpopulations of interest. In order to detect these two subpopulations, we use subgroup cohesion, specifically cliques or sets of maximally complete subgraphs, as described in the following subsection.

2.2 Selection algorithm for detecting communities

For this study, we need to fully identify morbidity patterns with both subpopulations of interest, namely victims of internal conflict and beneficiaries of subsidy programs, SISBEN I and II. To do so, we chose the k-communities algorithm of [31-32], because it keeps the superposition of diagnoses in the subgraphs even though many individuals share the same initial diagnosis, but with different final diagnoses.

For this algorithm, we must first quantify the total number of cliques in the network following [33] (see Figure 5, panel 1). In this case, the maximum number of diagnoses per individual medical event is k = 3, and this becomes the value k for percolation. The second step is to find the adjacent cliques, it is those that share k-1 nodes. Again, we followed [32] and [31] (see Figure 4, panels 2 and 3). The final step is to join all cliques reached by the series of adjacent cliques to conform the k-community (see Figure 4, panel 4). Figure 4 shows each step of this algorithm, which allows us to distinguish between the two subpopulations of interest. For consistency purposes, it is necessary to analyze each subpopulation's subgraphs, for which we use motif analysis.

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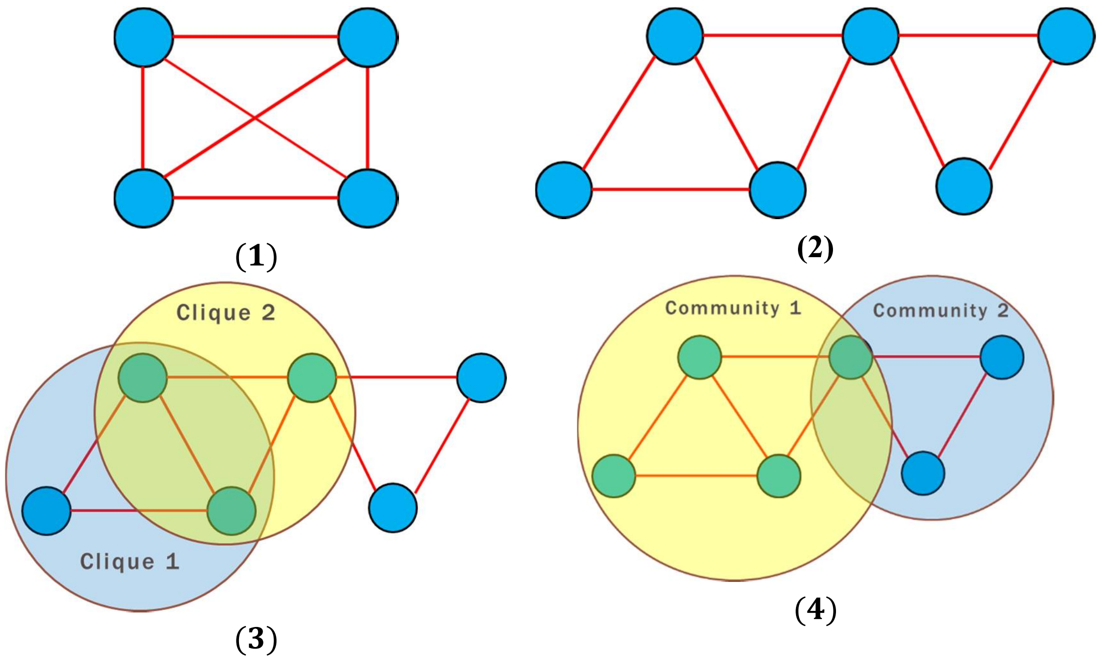

Figure 4. Detection algorithm for k-communities.

Source: [31-32].

2.3 Intensity Analysis and Motif Coherence

In complex networks, motifs are interconnected patterns with a much larger frequency than random graphs [33]. They are common in systems studied in biology [34-35] (Green et al., 2017; Smoly et al., 2017), ecology [36-37], among other. Motifs have intrinsic characteristics that condition the probability of occurrence of certain values in nodes, despite their application to particular cuts of the network [33] This allows to generate a series of trends in the network circumvent information, such as nodes' consensus that control their flow. This characteristic is essential to associate diagnoses and illness to lifestyles in the province of Risaralda.

To incorporate topological aspects of motifs in weighted networks (or strength), we use the intensity metrics and motif coherence developed by [38]. Intensity, $I(g)$, for subgraph g with vertices V_g and edges l_g, is defined as:

$I(g) = \left(\prod_{(kj)\in l_g} W_{kj}\right)^{1/|l_g|}$ (3)This guarantees link qualification in motifs from W_{kj} values, and leads to prioritizing communities that build up morbidity. After that, we establish the coherence as $Q(g)$, which allows us to study the consensus between people at the edges inside motifs. Coherence takes values near to the most important unit in its subgraph to establish the association between subpopulations, and it is defined as the ratio between intensity, $I(g)$, and the geometric mean of their weights, W_{kj}, as presented in equation (4):

$$Q(g) = \frac{I_g}{\sum_{(ij)\in l_g}^{n} W_{kj}} \qquad (4)$$

2.4 Mortality Network Analysis

Mortality is a much simpler network than morbidity and does not need to processes all morbidity data, as mentioned in Sections 3.1 to 3.3. The structure of this network is described in Figure 6. Node

C1 is the main cause of death in the diagnosis, and C2 and C3 are the secondary or underlying causes of death. Because the aim of this study is to observe the relationship between lifestyles that end up resulting in a particular cause of death, it is not necessary to run the topological measurements for this mortality network.

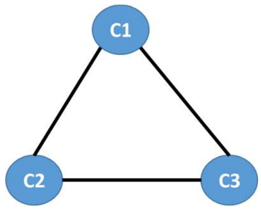

Figure 6. Structure of the Mortality Network.

Nodes or vertexes represent causes of death, C_1 is the main cause, while C_2 and C_3 are the secondary ones. Edges or links represent the number of cooccurrences of both primary and secondary causes for every individual.

Source: Authors' scheme.

3. Results and Discussion

First, we present the morbidity and mortality networks for the victims of internal armed conflict, as recorded in the BDUA dataset. Thereafter, the results for non-displaced population who qualify for SISBEN I and II are presented.

3.1. Results for the victims of Internal Armed Conflict

Figure 7 is the complementary cumulative distribution function that results from applying the methodology for studying morbidity that was described above. It summarizes the complex network of diagnoses for all the individuals included in the BDUA database that were identified as the victims of armed conflict.

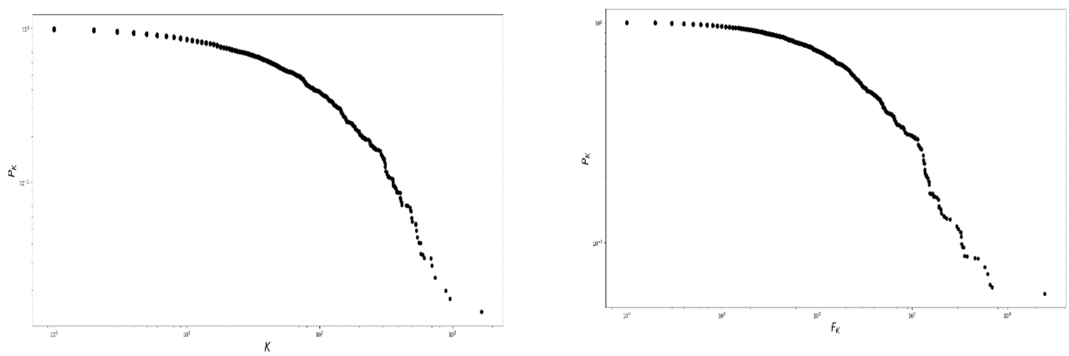

Figure 7. Nodal degree and nodal strength for the victims of the armed conflict in Colombia, resident in the province of Risaralda.

Complementary cumulative distribution functions of the nodal degree, K (left), and the nodal strength F_K (right) for the Morbidity Network of Diagnoses for the victims of the armed conflict in Colombia, resident in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

The results are similar to those of the morbidity network for the whole province of Risaralda, in the full range of P_K for K_i, and F_{ki}. The algorithm described in the section of methods allows the detection of communities and measures of the intensity and the coherence of motifs. Figure 8 presents the results, showing the coherence values for the two motifs selected to analyze the network diagnoses for the victims, with cohesive subgraphs due to cliques and communities. In both cases, motifs have low coherence values, between 0.05 and 0.1, with the exception of a small set with values close to 0.3. The motifs with the highest coherence are the cliques labeled 80 and 82 as well as community 50 composed by the diagnoses in Figure 9 (E782, E781, I119, E119 and E039).

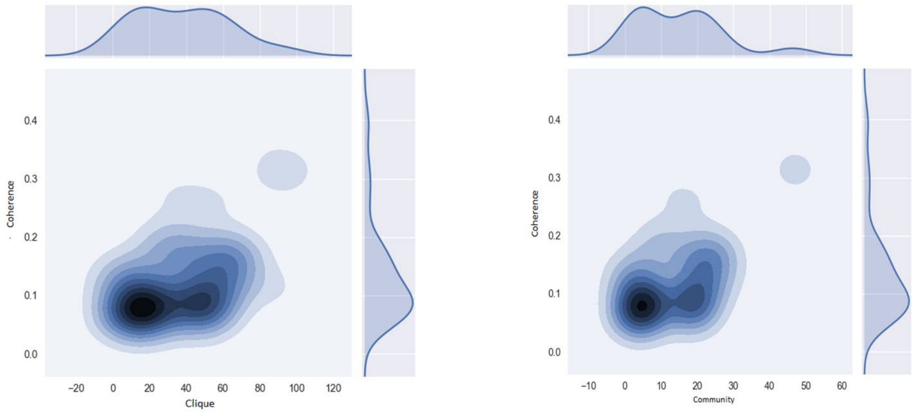

Figure 8. Motif coherence for cliques and communities.

Motif coherence for cliques (left) and for communities (right) for the Morbidity Network of Diagnoses of the victims of the armed conflict in Colombia, residents in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

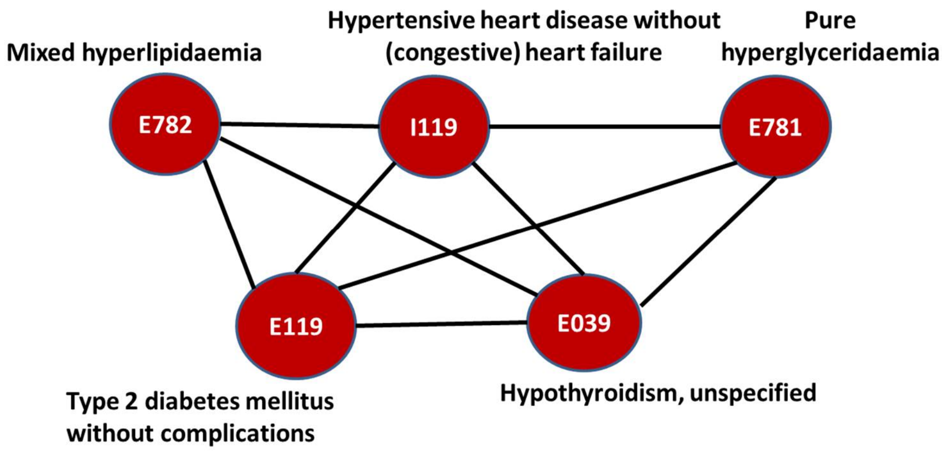

Figure 9. Community of diagnoses with the highest coherence level. Morbidity Network of Diagnoses for the victims of the armed conflict in Colombia, residents in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

This community analysis evidences a relation between lifestyle and some diseases, reflected in all portrayed illnesses except hypothyroidism unspecified (E039). For instance, mixed hyperlipidaemia (E782) is high cholesterol and triglycerides in an individual, and pure hyperglyceridaemia (E781) is the unusual increase of triglycerides. In most cases, the medical literature relates both diseases to "unhealthy lifestyles", such as sedentary behavior, diets based on a high intake of saturated fat, mostly from animal sources and/or empty carbohydrates, and smoking and alcohol consumption [39]. Similarly, hypertensive heart disease without (congestive) heart failure (I119) holds a larger genetic component [40-41]; its risk factors include the intake of too much salt, saturated fats and empty calories. The same risk factors apply to diabetes mellitus without complications, non-insulin dependent (E119) [42-43] and this could deepen other conditions such as hypothyroidism unspecified (E039). Moreover, all five of these diseases have obesity as a risk factor [44-45], and also have a high prevalence in Risaralda and Colombia, according to the Ministry of Health [46].

The mortality network results are summarized in Figure 10. Unsurprisingly, there is some overlapping of the three denoted diseases. Both diabetes mellitus without complications, non-insulin dependent (E119) and hypertensive heart disease without (congestive) heart failure (I119) are common to both results, denoting the final fatal outcome in both illnesses.

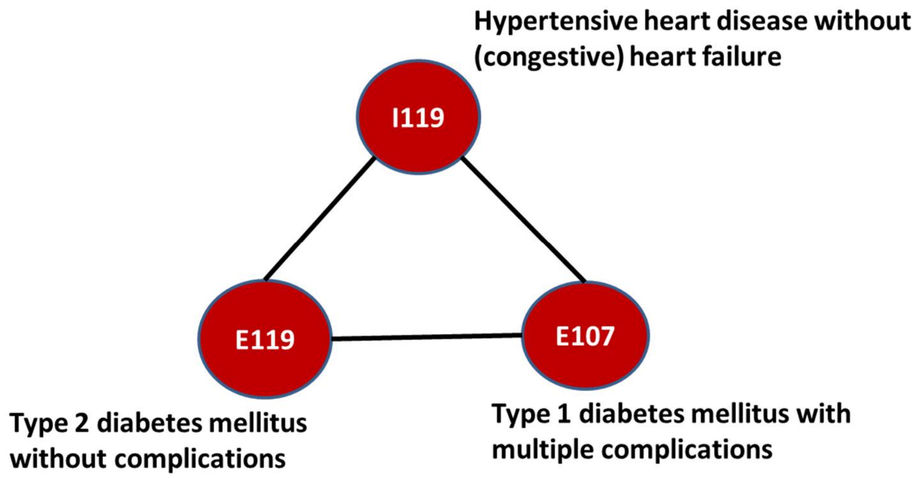

Figure 10. Clique with the highest overlapping in morbidity and mortality networks.

Mortality Network of Diseases for the victims of the armed conflict in Colombia, residents in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

The remaining disease in Figure 10 is diabetes mellitus with multiple complications, insulin dependent, which is mostly due to genetic conditions; however, some Type II diabetes patients may develop Type I diabetes mellitus if the risks of the former are not controlled, despite medical treatment.

3.2 Results for the Population Classified as SISBEN I and II

Similar to the previous results for the victims of armed conflict, we identified from the BDUA dataset those residents in the province of Risaralda who qualify for subsidies from the State

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welfare programs, namely those recorded in the subsidiary system SISBEN I and II. The SISBEN system is a central government program designed to properly identify the poorest households in Colombia. The SISBEN system collects the socioeconomic characteristics of all households in Colombia who are potentially poor. All local Majors report this information of potential households to the National Planning Department (*Departamento Nacional de Planeación*) is in charge of running the surveys and producing a wealth index that categorizes households into six SISBEN levels, with I the poorest and VI the richest. As a result, this stratification allows for the allocation of national subsidy programs. Households can check their SISBEN status and ask for a (re)categorization when they think they were not included in the database or when sudden economic changes make them fall into poverty. The index construction follows a secret formula to avoid moral hazard.[1]

The results are shown in Figures 11 and 12; for simplicity, we refer to this population as SISBEN I and II. The pattern in the degree distribution and node strength for morbidity is very much the same as that reported for the victims of internal armed conflict. Therefore, the cut was done at the same interval than before, the results are portrayed in Figure 12.

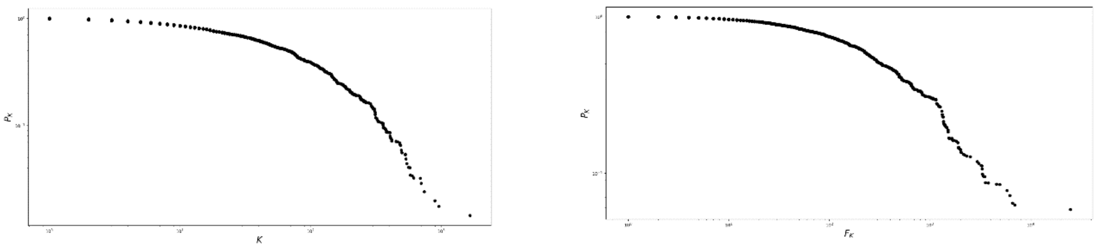

Figure 11. Nodal degree and nodal strength for the SISBEN I and II population resident in the province of Risaralda.

Complementary cumulative distribution functions of the nodal degree, K (left), and the nodal strength F_K (right) for the Morbidity Network of Diagnoses of the SISBEN I and II population, resident in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

[1] See http://govco.co/sisben/ (accessed on September 13, 2017).

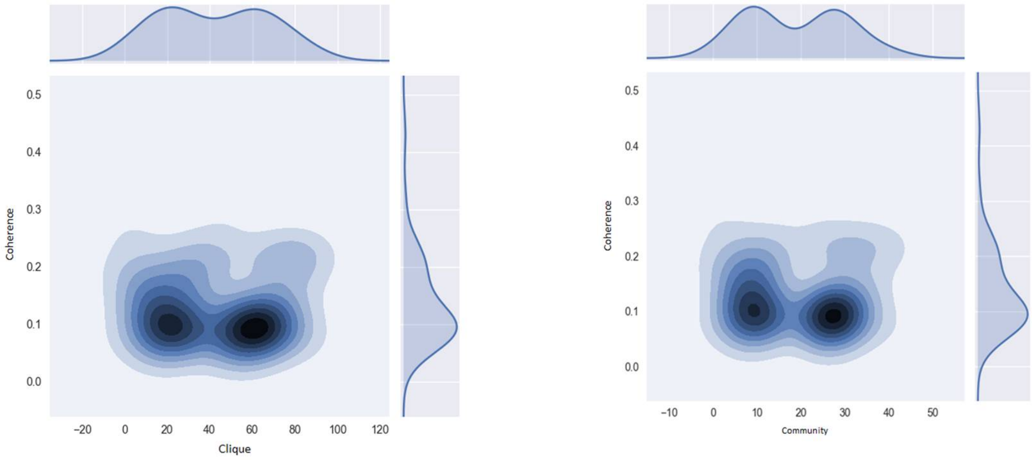

Figure 12. Motif coherence for cliques and SISBEN I and II. Motif coherence for cliques (left) and SISBEN I and II (right) for the Morbidity Network of Deseases for victims of the armed conflict in Colombia, resident in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

By contrast, motif coherence levels for SISBEN I and II are dissimilar to those of the victims of the armed conflict, despite most cliques being between 0.05 and 0.1. In fact, the highest coherence level is 0.27 and allows the construction of Figure 13. Despite one clique having this 0.27 level, it overlaps with its own value and replicates for the entire network, meaning it has the largest influence for most diseases for SISBEN I and II.

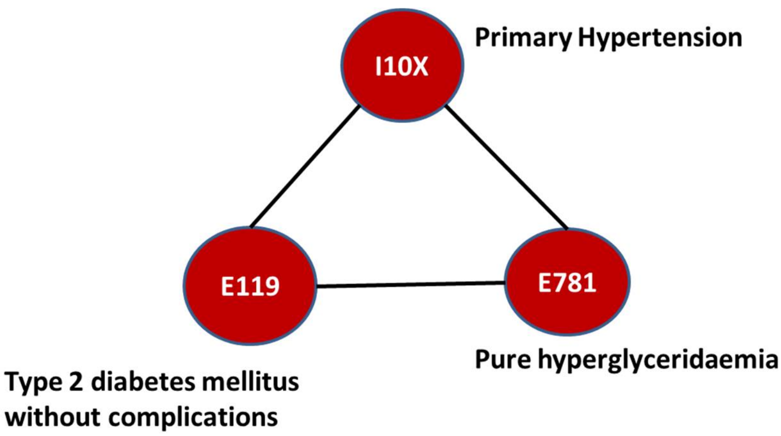

Figure 13. Highest overlapping in morbidity and mortality for SISBEN I and II. Mortality Network of Diseases from SISBEN I and SISBEN II population resident in the province of Risaralda. Years from 2011 to 2016.

Source: Authors' own calculations.

This motif is smaller than that of the victims of armed conflict; however, it coincides for one diagnosis, diabetes mellitus without complications (E119). The other two diseases, pure hyperglyceridaemia (E781) and primary hypertension (I10X), are not fatal outcomes for victims of internal armed conflict, but the former is part of the morbidity network. In general, these results show differences between both populations. Nonetheless, unhealthy lifestyles lead to similar but different mortality outcomes. For instance, a hazard risk for hypertension, beyond an unhealthy lifestyle, is diabetes mellitus [39,

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47-50]. Thus, the causes of these fatal consequences are all connected and in most cases linked to unhealthy lifestyles, as described before.

Both populations under study are, without question, highly vulnerable to poor health conditions, as a consequence of the extreme socioeconomic conditions that both face. This study's results show an unhealthy lifestyle as the common ground for the different diseases. More importantly, the differences in the final causes of death reported in each case, which result in access to health treatments and prognoses for both populations, are different.

4. Conclusions

Despite the evidence in the literature that refugees and IDPs have worse health conditions than the rest of the population, little had been studied in terms of morbidity and its link to mortality for the victims of the internal armed conflict in Colombia. In part, this is due to the lack of reliable data. However, this paper presents enough evidence from newly released administrative records with health-related micro data to show the main morbi-mortality causes for the victims of armed conflict, as recorded in those databases. The vast majority of self-reported victims in the dataset are IDPs, 80%; however, it is a novelty to account for health issues for victims of all human rights violations due to the conflict in Colombia.

Combining micro data from administrative records is stimulating, but linked unique identification allows this process. More challenging, however, is the analysis of such large datasets. The proposed methodology, based on complex network analysis, led us to fully identify the exact morbidity and mortality patterns from an ocean of chaotic information.

To establish a reference point, we analyzed the morbi-mortality frequencies of the victims of internal armed conflict and the poorest population (SISBEN I and II) resident in the province of Risaralda in Colombia. The results proved that both subpopulations are vulnerable and suffer non-communicable diseases mostly related to unhealthy lifestyles, such as Type II diabetes, hypertension and hyperglyceridaemia. However, victims of armed conflict show mortality outcomes that prove the deepening of those conditions (e.g., Type I diabetes).

This first approach to measure the morbi-mortality profiles of the victims of armed conflict in Colombia poses interesting results that can be useful for the design of targeted public health policies, particularly in a post-conflict scenario such as the one Colombia faces. As all first approaches, however, it comes with its limitations. First, and as stated before, the administrative records do not fully account for all the victims of armed conflict. As they are probably under-reported, the results presented here are to be read carefully and can be stated as a lower bound of the total number of victims.

Second, morbi-mortality patterns differ by age and sex in most populations, and the victims of internal armed conflict may not be an exception. We expect to expand, in the near future, this kind of analysis to subdivisions of the information by sex and age groups to show a more detailed morbi-mortality map for the victims of armed conflict.

Lastly, processing massive datasets requires powerful hardware. Similar to the analysis of other large datasets, we recommend using partition data, rather than working with a much larger set such as, for instance, information on the entire Colombian territory. We suggest dividing data in a country into subnational entities such as provinces (*departamentos*) as we have done, by starting with one of the smallest provinces in Colombia, and replicating this exercise with other provinces. Researchers should also use information from multiple years to avoid misinformation from a potential morbi-mortality shock, bust or registration issue.

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