Essays on Fuzzy Multidimensional Poverty and Vulnerabilities: Analyzes of Socioeconomic Deprivations and Inequalities in Brazil

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Contents

Introduction

Carolina Maria de Jesus's *Quarto de Despejo* authentically describes her day-to-day reality as a resident of a favela in São Paulo in the 1950s. Her lucid, direct, and touching self-description of poverty demonstrates the many interlinked aspects affecting people's wellbeing and (re)producing disadvantages. For example:

"I got out of bed at 6. I was upset because I didn't sleep. I spent all night repairing the roof where it leaks. I fix one side and it drips in on the other. When it rains I almost go crazy because I can't go for [collecting] paper to get any money.
I feel very cold. I put on three jackets and people who see me in the streets say: "Oh, how fat you got!"
The era has passed when a person can put on weight." (Jesus, 2003, p. 117).

Carolina Maria de Jesus's diary is also an invitation to reflection. How can people take care of their health if they are uncertain whether they will have food for their family at the end of the day? How to get and keep a full and productive job if they live in unsafe housing conditions? How difficult is it to access good quality education if they must work in precarious conditions since they are very young? These and many other situations illustrate the complex and multidimensional nature of poverty and the different ways that people can be vulnerable. In addition, heterogeneities such as gender, skin color, and region highly influence the probability of being and remaining poor in Brazil.

Clearly, many things have changed and improved in Brazil since the 1950s. Yet, many people still live in conditions not so far from the one of Carolina Maria de Jesus and her family. The book *Vozes do Bolsa Família* is a more recent source that gives voice to people receiving benefits from the Brazilian conditional cash transfer program *Bolsa Família*. The interviews reveal that often the *Bolsa Família* benefit is the only source of income and represents the first time they have a stable source of income. Although the importance of a regular income is evident, their own descriptions of deprivations, and their situation expose that many difficulties still were revolving their life. For instance:

“In 2007, we interviewed the female marinara shellfish harvesters again. The choice to interview these women is due to the hardness of their work to try to increase the family's income, as well as to the existence of a certain prejudice in relation to the job. They are forced by the very nature of the harvesting they do to remain in the sea at low tide, kneeling, collecting these small mollusks that they sell in fairs and hotels in the region. This is evidently considered humiliating work, for desperate people.” (Rego and Pinzani, 2014, p.106, my translation).

Motivated mainly by these books and the reality they portray, this thesis aims to shed light on the complexity and multidimensionality of poverty and vulnerabilities in Brazil. Evidently, it is impossible to cover all the aspects affecting people and capture all the details and contexts as in a diary or a qualitative study. Instead, I directed my effort to translate some of the deprivations exposed in the mentioned books into numbers. In that sense, this thesis contributes to the literature of multidimensional social indicators mainly by proposing new indexes, measures, and innovative applications with the fuzzy set approach as the main tool. The thesis contains three chapters, each focusing on different aspects of poverty or aspects related to poverty.

In the first chapter, Gianni Betti and I explore deprivations associated with the capacity to prevent and recover from infection with COVID-19. We wrote this article during the first wave of the pandemic outbreak to show that multidimensionally poor people are also the most vulnerable in emergencies and expose the need for coordinated national action prioritizing the most exposed groups in Brazil. Using the Alkire-Foster method and a fuzzy set approach, we propose two pandemic-specific indexes to measure vulnerability in terms of the capacity to prevent infection with and to recover from the disease. The outcomes reveal structural deprivations in the country and considerable inequality among regions and ethnic groups. In the period studied, rank correlations confirm that the most vulnerable states were also among those with the highest pandemic-related deaths per million people. The article was published in World Development.

In the second chapter, the focus is on gender differences in multidimensional poverty in Brazil. The chapter contributes to the literature on multidimensional poverty measurement by applying and proposing procedures to improve individual-level estimations considering the limitations of household surveys. I create two individual-based indexes with indicators that are key aspects in gender and feminist analyses. Applying a fuzzy approach and the Alkire-Foster method, I estimate multidimensional poverty and gender differences in three perspectives: intrahousehold, interhousehold, and intracouple. I also calculate inequality among the poor and intracouple gender gaps proposing fuzzy versions for these analyses. The results suggest that women are disadvantaged in dimensions that are crucial components of agency or degree of empowerment. In most specifications, individuals living in female-headed households are poorer than those living in male-headed households, but in female-headed households, women are in advantage compared to men, or at least the disparity decreases.

In the third chapter, I concentrate on labor market vulnerability in Brazil. Here, vulnerability refers to the capacity of achieving full potential in work and career, finding and seizing employment opportunities, and having a decent job. The chapter aims to propose two labor market vulnerability indexes (LMVI) that include people inside and outside the labor market. Using a fuzzy set approach and comparing two years, I estimate vulnerability from two perspectives: individual and household. One of the innovations of the household-based measure is to understand if people that are vulnerable or outside the labor force (e.g., dependents) can have support from members of their household that are working and are not vulnerable. The outcomes reveal that the average degree of vulnerability was high and had a slow change between the years. Although education levels improved, precarity and other labor deprivations did not make progress in the period.

These three chapters present different perspectives of multidimensional social indicators, but the subgroup inequalities are similar. Persistently, Black, Brown, and Indigenous people are disadvantaged compared to White and Asian people, rural areas are always worse than urban, and the North and Northeast regions are in worse conditions than the other regions. Hopefully, the insights of this thesis joined and will join other contributions to understand better how to decrease these inequalities and reduce poverty in all its forms.

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Chapter 1

The Pandemic of Poverty, Vulnerability, and COVID-19: Evidence from a Fuzzy Multidimensional Analysis of Deprivations in Brazil

Co-authored with Gianni Betti (University of Siena)

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Abstract

This chapter aims to show how much and in which way people in Brazil are deprived in terms of indicators directly related to the capacity to prevent and recover from infection with COVID-19. We use the Alkire-Foster (AF) method and a fuzzy-set approach as complements to measure multidimensional poverty within the context of the coronavirus pandemic. We propose two pandemic-specific indexes to account for the vulnerability related to the capacity to prevent infection with and to recover from the disease. The outcomes reveal structural deprivations in the country and considerable inequality among regions and ethnic groups. Rank correlation analyses suggest that the proposed indexes can trace the trends in increasing infection and a higher mortality rate in vulnerable regions. Compared to headcount ratio results, the fuzzy measures have more precise outcomes and are better able to capture the evolution in mortality patterns. Our empirical evidence offers an additional warning that the pandemic responses need to prioritize the most vulnerable groups and reinforces the need for coordinated national action.

Keywords: COVID-19 · Multidimensional poverty · Fuzzy-set approach · Alkire-Foster (AF) method · Latin America · Brazil

1.1 Introduction

The COVID-19 outbreak has exposed the inequality and interlinked socioeconomic deprivation affecting global south countries to a greater extent than before. The fact that some of the population has these problems not only is related to the pandemic but mainly reveals historical gaps that are exacerbated by the virus. In Brazil, minority groups are at a disadvantage in terms of economic, social, and health deprivations (Hoffman, 2018; Fernandes, 2017; Raupp et al., 2017). Planning an efficient response to the pandemic requires an understanding of the increased risk of exposure, especially among those living in unsafe conditions. In this sense, interest in analyzing the vulnerability to infection with COVID-19 among subgroups has grown (Pareek, 2020; Khalatbari-Soltani et al., 2020). By examining how much and in what ways people in Brazil are deprived in terms of indicators directly related to the ability to prevent infection with and recover from COVID-19, this study joins others on this topic.

The first confirmed case in Brazil was diagnosed on February 25, 2020. By May 10, the country had 162,699 confirmed cases in a pattern of rapid infection (DATASUS, 2020). Even though Brazil climbed to second in the worldwide number of confirmed COVID-19 cases on May 22 and in the number of confirmed deaths from COVID-10 on June 12, its national government is still struggling to recognize the problem and promote coordinated action (see Lancet, 2020). The pandemic is worsening the quality of life in entire communities, and the lack of effective policies poses an additional threat to the population. Families experiencing multidimensional poverty face at least two sets of additional risk factors.

First, people living in poverty might not be able to follow the recommendations for prevention (see WHO, 2020a, 2020b). Sheltering at home might be infeasible if their housing is inadequate for keeping them safe and comfortable during a quarantine. It is not always possible to wash hands, clean and disinfect the home properly if one has inadequate access to clean water and sanitation conditions are poor. Keeping a safe distance from others is not practicable in an overcrowded residence. Furthermore, transmission of the virus might be enhanced in high-density communities (Lusignan et al., 2020; Rubin et al., 2020) and in places with insufficient social distancing (Rubin et al., 2020, Chu et al., 2020); and the spread of COVID-19 can be mitigated where the mobility control measures are stricter (Kraemer et al., 2010).

Second, poor living standards and insufficient health services reduce the ability to recover from COVID-19. Drinking unsafe water and being exposed to improper sewage disposal is highly correlated with the contraction of preventable diseases (WHO, 2019a, 2019b), which can compromise the immune system. Families who use highly polluting fuels for cooking might be a risk group as indoor air pollution is associated with respiratory diseases (WHO, 2018a). Because the schools are closed, food security is now under threat for families with schoolchildren who depend on schools for daily free meals. The lack of physicians and intensive-care beds in hospitals is critical for people in need of treatment. The distance from hospitals is an additional factor in vulnerability, particularly for several Indigenous communities that live far from urban areas.[1]

The literature on infectious disease outcomes for subgroups suggests that risks are higher among minority groups and in more deprived regions. For instance, Zhao et al. (2016) show that, during the 2009/2010 influenza A(H1N1) pandemic, the risk of mortality in England was higher for non-White populations than White populations and for people living in the most deprived areas compared with those in less deprived areas. Lusignan et al. (2020) estimate that, within the Oxford Royal College of General Practitioners Research and Surveillance Centre primary care network, Black people have higher risk factors for testing positive for COVID-19 than White people and so do individuals in more deprived areas.

Studies about racial and ethnic disparities in the United States in terms of infection with and mortality from COVID-19 also show that minorities are the hardest hit. Laurencin and McClinton (2020) demonstrate that in Connecticut, the Black population had a proportion of infection and death that exceeded its share of the population even at the beginning of April. Yancy (2020) shows that this disproportion is also present in Chicago, Louisiana, Michigan, and New York City. In Chicago, for example, Black people make up 30% of the population but more than 50% of the confirmed cases and almost 70% of the deaths. Millett et al. (2020) and Holtgrave et al. (2020) confirm these

[1] InfoAmazonia (2020) estimates that, in the Amazon Forest region, the Indigenous tribes live on average about 315 km away from public hospitals equipped with intensive-care departments.

discrepancies among racial and ethnic minorities, and they conclude that social characteristics, structural racism, less access to health care, and other factors might be driving these results.

Research on the impact of the COVID-19 pandemic on minority groups and in different regions in Latin America is still thin, but it confirms the same outcomes there. A pioneering study by Baqui et al. (2020) uses the SIVEP-Gripe (*Sistema de Informação de Vigilância Epidemiológica da Gripe)* dataset to analyze COVID-19 hospital mortality in Brazil. The analysis selects only observations that account for ethnicity to assess the relation between health risk, ethnicity, and regional differences. The authors find that Black and Brown people are at the highest risk of a hospital death. They also show that people at hospitals in the northern region had comorbidities more often and a higher risk of mortality than people in most of the central-south region.

To contribute to the pandemic literature on Brazil, we use the Alkire-Foster (AF) method and the fuzzy-set approach as complementary measures of multidimensional poverty in the context of COVID-19 (Alkire and Foster, 2011; Betti and Verma, 2008). Because families have multiple difficulties at the same time, unidimensional poverty measures—which usually focus only on monetary poverty—are insufficient to account for the reality for these people. Therefore, the methods proposed in this work are appropriate for collecting clear evidence of overlapping kinds of deprivation. The latter, also seen as the intersection of multidimensional aspects of poverty, are considered high-risk factors in any multidimensional approach (Lemmi and Betti, 2006), and this is particularly evident when poverty and deprivation are analyzed at the regional or subnational level (Betti et al., 2012).

This chapter is inspired by the policy briefing on multidimensional poverty and COVID-19 risk factors written by Alkire et al. (2020). They show that the Global Multidimensional Poverty Index (GMPI) (OPHI and UNDP, 2019) provides information that is useful for identifying risks and vulnerabilities related to COVID-19. They estimated that 472 million people in the world face simultaneous deprivation in terms of water, nutrition, and indoor air pollution.

This chapter innovates in at least three lines of research, both theoretical and applied:

1. it proposes two COVID-19-specific multidimensional indices: the COVID-19 prevention index and the COVID-19 recovery index;
2. it proposes a rank correlation analysis to determine how the vulnerability indexes can capture the mortality patterns in vulnerable regions;
3. it introduces a fuzzy counterpart to these indices.

To achieve these original contributions, we have moved step by step; the first step was to adapt the GMPI in the context of COVID-19 in Brazil, creating a multidimensional vulnerability index (MVI). We selected eight interlinked vulnerability indicators in the dimensions of sanitation, home shelter, physical distance, and recovery from illness. Five of those indicators are also among the ten GMPI[2] indicators. To better account for groups and regional disparities, we took a further step in building an appropriate multidimensional index. The fact that the variables previously selected for the MVI are all interlinked makes it difficult to observe the immediate relation to COVID-19. Therefore, we propose two multidimensional poverty indexes related to the COVID-19 pandemic in terms of prevention and the ability to recover as the first contribution of this chapter. In this way, we can obtain a more comprehensive and detailed picture of deprivation in these two aspects. The indexes reveal considerable inequality between regions and ethnic groups, confirming the existing evidence that minority groups and vulnerable regions have more exposure to the virus.

The second contribution of the chapter is our estimation of rank correlations to clarify whether the states with the highest vulnerability are also those with highest death rates. In Brazil, the first cases emerged in the wealthiest states in the southeast and gradually spread to some of the poorest states in the north and northeast. By calculating the evolution of the correlations, our indexes identify this path, showing that the virus is progressively hitting harder the most vulnerable regions. This trend

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[2] The GMPI indicators are nutrition, child mortality, years of schooling, school attendance, cooking fuel, sanitation, drinking water, electricity, housing, and assets.

is observed in the two COVID-19 multidimensional poverty indexes and the unidimensional monetary poverty index. Interestingly, the index of monetary poverty shows the highest correlations in almost all of the epidemiological weeks, which suggests that a lack of money is an immediate factor of vulnerability when people face unexpected shocks and reinforces the importance of using both monetary and nonmonetary indexes as complementary tools in a multidimensional poverty analysis.

Our third contribution is in using the fuzzy approach to overcome the limitation of standard poverty measures, which treat poverty as a binary phenomenon (poor/non-poor). Using this approach enriches the other two contributions. Fuzzy measures are more suitable for analyses at the subnational level and for subgroups because they have smaller standard errors in the estimation of poverty and are better at capturing mortality trends by showing higher rank correlations in most of the results.

The chapter is organized as follows. Section 1.2 presents the empirical strategy, as well as the description and sources of the data, and the scope of the indexes. Section 1.3 presents and discusses the results, and Section 1.4 concludes.

1.2 Methodology and data

1.2.1 Empirical strategy

1.2.1.1 The Alkire-Foster method

The most traditional measure of poverty is the headcount ratio (HCR), also known as the incidence of poverty or poverty rate, which shows the percentage of people identified as poor. In this approach, by defining a poverty line, the result is a dichotomic measure that splits the population into the poor and the non-poor.

The Alkire-Foster methodology (AF), developed by Alkire and Foster (2009, 2011), goes beyond the traditional approach by measuring multidimensional poverty based on its incidence (HCR) and intensity (A). The latter is the average share of deprivation across individuals who are identified as poor. The adjusted headcount ratio (M_0), or multidimensional poverty index (MPI), is defined as the product of incidence and intensity, $M_0 = HCR*A$.

The identification of multidimensional poverty is calculated using the two-cutoff approach. The first is the deprivation cutoff set for each variable. In this way, individuals can be identified as being deprived in terms of a specific indicator, which means that we must define a deprivation threshold for each of the variables. We apply the second cutoff by calculating the weighted sum of deprivation and classifying an individual as poor if the resulting score is above the chosen poverty cutoff. Because the estimation of M_0 is particularly well-suited to ordinal/binary data (Alkire and Foster, 2009), when applying the AF method, we use our variables as ordinal indicators and transform the continuous variables into binary indicators.

1.2.1.2 The Fuzzy-Set approach

Both the traditional monetary approach (HCR) and the MPI approach are based on deprivation cutoffs (poverty lines), which treat poverty indicators as binary (poor/non-poor); instead, the fuzzy-set approach treats poverty and multidimensional deprivation as matters of degree, determined in terms of the individual's position in the distribution of the monetary variable concerned (either income or consumption expenditure) and other aspects of living conditions (Betti and Verma, 2008). The state of deprivation is thus seen in the form of fuzzy sets, to which all members of the population belong in varying degrees. In particular, within a determined poverty range, the approach uses membership functions to identify the degree of certainty of individual poverty in a specific dimension (Alkire et al., 2015).

The fuzzy-set approach was first proposed by Cerioli and Zani (1990) and developed by Cheli and Lemmi (1995) in the so-called totally fuzzy and relative approach. Later, Betti et al. (2006) proposed the integrated, fuzzy, and relative (IFR) approach, in which the membership function used for the fuzzy monetary (FM) measure is defined as:

$$\mu_i = FM_1 = (1-F)^{(\alpha-1)}[1-\mathrm{L(F)}] = \left(\frac{\sum_\gamma w_\gamma \mid y_\gamma > y_i}{\sum_\gamma w_\gamma \mid y_\gamma > y_1}\right)^{\alpha-1} \left(\frac{\sum_\gamma w_\gamma y_\gamma \mid y_\gamma > y_i}{\sum_\gamma w_\gamma y_\gamma \mid y_\gamma > y_1}\right) \quad (1)$$

where F is the cumulative distribution function for consumption expenditure, L is the corresponding Lorenz curve, ω_γ is the ranked individual sample weight, y_l is individual consumption expenditure, and α is a parameter. The definition of the membership function is based on the monetary variable, in which the alpha parameter is chosen such that the mean is "anchored" to the headcount ratio. The FM measure, as defined previously, can also be applied in terms of the generalized Gini measures when we define α = 1.

In a multidimensional context, y_l is an individual composite index, in which the weights of the single indicators are not predetermined but, rather, follow the prevalence-correlations principles proposed by Betti and Verma (2008). If the prevalence of an indicator is high, then its weight is low, and if correlations with other vulnerable variables are high, then its weight is low. In this way, we determine appropriate weights without the necessity of recurrence in potential arbitrary weight choices.

Another important advantage of fuzzy measures is that they are more informative and have smaller standard errors (Betti et al., 2018). Therefore, fuzzy measures are more useful for subnational poverty measures (Betti et al., 2012), which means that we can obtain poverty estimations for areas with relatively small samples that are more statistically significant than those yielded by other measures.

The fuzzy approach and the AF method are complementary measures. The latter has the advantage of providing intuitive measures that can be decomposed by population groups. In contrast, the former has the advantage of overcoming the poor/non-poor dichotomy and enables more precise measures for subnational regions.

1.2.2 Data

To construct the multidimensional indexes, we combine different publicly available sources. In this subsection, we describe the data sources and the indicators.

1.2.2.1 Household expenditure survey

The primary source of data is the Brazilian Consumer Expenditure Survey (POF) for 2017-18, the most recent round, released by the Brazilian Institute of Geography and Statistics (IBGE) on May 3, 2020. The POF is a high-quality household survey conducted to investigate the profile of consumption expenditure, income, and living standards of Brazilian households. The data are widely used in poverty and inequality research and have particular national importance because they are used to construct consumption baskets in order to calculate official consumer price indexes.

The sample design of the POF is structured to cover the entire territory of the country; it is representative in terms of the country, major regions, capitals, metropolitan regions, other parts of the states, and urban or rural areas. The survey sample in 2017-18 totals 69,660 households, providing information at the household and individual level.

The variables derived from the POF are *Drinking water*, an indicator that accounts for the household's frequency of supply, whether the household has running water, and the system of distribution; *Sanitation,* which represents whether the household has at least one indoor bathroom with shower and toilet, whether it is shared with other households, and whether it is connected to the public sanitation system; *Electricity*, which represents whether the household has access to electricity and the frequency of this access; *Housing*, which assesses the materials used in the household's flooring, walls, and roof; *School meals*, which, for households that have children who used to have daily free meals at school, calculates how many children had access to this service, and how many meals per day; *Share of food consumption expenditure,* as a proxy for a household's food security; *Overcrowded housing,* calculated as the number of residents per permanent bedroom in the household; *Older adults per resident,* calculated as the number of people age 60 or more per number of members of the household who are younger; *Commuting time*, which represents the number of members of the household who spend more than an hour to get to work; *Indoor air pollution by cooking fuel*, which refers to the kind of fuel used by the household for cooking; and *Private insurance*, which shows whether the individual has private health insurance. The scores are presented in Table 2.

The remaining variables (described below) come from other sources and were merged with the most possible disaggregated subnational level in the POF (state, capital, metropolitan region, or other parts of the state). These variables are uniform across the population at the corresponding merged level.

Studies on COVID-19 stress that demographic and social variables matter when it comes to the consequences of the pandemic (Oke and Heneghan, 2020; Souza et al., 2020).

Table 1 shows demographic and social characteristics estimated from the POF 2017-2018 dataset for the Brazilian population[3]. Age and gender are two important factors in COVID-19 risk. According to the estimations of Oke and Heneghan (2020), the case fatality rate is 66% higher for males older than 30 than for women and 4.47 times higher for people age 80-89 than for those age 60-69. The median age in Brazil is 33 (the mean is 35.26), while the median age across Europe Union members in 2018 range from 37.3 years in Ireland to 46.3 years in Italy (Eurostat, 2019). This difference could reflect lower risk in terms of age in Brazil, but other factors that affect risk remain to be proved.

[3] The color/ethnicity classification follows the POF/IBGE, in which the individuals in the survey declared their race identity without any influence from the interviewer. The categories are White, Black, Yellow (people that claimed to have Asian origin), Brown (people that claimed to be *parda, mulata, cabocla, cafuza, mameluca*, or black mixed-race), indigenous, and not identified (not declared). For an ethnic background, a discussion about race as a social construction, and segregation in Brazil, see Fernandes (2017).

Table 1 - Mean of Demographic and Social Variables

Variable	Mean
Gender	
Women	51.61%
Men	48.39%
Color/ethnicity	
White	44.00%
Black	10.22%
Asian	0.68%
Brown	44.42%
Indigenous	0.38%
Not identified	0.30%
Area type	
Urban	85.26%
Rural	14.74%
Age in Years	35.26
Literacy ratio (>14 years)	92.41%
Years of education (>14 years)	9.37
Number of observations	178,431

For instance, as mentioned in the Introduction, few analyses are available about the impacts on ethnic minorities. In Brazil, this is particularly important because ethnic minorities are at a relative disadvantage in terms of the risk of infection. As we discuss in the next section, Indigenous people, who make up 0.4% of Brazil's population, predominantly live in regions with higher vulnerability to infection with COVID-19 (22.7% live in the northern region) and have the highest vulnerability scores.

1.2.2.2 Data on access to health care and risk ratio by age and gender

The survey Area of Influence of Cities (REGIC) conducted by the IBGE in 2018 is used to provide information on the distance that people need to travel from their city to other cities to access intensive-care health services. To calculate the distance, we used geographic coordinates to measure the length in kilometers of the shortest path between two cities. The final indicator is the mean for each POF subnational level (capitals and other parts of the states) of the distance, weighted by the frequency of the corresponding destination.

The data on the number of physicians and intensive-care hospital beds in the public health system is available at the city level on the National Registry of Health Facilities (CNES) website. We used the CNES data processed by the IBGE at the municipal level for December 2019, calculating the mean for each POF subnational level. Both indicators are calculated per 1,000 people.

The risk ratio by age and gender was built based on the estimation of Oke and Heneghan (2020), which use Italian data from the Italian National Institute of Health (ISS). The indicator sets the risk reference score to the age between 60-69 and increases/decreases if the age is above/below this range.

1.2.2.3 Legal measures of social distancing and mobility indexes

In Brazil, to date there has been no coordinated social distancing policy implemented at the national level. The federal states and municipalities started to adopt measures to contain the spread of COVID-19 regardless of the decisions of the national government. However, these policies were implemented at different times and in different ways. To capture the differences in the level of each state's strictness, we used the index of legal measures for social distancing developed by Moraes (2020a, 2020b). Moraes considered all the decrees by state legislatures adopted April 6-24, 2020, to construct the index. The measure considers the suspension or restriction of six types of activities: cultural, athletic, and religious; bars and restaurants; non-essential services and business; non-essential industries; schools and universities; and transportation. In this chapter, the score was adapted to range from 0 (strict restrictions) to 10 (no restrictions) (see Table 2).

For the mobility index, we used the Google Community Mobility Report from March 11, 2020, which is the day on which the World Health Organization (WHO) declared COVID-19 a pandemic, to April 30, 2020. The Google indicator provides population-wide information on the relative change in mobility in each state and in the following categories: retail stores and recreation, grocery stores and pharmacies, parks, transit stations, workplaces, and residents. The change in mobility is the percentage change from a baseline day before the pandemic. We use the mean of the changes in mobility in retail and recreation, parks, transit stations, and workplace categories as a proxy for changes in behavior regarding daily activities.

1.2.2.4 COVID-19 indicators

The data on confirmed cases of COVID-19 and deaths from it are available on a daily basis on the coronavirus website of the Ministry of Health (https://covid.saude.gov.br). The first confirmed case was identified on February 25 and the first confirmed death on March 17, 2020. We collected statistics for the states and capitals using official data from the Brasil.io (2020) website, https://brasil.io/dataset/covid19/caso_full/. Based on the number of deaths confirmed as being due to COVID-19 and the population estimated by the POF, we calculated the number of confirmed deaths per one million people. It is important to stress that the official number of confirmed deaths from COVID-19 underestimates the actual number, mostly due to limited testing.

1.2.2.5 Descriptive statistics

Table 2 shows the score range and descriptive statistics for all the indicators used in the COVID-19 multidimensional poverty indexes.

Figure 1 presents the correlations between each pair of indicators calculated as Pearson coefficients. The heatmap is colored using a range from -1 (blue) to +1 (red). The deprivations that are commonly explored in research on multidimensional poverty—such as having clean drinking water, sanitation, electricity, housing, housing density, and indoor pollution—are all positively correlated. The correlations of these variables with the share of expenditure on food, the distance from a hospital, monetary poverty (measured by the household consumption expenditure per capita, $3.20 a day, in 2018 purchasing power parity [PPP]), and COVID-19 deaths per million people are also positive. However, they have a negative correlation with population density and indicators related to health-care resources, such as private health insurance, physicians per 1,000 people, and intensive-care beds per 1,000 people. The correlations with the remaining variables are negative or near zero.

Table 2 - Score range and descriptive statistics for the variables used in the COVID-19 multidimensional poverty indexes

Variable	Score Range	Mean	Standard Error	Min	Max
Drinking water	0-6	0.605	0.003	0	6
Sanitation	0-4	0.494	0.002	0	4
Electricity	0-4	0.056	0.001	0	4
Housing	0-9	1.027	0.003	0	9
School meals	0-16	0.476	0.003	0	16
Share of expenditure on food	Continuous	0.177	0.0003	0	1
Overcrowded housing (residents per permanent bedroom)	Continuous	1.905	0.002	0.333	13
Older adults per household	Continuous	0.193	0.001	0	4
Commuting time	0-4	0.1501	0.001	0	4
Population density (inhabitants per km^2)	Continuous	1261.859	5.827	0.673	8435.358
Index of legal measures of social distancing	0-10	3.269	0.004	0.8	6.7
Mobility index (% reduction from a baseline day before the pandemic)	Continuous	51.294	0.011	39	61.392
Risk ratio by age and gender (1 is the risk reference score set for age 60-69)	Continuous	0.496	0.003	0	8.018
Indoor pollution due to cooking fuel	0-2	0.010	0.0002	0	2
Private insurance	0/1	0.260	0.001	0	1
Distance from hospital (in km)	Continuous	30.503	0.101	0	606.544
Physicians per 1,000 people	Continuous	1.174	0.002	0.365	4.695
Intensive-care hospital beds per 1,000 people	Continuous	0.441	0.001	0	3.01

Note: For ordinal variables, the score ranges are from no deprivation to total deprivation. The variable for private insurance is the only binary variable, in which 0 means no insurance, and 1 means the person has insurance. The continuous variables are identified as such.

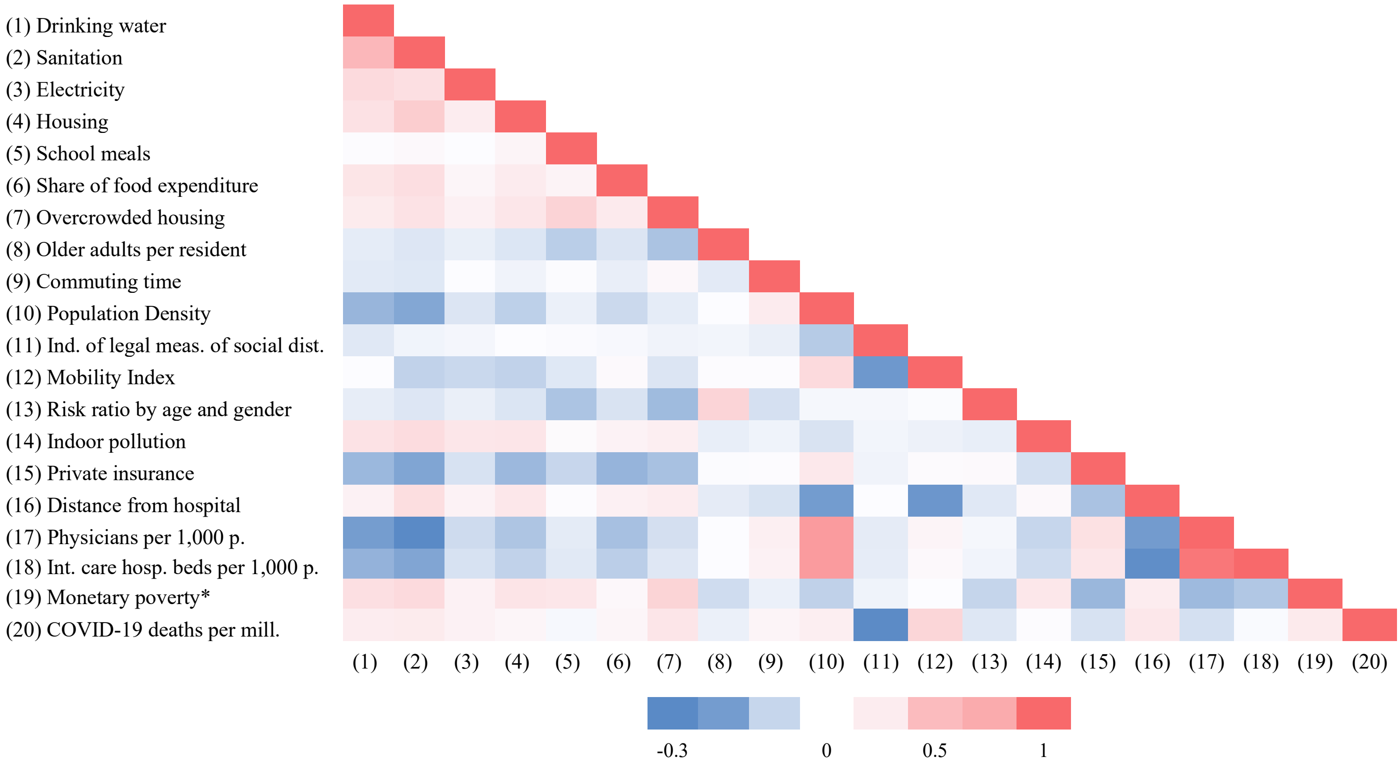


Figure 1 - Pearson correlation matrix of the variables used in the COVID-19 multidimensional poverty indexes, monetary poverty, and COVID-19 deaths per million people

*Monetary poverty is measured by the household consumption expenditure per capita ($3.20 a day, 2018 purchasing power parity).

1.2.3 Multidimensional Poverty Indexes: defining the scope

This section proposes in detail the two COVID-19-related multidimensional poverty indexes (CMPIs), comprising variables directly related to the capacity for preventing infection with COVID-19 and for recovery from it. Table 3 shows the dimensions and variables of each index, the definition of the deprivation cutoffs and weights used in the AF method, and the resulting prevalence-correlation weight scores for the fuzzy analysis.

Most of the cutoffs in the AF analysis were adapted from the United Nations sustainable development goals and consider the Brazilian context and data availability. In the fuzzy application, to avoid dichotomization of the variables and to obtain more information, we regard the variables as ordinal or continuous indicators when possible. Only the indicator for private insurance is binary in both approaches.

Table 3 - Structure of the COVID-19 multidimensional poverty indexes, variable cutoffs, and weights

Index	Dimension	Variable	AF Deprivation Cutoff	AF Weight	Prevalence correlation weight
COVID-19 prevention	Hygiene	Drinking water	The household does not have daily access to water, or does not have indoor running water, or the water does not come from a public water system.	0.100	0.103
		Sanitation	The household does not have indoor bathroom with shower and toilet, or the bathroom is shared with other households, or the disposal of human waste is not connected to a public sewage system.	0.100	0.097
	Staying at home	Electricity	The household has no access to electricity.	0.100	0.103
		Housing	The household's housing materials for at least one floor, wall, and roof are inadequate.	0.100	0.097
	Food security	School meals	One or more children in the household have breakfast, lunch, snacks, or dinner free at school every day.	0.100	0.094
		Share of food consumption expenditure	Food represents 75% or more of the total consumption expenditure of the household.	0.100	0.106
	Household density	Overcrowded housing	There are three or more residents per permanent bedrooms in the household.	0.100	0.098
		Older adults per household	Two or more older adults per members of a household.	0.100	0.102
	Public social distancing	Commuting time	At least one individual in the household spends more than an hour to get to work.	0.050	0.063
		Population density	The household is in a region* where the pop. density is higher than the mean of the Brazilian capitals (> 2,700/km^2)	0.050	0.062
		Index of legal measures of social distancing	The household is in a state where the index is higher than 2 (out of 10, which is the least restrictive)	0.050	0.040
		Mobility index	The household is in a state where the index is less than 60% of the relative reduction in mobility	0.050	0.035
COVID-19 health recovery	Living standards	Electricity	The household has no access to electricity.	0.083	0.087
		Housing	The household housing materials for at least one of floor, wall, and roof are inadequate.	0.083	0.082
		Overcrowded housing	There are three or more residents per permanent bedrooms in the household.	0.083	0.081
	Risk groups	Risk ratio by age and gender	The indicator is 1 or more;1 is the risk reference score at age 60-69 (Oke and Heneghan, 2020). It is an individual-level indicator.	0.125	0.120
		Indoor air pollution due to cooking fuel	The household's cooking fuel is wood, oil, kerosene, or another liquid fuel.	0.125	0.130
	Healthy immune system	Drinking water	The household does not have daily access to water, or does not have indoor running water, or the water does not come from a public water system.	0.062	0.057

Index	Dimension	Variable	AF Deprivation Cutoff	AF Weight	Prevalence correlation weight
		Sanitation	The household does not have indoor bathroom with shower and toilet, or the bathroom is shared with other households, or the disposal of human waste is not connected to a public sewage system.	0.062	0.060
		School meals	One or more children in the household have breakfast, lunch, snacks, or dinner free at school every day.	0.062	0.063
		Share of food consumption expenditure	Food represents 75% or more of the total consumption expenditure of the household.	0.062	0.071
	Access to health care	Private insurance	The individual has no private health insurance.	0.062	0.054
		Distance from hospital	The household is in a region* where the weighted mean distance from a hospital is more than 100 km.	0.062	0.083
		Physicians per 1,000 people	The household is in a region where the mean of the indicator is less than 1 physician per 1,000 people.	0.062	0.063
		Intensive-care hospital beds per 1,000 people	The household is in a region* where the mean of the indicator is less than 1 bed per 1,000 people.	0.062	0.050

Notes: AF deprivation cutoff refers to the description of the cutoff in the AF method. A cutoff definition is not necessary in the fuzzy approach, because it does not treat the variables as binary measures. AF weights are the values of the weights used in the AF method. Prevalence-correlation weights are the weights calculated in the fuzzy approach analysis.
* Capital, metropolitan region, or other parts of the state.

With respect to the weights in the AF method, for simplicity, we follow the GMPI by assuming that the dimensions are of equal weight. Also following the GMPI standard, for each multidimensional index, we consider people vulnerable[4] (VN) to infection with COVID-19 if they are deprived of at least one-third of the weighted indicators and consider people at severe risk (SR) of infection with COVID-19 if they are deprived of at least half the weighted indicators.

In Table 4, we present the number and percentage of deprived people in terms of all the variables used in the two CMPIs. The indicator with the highest percentage of deprived people is the index that measures mobility reduction, with 95.6% of the population deprived. This means that most of the

[4] In GMPI deprivation, the cutoff for being considered poor is deprivation of one-third of the ten indicators. In the GMPI, the term "vulnerable" is used differently: a person is considered vulnerable to poverty if he/she is deprived of between one-fifth and one-third of the indicators.

Brazilian population lives in states in which the mean reduction in daily mobility was less than 60% (from March 11 to April 30). The lack of national coordination in social distancing measures, as the result for the index of legal measures suggest (81.7% of people deprived), is one possible factor in the small reduction in mobility. Moreover, the participation in protests opposing coronavirus lockdowns and the continuous calls by the president to end social distancing is another possible factor that demotivated people to decrease mobility.

Table 4 - Number and percentage of deprived people per indicator

Variable	AF Pop. Deprived	AF % Deprived
Drinking water	62,511,394	30.18%
Sanitation	80,970,486	39.09%
Electricity	457,742	0.22%
Housing	22,155,805	10.69%
School meals	47,170,894	22.78%
Share of food consumption expenditure	283,702	0.14%
Overcrowded housing (residents per permanent bedroom)	26,313,116	12.71%
Older adults per household	6,666,591	3.22%
Commuting time	26,390,282	12.74 %
Population density (people per km^2)	34,501,439	16.66%
Index of legal measures of social distancing	169,164,425	81.68%
Mobility index (% reduction from a baseline day before the pandemic)	198,056,358	95.63%
Risk ratio by age and gender (1 is the risk reference score set for age 60-69)	31,702,592	15.31%
Indoor pollution due to cooking fuel	2,094,513	1.01%
Private insurance	153,306,719	74.02%
Distance from hospital (in km)	8,187,121	3.95%
Physicians per 1,000 people	105,612,592	51.00%
Intensive-care hospital beds per 1,000 people	172,871,751	83.47%
Total population	207,103,790	

Note: AF Pop. Deprived and AF % Deprived refers, respectively, to the number and incidence of deprived people using the cutoff defined in the Alkire-Foster (AF) model.

By looking at the data, it is possible to observe that, independent of the pandemic context, a large proportion of Brazilians do not have access to basic public services. The lack of public health-care infrastructure is widespread. More than 83% of the population is deprived in terms of intensive-care hospital beds, and the mean is 0.44 beds per 1,000 people (see Table 2 and Table *4*). Moreover, 51%

of the population has access to less than one physician per 1,000 population. In some states, the private health sector offers proportionately more physicians and hospital beds. In any case, although only 26% of the population has private insurance, it does not mean that they will have access to all the private health infrastructure, only to the hospitals and services specified by their contract[5]. It is also evident that for several people the access to sanitation and drinking water is inadequate: 30.2% and 39.1%, respectively. Clean water is crucial for preventing infection with COVID-19 because it is needed for frequent and sufficient hand washing (WHO, 2020b) and is essential for human health and well-being (WHO, 2019a). Moreover, improper sanitation is a major cause of infectious disease (WHO, 2018b, 2020b) and can compromise the immune system, with a possible impact on recovery from COVID-19.

1.3 Results

1.3.1 Multidimensional poverty analysis

This section presents the results for both the AF and fuzzy approaches. For the AF method, Table 5 shows the outcomes for the multidimensional headcount ratio (HCR), the poverty intensity (A), and the adjusted headcount ratio (M0). In addition, the results for each CMPI are shown for VN and SR. For group decompositions, we use only the HCR indicator, as it is more intuitive and the comparison with the fuzzy measure is more appropriate.

According to the AF and fuzzy results, between 16.2% and 15.6% of the population is vulnerable to infection with COVID-19 as measured by the prevention index. This implies that between 32.4 million and 33.5 million people cannot implement proper prevention measures related to at least one-third of the weighted indicators. Severe risk, which represents deprivation in half the weighted

[5] Brazil's health-care is provided by both public and private sectors, and people can use the two sectors depending on accessibility and ability to afford costs. The public health system, through the Unified Health System (SUS), aims to offer universal, free of charge, health service provision. The private sector offers services mainly through health plans, insurance premiums, out-of-pocket payments, and provides services for the SUS. For more details, see Paim et al. (2011) and Massuda et al. (2018).

indicators, is 3.4% in the AF and 4.1% in the fuzzy results, respectively. In the health recovery index, the two approaches diverge more. The AF estimates 19.8% of people are vulnerable (41 million people), while the fuzzy estimate is 13.7% (28.4 million people). In terms of severe risk, the results are 2.2% for AF and 2.6% for fuzzy.

Table 5 - COVID-19 multidimensional poverty indexes per approach and indicators

Index	AF						Fuzzy	
	M_0 VN	HCR VN	A VN	M_0 SR	HCR SR	A SR	VN	SR
Prevention	0.068	16.17%	0.419	0.018	3.43%	0.528	15.64%	4.11%
Health recovery	0.081	19.81%	0.409	0.012	2.15%	0.555	13.72 %	2.60 %

Table 6 presents the results for each state, showing the number of confirmed COVID-19 deaths per million people and the share of the monetarily poor people measured by household consumption expenditure per capita ($3.20 a day, 2018 PPP). Alternatively, Figure 2 illustrates in maps the distribution of confirmed deaths per million, FM poverty, and fuzzy vulnerability for the health recovery index by state. The outcomes demonstrate the vast regional inequality in Brazil. The northern and northeastern regions have the highest proportion of vulnerability and severe risk of infection with COVID-19. For instance, Amazonas state (AM) has the most deaths per million people and among the highest risk: the incidence of vulnerable people according to the health recovery index is 50.5%. By comparison, in São Paulo (SP), the state with the most infections in absolute terms, it is 3.9%.

Table 6 - COVID-19 death indicator and estimation results for the COVID-19 multidimensional poverty indexes and unidimensional monetary poverty by state

State	COVID-19	Prevention Index				Health Recovery Index				Monetary Poverty	
	Death per million	HCR VN	HCR SR	Fuzzy VN	Fuzzy SR	HCR VN	HCR SR	Fuzzy VN	Fuzzy SR	HCR	Fuzzy
RO	39.70	36.74%	7.28%	45.72%	2.47%	35.10%	1.43%	16.04%	1.55%	14.28%	14.01%
AC	69.61	52.05%	24.79%	48.19%	22.99%	58.45%	24.64%	44.02%	14.90%	16.42%	16.06%
AM	353.17	45.14%	17.48%	27.34%	11.43%	50.45%	16.18%	27.52%	7.52%	25.48%	23.60%
RR	96.74	26.81%	8.43%	16.17%	2.78%	48.12%	7.72%	19.75%	3.26%	21.00%	20.15%
PA	144.91	41.55%	14.10%	48.98%	17.19%	44.20%	6.22%	32.34%	7.78%	22.13%	20.16%
AP	132.70	41.71%	12.94%	24.69%	6.31%	51.63%	9.02%	25.81%	4.51%	11.77%	12.13%
TO	17.59	20.35%	5.70%	34.35%	4.67%	34.65%	2.47%	13.64%	2.65%	21.57%	19.74%
MA	78.61	44.37%	14.78%	36.19%	18.26%	50.13%	9.14%	35.86%	13.28%	22.34%	21.45%
PI	22.08	29.03%	8.58%	18.84%	9.61%	51.83%	13.79%	23.05%	7.92%	14.68%	15.46%
CE	178.39	8.13%	0.92%	11.89%	4.45%	29.17%	3.56%	21.28%	5.43%	22.81%	20.36%
RN	39.23	29.09%	5.54%	21.27%	5.69%	31.51%	2.74%	22.68%	3.97%	10.81%	10.86%
PB	46.16	23.93%	3.76%	28.85%	9.59%	27.57%	1.92%	25.80%	5.58%	23.89%	21.39%
PE	155.20	20.73%	1.19%	17.51%	5.46%	25.59%	2.10%	22.91%	5.45%	17.93%	16.68%
AL	60.12	22.93%	1.78%	21.34%	5.31%	31.26%	2.44%	25.14%	3.48%	31.07%	27.45%
SE	23.36	15.39%	1.71%	9.12%	3.82%	22.80%	2.19%	13.59%	2.59%	10.02%	10.24%
BA	19.37	19.56%	4.32%	28.92%	8.05%	26.71%	2.34%	20.78%	5.21%	15.71%	14.88%
MG	7.15	8.32%	1.38%	8.64%	1.17%	13.97%	0.88%	9.82%	0.85%	5.70%	6.23%
ES	68.65	12.22%	1.74%	10.15%	0.98%	15.23%	0.31%	8.31%	0.43%	7.68%	8.38%
RJ	152.77	15.79%	2.45%	8.57%	1.36%	9.50%	0.04%	7.77%	0.39%	8.25%	8.86%
SP	103.37	8.17%	1.47%	6.67%	1.20%	3.89%	0.01%	6.19%	0.28%	2.56%	3.65%
PR	11.15	9.26%	1.00%	16.74%	2.22%	12.78%	0.37%	7.61%	0.97%	7.12%	7.40%
SC	11.54	8.04%	0.08%	2.71%	0.38%	16.50%	0.55%	7.92%	0.70%	2.81%	3.42%
RS	12.23	10.22%	1.50%	5.69%	0.51%	16.29%	0.79%	7.38%	0.63%	2.37%	3.22%
MS	5.63	14.47%	2.26%	37.39%	4.00%	21.29%	0.59%	7.69%	0.96%	5.23%	5.64%
MT	8.01	23.32%	5.63%	36.31%	4.54%	48.58%	6.58%	13.79%	0.93%	7.13%	7.51%
GO	10.03	10.18%	0.59%	6.39%	0.40%	19.27%	0.54%	7.79%	0.32%	4.97%	5.76%
DF	18.96	13.66%	1.47%	5.50%	0.83%	7.62%	0.03%	3.85%	0.28%	3.74%	3.66%
Total	75.79	16.17%	3.43%	15.64%	4.11%	19.81%	2.15%	13.72%	2.60%	9.96%	9.96%

Notes: Covid-19 deaths per million as of May 10, 2020.
Northern region: RO = Rondônia; AC = Acre; AM = Amazonas; RR = Roraima; PA = Pará; AP = Amapá; TO = Tocantins.
Northeastern region: MA = Maranhão; PI = Piauí; CE = Ceará; RN = Rio Grande do Norte; PB = Paraíba; PE = Pernambuco; AL = Alagoas; SE = Sergipe; BA = Bahia.
Southeastern region: MG = Minas Gerais; ES = Espírito Santo; RJ = Rio de Janeiro; SP = São Paulo.
Southern region: PR = Paraná; SC = Santa Catarina; RS = Rio Grande do Sul.
Central-western region: MS = Mato Grosso do Sul; MT = Mato Grosso; GO = Goiás; DF = Distrito Federal.

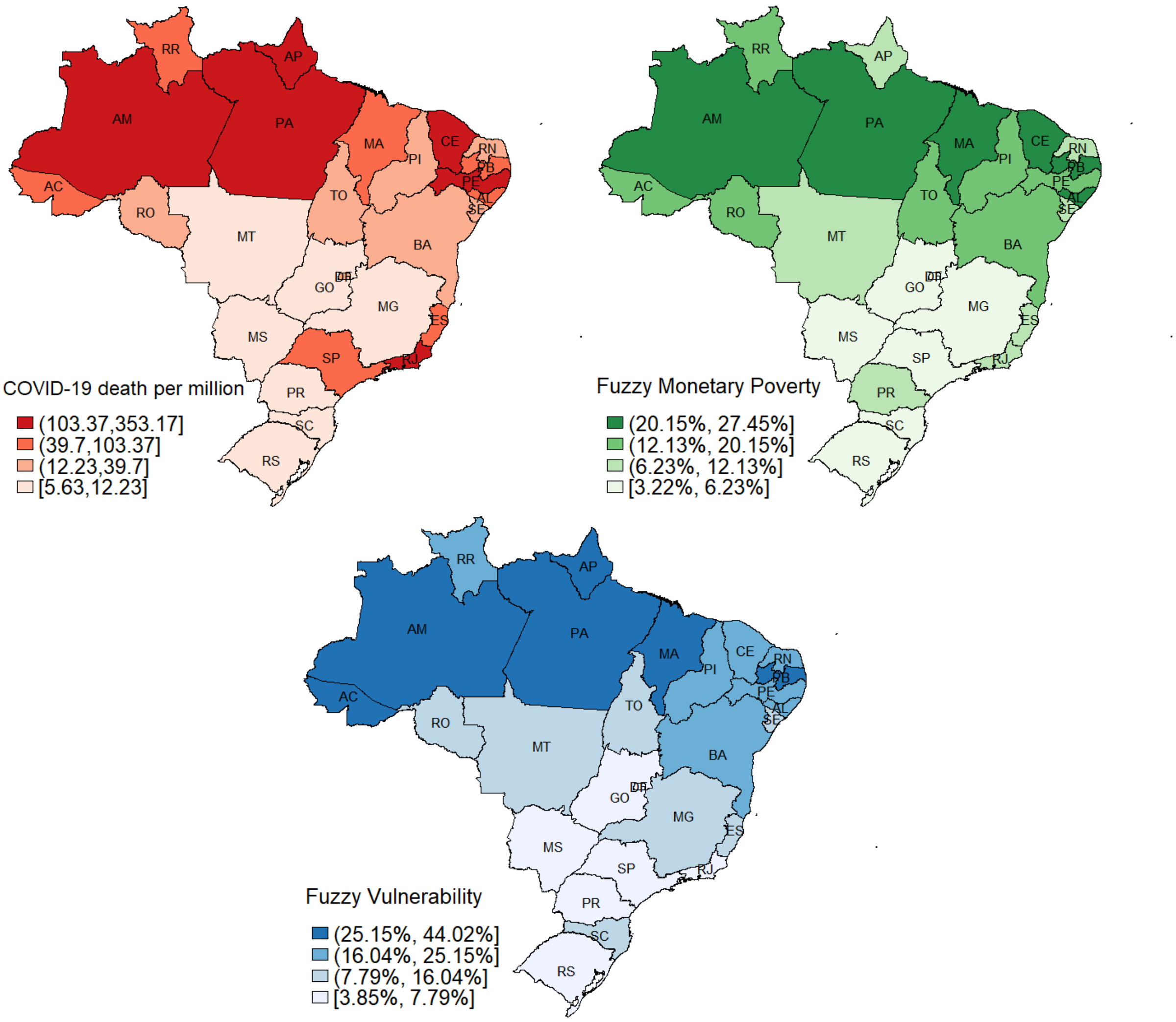


Figure 2 - Distribution of COVID-19 confirmed deaths per million population, fuzzy monetary poverty, and fuzzy vulnerability for the COVID-19 health recovery index by state
Note: For abbreviations, see note to Table 6.

The risk of infection with COVID-19 also differs among ethnic groups. Table 7 shows the indexes for each group. Overall, the picture is not favorable for the Indigenous population, which has the worst conditions in all indicators. Brown and Black groups also are at a disadvantage to the White and Asian groups and the total population.

The fact that the virus is spreading toward the northern region is an additional concern, as it is the region with the highest proportion of the population that is vulnerable and at severe risk of infection with COVID-19, and, as mentioned previously, where 22.7% of the Brazilian Indigenous population is concentrated.

Table 7 - Estimation results for the COVID-19 multidimensional poverty indexes and unidimensional monetary poverty by color/ethnicity

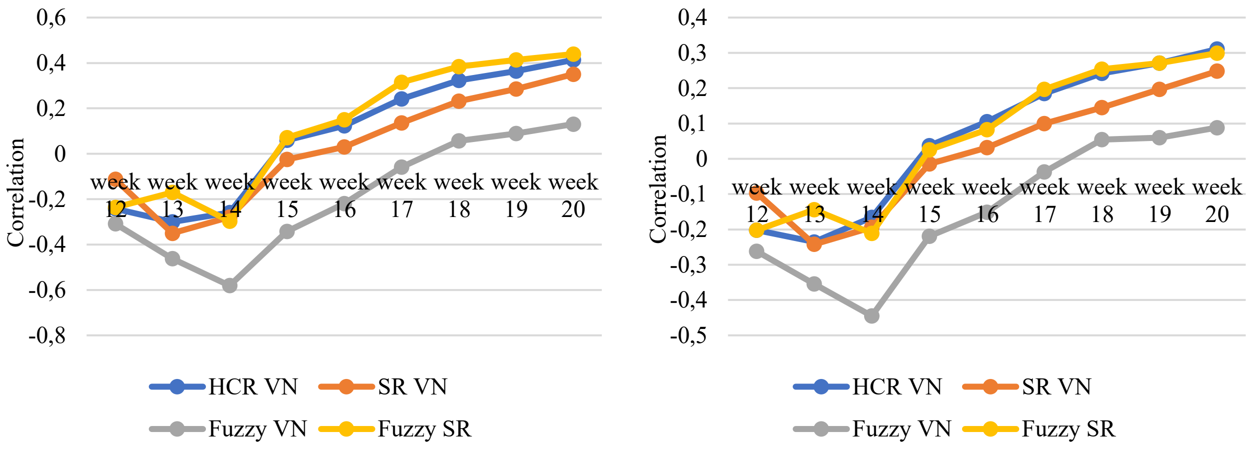
Color/Ethnicity	Prevention Index				Health Recovery Index				Monetary Poverty	
	HCR VN	HCR SR	Fuzzy VN	Fuzzy SR	HCR VN	HCR SR	Fuzzy VN	Fuzzy SR	HCR	Fuzzy
White	10.57%	1.69%	9.80%	1.84%	13.49%	0.94%	9.53%	1.24%	5.25%	5.79%
Black	19.54%	4.23%	19.12%	5.01%	21.52%	2.35%	14.95%	3.11%	13.06%	12.31%
Asian	6.71%	0.89%	5.72%	0.73%	7.31%	0.47%	6.98%	0.84%	4.19%	4.61%
Brown	20.96%	4.96%	20.71%	6.20%	25.88%	3.28%	17.67%	3.85%	13.98%	13.62%
Indigenous	34.98%	9.46%	28.64%	7.43%	28.58%	8.88%	23.33%	6.61%	14.97%	13.72%
Not identified	10.60%	0.99%	8.87%	0.39%	8.33%	0.03%	5.68%	0.10%	8.21%	9.40%
Total	16.17%	3.43%	15.64%	4.11%	19.81%	2.15%	13.72%	2.60%	9.96%	9.96%

1.3.2 The link between the Multidimensional Poverty Indexes and COVID-19 deaths

The first confirmed cases were in São Paulo, the richest state and one of the least vulnerable to infection with COVID-19 according to the CMPI. At the beginning of March, it was estimated that 85.3% of the transmission came from outside the country, with 54.8% probably coming from travelers infected in Italy, 9.3% in China, and 8.3% in France (Candido et al., 2020). This suggests that in Brazil the initial infection was concentrated among the middle and upper classes (who could afford to fly outside the country). Later data show the spread of the virus to the most vulnerable regions (see Table 6 and Figure 2).

In this section, we propose an innovative analysis, measuring rank correlations at the state level for the unidimensional and multidimensional poverty indexes and the number of COVID-19 deaths in Brazil per million people for many consecutive weeks. We used Spearman and Kendall rank correlation coefficients; for each subgroup, the latter calculates the average of the square difference between the two ranks, and the former is based on the difference in the number of pairs that do and do not match. The coefficients are between -1 and +1; an extreme value means that the rankings are perfectly associated either negatively or positively. Even if the analysis does not imply causality, our indexes can be tested by determining the evolution in the correlation throughout over the epidemiological weeks.

The results are given for week 12 (April 5) to week 20 (May 10). Figure 3 and Figure 4 illustrate the results for the HCRs of vulnerability and severe risk (blue and orange lines) and the fuzzy indicators of vulnerability and severe risk (gray and yellow lines). Figure 5 plots outcomes for the HCR of monetary poverty (green line) and FM poverty (light blue line).

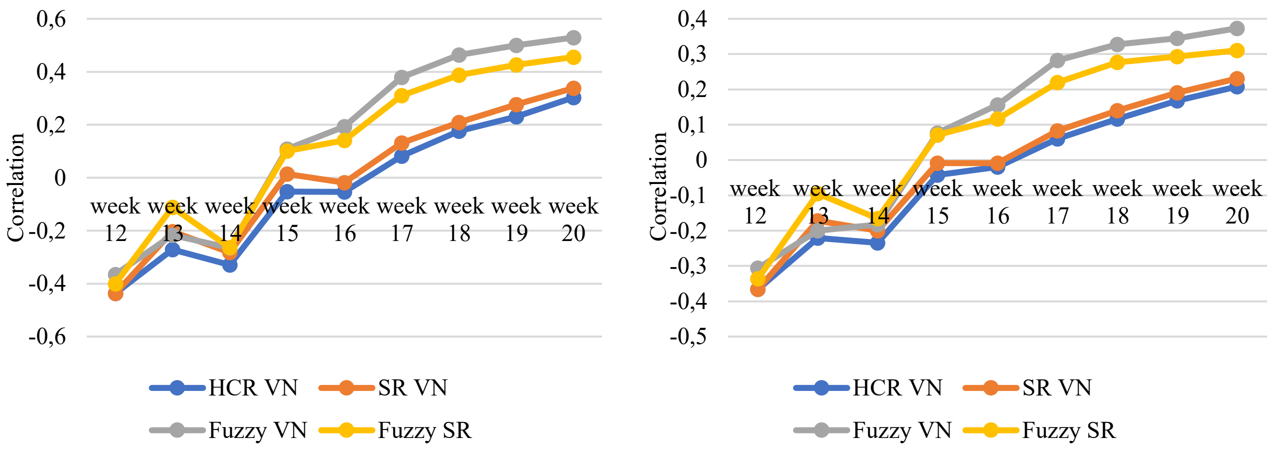


a. Spearman b. Kendall

Figure 3 - The evolution per week in the rank correlations between the prevention index and deaths per million people at the state level

Overall, the outcomes confirm that our indexes capture the trend in infection from the richest regions, which are less vulnerable, to the more vulnerable regions. Initially, all the measures show a negative relation between the vulnerability indicators and deaths per million people. Beginning in week 14, the correlations increase, meaning that states with the highest vulnerability and severe risk scores have increasing numbers of deaths per million people.

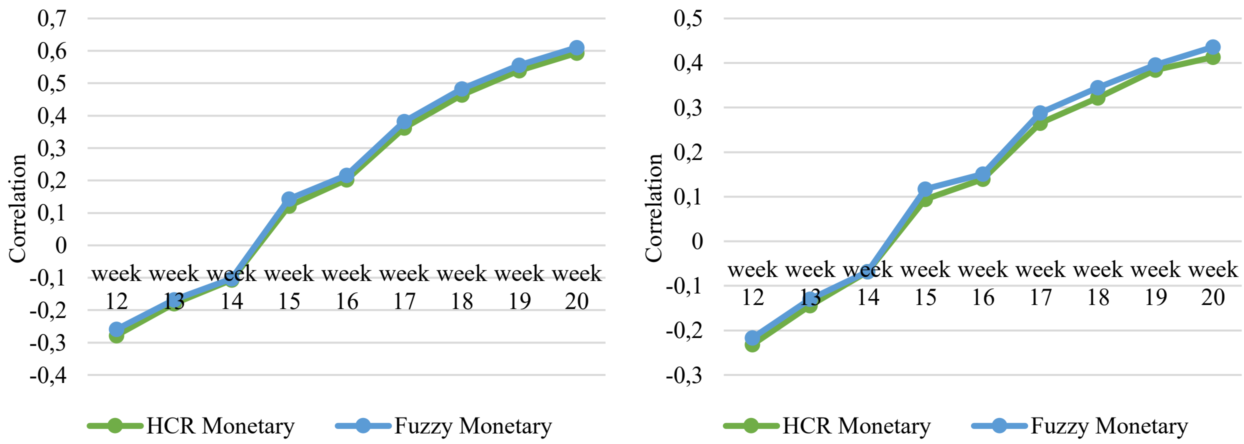
The health recovery index has greater correlations than the prevention index. The highest Spearman coefficients in the prevention index are 0.41 and 0.44 (for HCR vulnerability and fuzzy severe risk), whereas for the health recovery index they are 0.46 and 0.53 (for fuzzy severe risk and fuzzy vulnerability). In addition, most of the results suggest that fuzzy measures are more appropriate for explaining the link with deaths because they show the highest correlations in Figure 4 and Figure 5.



a. Spearman b. Kendall

Figure 4 - The evolution per week in rank correlations between the health recovery index and deaths per million people at the state level

Finally, beginning in week 14, the correlations are predominantly steeper and higher for unidimensional monetary poverty than for the other two indexes. One possible interpretation is that monetary poverty is an immediate factor of vulnerability and risk to shocks. In times of difficulty, money seems to be the first thing that plays an essential role in addressing the increasing threat from the pandemic. Because vulnerability is a multidimensional phenomenon, these results reinforce that nonmonetary and monetary variables are complementary indicators.



a. Spearman b. Kendall

Figure 5 - The evolution per week in rank correlations between the unidimensional monetary poverty indicators and deaths per million people at the state level

Because the official numbers of confirmed deaths from COVID-19 are probably underestimated, and this underestimation may be inconsistent among the states, the results from this section may be biased. Considering this possibility, to analyze the robustness of my findings, I also calculate the raking correlations between the poverty indexes and the proportion of excess mortality[6] by state. The excess mortality data is based on the number of deaths by natural causes, which are much less subject to underestimation. The resulting correlations are consistent with those that I find in this subsection. The correlations are positive and tend to grow in the period. Moreover, on average, the health recovery index also has higher correlations than the prevention index, and the fuzzy indicators of the health recovery index also have the highest correlations in most weeks. Finally, the monetary indicators also have the greatest correlations compared to the other two indexes.

1.4 Concluding remarks

This chapter contributes to the literature on the potential social impacts of the COVID-19 pandemic. We use the AF method and fuzzy-set approach as complements to measure multidimensional poverty within the context of the coronavirus pandemic in Brazil. We propose two multidimensional poverty indexes to account for the vulnerability related to the ability to prevent the spread of infection and to recover from infection with the virus.

The data reveal structural deprivations in the country due to the fact that a big part of the population cannot fully implement the recommended preventive measures and because the social conditions and the health-care system do not meet the basic requirements for avoiding preventable

[6] In epidemiological studies, scholars widely use excessive mortality to overcome potential underestimation during crisis outbreaks and see the crisis' direct and indirect impacts. The intention is to project the death numbers we would expect in 2020 if there was no pandemic and compare them with the observed deaths. I used the data on excess mortality calculated by the National Council of Health Secretaries (CONASS), available at https://www.conass.org.br/indicadores-de-obitos-por-causas-naturais/. Using administrative data of deaths by natural causes from historical series from 2015 to 2019, they use an exponential model to project the weekly number of deaths in 2020.

deaths. Moreover, the estimations of the indexes illustrate the considerable inequality among regions and ethnic groups. This is in line with the extensive literature on inequality in Brazil.

Two of the innovations in this chapter are presenting pandemic-specific indexes and proposing a rank correlation analysis that can trace the increasing spread of infection and higher mortality rate in vulnerable regions. Most of the correlations increase weekly, which means that most states with the highest vulnerability and severe risk outcomes also have the largest increase in death rates. The monetary poverty indicator has the highest correlation when compared with the two CPMIs for almost all the epidemiological weeks. This indicates that money is very important in battling the threat of the pandemic and that nonmonetary and monetary indexes are complementary variables, rather than competing variables, in multidimensional poverty analysis.

Another innovation is the application of fuzzy measures, which are more appropriate for the characteristics of the vulnerability variables because they avoid a binary split between deprivation and non-deprivation, have more precise measures in subnational analysis, and have higher rank correlation.

Despite the limitations of the data on confirmed deaths from COVID-19, our empirical evidence offers an additional warning that responses to the pandemic need to prioritize the most vulnerable groups, and our analysis reinforces the need for coordinated national action. In the short run, rapid measures are needed to stop the virus from spreading, to ensure that the entire population follows the recommendations for prevention as well as they can, and to guarantee universal coverage by public health services. In the medium and long run, this analysis reinforces the urgent necessity of public policies that promote health, adequate housing, and sanitation.

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Chapter 2

Individual-based fuzzy multidimensional poverty indexes: a comprehensive analysis of gender inequalities in Brazil

Abstract

This study examines gender differences in multidimensional poverty in Brazil. To properly analyze gender disparities, it addresses three problems that the literature often neglects: disregard for within-household inequalities in household-level indicators; disregard for ineligible populations in indicators that represent only a specific group; and disregard for intermediate deprivation situations in cutoff-based poverty estimations. Using data from the Brazilian Consumer Expenditure Survey 2017-2018, I create two individual-based indexes with indicators that are key aspects in gender and feminist analyses. Applying a fuzzy approach and the Alkire-Foster method, I estimate multidimensional poverty and gender differences in three perspectives: intrahousehold, interhousehold, and intracouple. I also calculate inequality among the poor and intracouple gender gaps proposing fuzzy versions for these analyses. The results suggest that women are disadvantaged in terms of work and time quality, economic security, and access to resources – which are crucial components of agency or degree of empowerment. In most specifications, individuals living in female-headed households are poorer than those living in male-headed households, but in female-headed households, women are in advantage compared to men, or at least the disparity decreases. The outcomes also confirm the usual geographical and racial inequalities in Brazil, as the north and northeast regions, the rural areas, and the Black, Brown, and Indigenous people are persistently disadvantaged in many estimations' specifications.

Keywords: Multidimensional poverty · Individual-based indexes · Fuzzy-set approach · Alkire-Foster (AF) method · Latin America · Brazil

2.1 Introduction

Economic analysis should be especially attentive to problems faced by women because they disproportionally bear the burden on development issues (Nussbaum, 2000). Multidimensional methods provide ways to account for gender differences considering the complexity of the poverty phenomenon. The literature on multidimensional poverty recognizes that focusing only on income or consumption expenditure is insufficient because people potentially have simultaneous deprivations (Alkire et al., 2015). This recognition is a significant advancement, but this literature often neglects aspects that are essential to estimate gender differences in multidimensional poverty.

For example, most studies on multidimensional poverty use households as the unit of identification (Deaton, 1997; Espinoza-Delgado & Klasen, 2018; Klasen & Lahoti, 2016, 2020). The problem is that many well-being elements are a characteristic of individuals (Deaton, 1997), and several inequalities are generated and experienced inside dwellings (Eek & Axmon, 2014; Griep et al., 2016; İlkkaracan & Memiş, 2021; Nussbaum, 2000; Rodríguez, 2016). By using household-level indicators, these studies define inequality within households as zero, as they set the same deprivation value among household members. In other words, household-based analyses ignore personal experiences within households and neglect inequalities among family members. Moreover, Klasen and Lahoti (2020) show that studies defining household-level poverty thresholds from individual-level indicators create biased poverty estimations. Consequently, studies using household-level indicators cannot estimate gender differences within households and are potentially biased.

Another issue is understanding how to address ineligible populations from indicators that represent only a specific population group. For instance, employment-related indicators tend to include only working-aged people. In this case, studies usually classify children and the elderly in pension as missing units or non-deprived, potentially underestimating poverty outcomes. Another source of complexity that receives little attention from the literature is the potential vagueness[1] nature of indicators. Frequently, researchers treat poverty indicators as a rigid binary phenomenon (deprived or non-deprived), defining a specific cutoff to decide who is poor. This kind of approach neglects intermediate situations and can be unrealistic.

Given these problems in the literature, this chapter aims to improve multidimensional poverty measurement to analyze gender differences better. The analysis focus on women's outcomes

[1] As stated by Qizilbash (2006, p.10), studies usually classify vague indicators as having these three characteristics: 1) they allow borderline cases (e.g., a level of deprivation that one is not sure whether a person is poor or not); 2) they have no sharp borderline (e.g., no exact poverty line where it is clear that an individual bellow it is poor and above it is non-poor) ; and 3) they are susceptible to a Sorites paradox.

compared to men, but it also contemplates household headship, age, family composition, regions, ethnicity/color, and area type (urban/rural) in Brazil. Moreover, this study considers three different perspectives: results for the whole population (intrahousehold), household heads (interhousehold), and couples (intracouple). This chapter applies the following three improvements to the problems discussed previously.

First, to avoid the problems of household-level analysis, I use individual-level indicators - when available - to build the multidimensional indexes. I propose two multidimensional poverty indexes. The first is the Standard Multidimensional Poverty Index (SMPI), which has similar dimensions as the Global Multidimensional Poverty Index (GMPI)[2] (OPHI & UNDP, 2019) but adapted for the Brazilian context and data availability. This index works as a benchmark by selecting indicators commonly used in the multidimensional poverty literature. The second is the Occupation-Resources Index (ORI), which aims to understand and compare the quality of employment and time of individuals, analyze their financial situation, and have a proxy for control and administration of resources.

The two proposed indexes use information that is commonly present in household budget surveys. Therefore, we can apply these indexes, at least in parts, in studies analyzing other countries. However, most household surveys lack individual data (Deaton, 1997). That is the reason I also analyze multidimensional poverty among household heads. Because they usually answer all the survey questions, more indicators are available at the individual level in the interhousehold perspective.

Second, to mitigate the problem of ineligible population, I create individual composite indicators adapting the variables, when possible, to account for non-applicable populations. In this way, we can include different age groups in the same indicator to represent how they would be damaged when the

[2] The GMPI dimensions are Education, Health, and Living Standards. The indicators are nutrition, child mortality, years of schooling, school attendance, cooking fuel, sanitation, drinking water, electricity, housing, and assets.

eligible individuals in their household are deprived. For example, this chapter considers children as deprived in employment- and financial-related indicators when every adult in their household is deprived in these indicators. Because children depend emotionally and economically on adults, the assumption is that children experience an external negative effect from the adults' deprivation situation.

Third, to account for the vagueness nature of indicators when measuring multidimensional poverty, I use a fuzzy set approach, which treats poverty as a matter of degree instead of a binary phenomenon. The approach also has the advantage of presenting smaller standard errors, giving us more precise subgroup outcomes (Betti et al., 2012; Betti et al., 2018). Besides the fuzzy set, I also use the Alkire-Foster method (AF). Even though the AF is a cutoff-based approach, it has the advantage of providing intuitive measures, vast possibilities of decompositions, and it is the current mainstream method in multidimensional poverty studies. The AF also works as a benchmarking for setting the parameters of the fuzzy analysis and gives complementary results from a distinct approach to measure poverty. Therefore, this chapter considers both approaches as complementary methodologies instead of contrasting ones.

This chapter also calculates a "crisp" and a fuzzy version of inequality among the poor and intracouple gender gap. To measure the crisp inequality among the poor measure, I apply the method proposed by Alkire and Seth (2014). For the fuzzy version, I propose a measure that calculates the inequality of membership degrees, considering a new benchmark for the fuzzy membership function (i.e., the incidence of extreme multidimensional poverty instead of multidimensional poverty). These inequality analyses are important for policy implications because, when inequality among the poor decrease, we know that it represents a reduction that have benefited people in extreme poverty – whereas, in poverty measures, we cannot ensure that it represents a reduction that have benefited them (Alkire & Seth, 2014). As for the intracouple gender gap indexes, I apply the index proposed by Alkire et al. (2013) for the crisp measure and adapt it to create a fuzzy version. The intention is to evaluate intracouple relative differences in more detail.

The recognition that the individual-level is the most appropriate unit of identification in multidimensional poverty analyses is not new (see Alkire & Santos, 2010; Deaton, 1997). One of the main reasons for the lack of individual-based studies is that household surveys usually focus on households (Alkire & Santos, 2010; Deaton, 1997). That is why most studies using individual-based indexes apply the analysis to specific subgroups such as occupied people (see Sehnbruch et al., 2019), women (see Alkire et al., 2013; and Batana, 2013), children (see Alkire et al., 2019), and adults (see Burchi et al., 2021; and Vijaya et al., 2014). Klasen and Lahoti (2016) were the first to propose individual-based poverty analysis for the whole population. Their article shows that it is better to use a mix of household and individual-level indicators than only household-level ones, as the household-based index underestimates poverty differences between women and men in India.

Following Klasen and Lahoti (2016), other studies use multidimensional indexes mixing household and individual-level data (see Burchi et al., 2021; Correa, 2014; Espinoza-Delgado & Klasen, 2018; and Espinoza-Delgado & Silber, 2021). However, they do not consider other perspectives, such as interhousehold and intracouple. Moreover, there are also studies on gender inequalities that rely on the sex of household heads (see Bradshaw, Chant, & Linneker, 2017; Liu, Esteve, Treviño, 2017; and Montoya & Teixeira, 2017). But they do not use individual-level indicators or employ multidimensional indexes, and some use household heads as a proxy for all women.

Considering these gaps in the literature, the contributions of this chapter are the following. Empirically, it offers a comprehensive individual-based analysis combining intrahousehold, interhousehold, and intracouple perspectives and evaluating multidimensional poverty, inequality among the poor, and gender gaps considering several subgroups and two approaches. As far as I am aware, this is the first study to estimate individual-based multidimensional poverty and gender inequalities for the whole population in Brazil and the first study to combine the three perspectives. Methodologically, this article creates the ORI, which uses indicators that are key aspects in gender and feminist analyses, and proposes a fuzzy version of the measures of inequality among the poor and intracouple gender gap.

The structure of this chapter is the following. Section 2.2 details the data and methodologies. Section 2.3 presents and details the indexes, dimensions, and indicators. Section 2.4 shows the results, and Section 2.5 concludes.

2.2 Data and methodology

2.2.1 The Brazilian Household Budget Survey

The analyses proposed in this chapter require as much individual-level data as possible. Usually, it is not possible to have individual-level information for all the potential individual-level indicators because most household surveys focus on households. In this chapter, I use the microdata from the Brazilian Consumer Expenditure Survey (POF) 2017-18, collected and processed by the Brazilian Institute of Geography and Statistics (IBGE). This survey is also mainly focused on households, so the information that we get is a mix of household-level and individual-level data (see Section 2.3 for details of the level of each indicator). Nevertheless, the POF is well suited for the current study because it has detailed information to build multidimensional poverty indexes, for the main objectives of this survey is to provide information on people's living conditions and the perception of quality of life (IBGE, 2020b).

As for the characteristics of the POF, the sample size is 69,660 households, and the data contains information at the levels of nation, major regions, states, state capitals, metropolitan regions (excluding the capital), other parts of the states (excluding the metropolitan regions and state capital), and at urban and rural areas. Following IBGE (2020b), I excluded from the data individuals classified in the households as domestic workers and domestic workers' relatives, accounting for 62 observations deleted. Table 1 shows the main demographic variables for the three perspectives: whole population, household heads, and couples.

Table 1 - Mean of Demographic Variables

Variables	Whole population	Household Heads	Couples
Gender			
Women	51.60%	41.85%	50.00%
Men	48.40%	58.15%	50.00%
Household Headship[1]			
Female Headed	40.25%	-	12.61%
Male Headed	59.75%	-	87.39%
Age Groups			
Child and Adolescent	22.00%	0.01%	0.00%
Adult	62.69%	71.53%	79.80%
Elderly	15.30%	28.47%	20.20%
Family Composition			
N° of family members	3.73	3.00	3.44
N° of child	1.00	0.66	0.81
Region			
North	8.58%	7.27%	8.23%
Northeast	27.27%	25.90%	25.74%
Center-west	7.66%	7.76%	8.09%
Southeast	42.19%	43.65%	42.15%
South	14.30%	15.42%	15.79%
Color/Ethnicity[2]			
White	44.01%	44.07%	45.34%
Asian	0.68%	0.76%	0.75%
Black	10.21%	11.76%	10.48%
Brown	44.43%	42.77%	42.84%
Indigenous	0.38%	0.46%	0.38%
Undeclared	0.29%	0.19%	0.21%
Area type			
Urban	85.26%	86.23%	84.14%
Rural	14.74%	13.77%	15.86%
Number of observations	178,369	58,039	73,510

Note: 1. People that live in male or female headed household. 2. Categories following the classification from the POF/IBGE.

Because this chapter relies on household heads as one of the analysis' perspectives, I now describe its definition in the Brazilian household budget survey. The POF considers as household head people that hold, in order of importance, at least one of these criteria: 1) the responsible for paying the rent; or 2) the responsible for paying the installment for the house purchase (installment contract owned by one of the residents); or 3) the responsible for paying the housing expenses (e.g., condominium fee, property tax, household services and fees, and others) (IBGE, 2017). If no household member satisfies any of these three conditions, the household members indicate the household head. In addition, if two members simultaneously satisfy one of the three criteria, the survey considers as household head the oldest one between them.

From this household head definition, we can observe that household heads are responsible for important payments or are the reference person in their home. Therefore, we can consider household headship as an indication of people's agency or empowerment - and that is another reason to consider this perspective in the poverty analysis.

2.2.2 Multidimensional poverty measures

2.2.2.1 The Alkire-Foster method

The Alkire-Foster methodology (AF) is a counting approach to measure multidimensional poverty proposed by Alkire and Foster (2009, 2011). According to this method, to measure poverty, we first need the incidence, or headcount ratio (H), which is the percentage of people identified as multidimensionally poor:

$$H = \frac{\sum_{i=1}^{n} \rho_k(x_i\,; z)}{n} = \frac{q}{n}\,, \tag{1}$$

where x_i is the achievement of individual i in a dimension, z is the deprivation cutoff of that dimension, q is the number of multidimensionally poor, and n is the number of the total population. This approach identifies as poor those with a deprivation score, c_i, higher than the poverty cutoff, k. That is, if $c_i(k) \geq k$, then $\rho_k(x_i\,; z) = 1$; if $c_i(k) < k$, then $\rho_k(x_i\,; z) = 0$.

The second element of the measure, the poverty intensity (A), is the average deprivation score among poor individuals:

$$A = \frac{\sum_{i=1}^{q} c_i(k)}{q}\,, \tag{2}$$

where $c_i(k)$ is the censored deprivation score of individual i, replacing with zero the deprivation scores of non-poor individuals. Formally, when $c_i(k) \geq k, c_i(k) = c_i$, and $c_i(k) < k, c_i(k) = 0$, otherwise.

Finally, the adjusted headcount ratio (M_0), or multidimensional poverty index (MPI), is the product of the headcount ratio and the intensity:

$$M_0 = H \times A \quad (3).$$

Following the standard definition by OPHI and UNDP (2019) for the Global MPI, I set the multidimensional poverty cutoff, k, as one-third of the weighted deprivations and the dimensions as having equal weights. Table 2 presents the resulting weights for each variable.

To estimate poverty using this approach, scholars should avoid mixing different types of indicators (binary, ordinal, continuous) in the same index (Alkire & Foster, 2009). Hence, according to a defined cutoff, I transform ordinal and continuous variables into binary variables (deprived or non-deprived).

This chapter focuses on the outcomes of the incidence (H) because, compared to the incidence and the MPI, it is the best measure to have appropriate comparations with the membership degrees of the fuzzy approach. Yet, I present the intensity (A) outcomes in the Appendix as complementary information to the incidence results.

2.2.2.2 The fuzzy set approach

The fuzzy set approach to measure multidimensional poverty accounts for the vagueness of the indicators. Instead of treating the deprivations as dichotomic measures (0 or 1), the methodology allows individuals to belong in varying degrees to the "fuzzy set" of being poor/deprived. Cerioli and Zani (1990) were the pioneers in applying a fuzzy set approach to measure poverty. Later, Cheli and Lemmi (1995) further developed the approach through the Totally Fuzzy and Relative (TFR) approach, and Betti et al. (2006) with the Integrated Fuzzy and Relative (IFR) approach.

To estimate the fuzzy multidimensional poverty, we need a membership function to calculate the degrees of membership in poverty. In this chapter, I use the IFR because it offers a more generalized membership function, in which we can apply for monetary and non-monetary indicators in a multidimensional context. This approach determines the membership degrees according to the individual's position in the indicators' scores distribution. The membership function, as defined by Betti et al. (2015), is the following:

$$m_i = \left(\frac{\sum_{\gamma} w_{\gamma} \mid X_{\gamma} > X_i}{\sum_{\gamma} w_{\gamma} \mid X_{\gamma} > X_1}\right)^{\alpha-1} \left(\frac{\sum_{\gamma} w_{\gamma} X_{\gamma} \mid X_{\gamma} > X_i}{\sum_{\gamma} w_{\gamma} X_{\gamma} \mid X_{\gamma} > X_1}\right), \tag{4}$$

where ω_{γ} is the individual sample weight ranked by γ, X is the monetary or non-monetary deprivation indicator, and α is a parameter. The calculation of α is such that the mean of the fuzzy indicator is equal to the incidence (*H*) estimated in the AF method.

In the fuzzy approach, I use the variables in their ordinal or continuous version when available because we can grasp more information from the data to calculate the membership degrees. For some variables, we can only have binary information (Section 2.3.3 details the type of each indicator), but to mix different types of data in the same index is not a problem in this approach.

Regarding the indicator's weights, I estimate them using the prevalence-correlation principle as proposed by Betti and Verma (2008) to avoid arbitrariness in choices. This principle is a data-driven method that sets lower weights when the prevalence of an indicator is high and when the correlation with other indicators is high, and it sets higher weights in the opposite cases. The intuition is to account for the dispersion of the indicators by considering critical the deprivations that affect only a small share of the population and to avoid redundancy of variables that are highly correlated with others. Moreover, because the analysis focuses only on one year, it does not violate poverty indices properties that may occur in data-driven weighting methods for multiple years[3].

2.2.3 Measures of inequality among the poor

To calculate inequality among the poor, I use a cutoff-based measure and a fuzzy measure. For the first, I use a positive multiple of variance as proposed by Alkire and Seth (2014). This cutoff-based inequality measure is the following:

$$I_q = \frac{3}{q}\sum_{i=1}^{q}[c_i(k) - A]^2\,, \tag{5}$$

where q is the number of multidimensionally poor individuals, $c_i(k)$ is the censured deprivation score of the individual i, and A the intensity of poverty.

As for the second measure, I propose a fuzzy indicator also using the variance. To build this measure, I set a new α in Equation 4 such that the mean of the fuzzy indicator is equal to the incidence of extreme poverty (the threshold is half of the weighted deprivations instead of one-third). After estimating the fuzzy extreme poverty indicator, I calculate the inequality of extreme poverty membership degrees as follows:

$$I_{fz} = \frac{1}{n}\sum_{i=1}^{n}[m'_i - \mu(m')]^2\,, \tag{6}$$

where n is the number of the total population, m'_i is the extreme poverty membership degree of the individual i, and $\mu(m')$ is the average value of the extreme poverty membership degree.

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[3] Violation of the properties "monotonicity" and "subgroups consistency" may happen in multiple-year analyses that use data-driven weights and recalculate the weights for each survey round (see Dutta, Nogales, & Yalonetzky, 2021).

2.2.4 Intracouple Gender Gap Indexes

To explore the intrahousehold analysis further, I also propose two measures. The first is the Gender Gap Index (GGI), a variation of the Gender Parity Index by Alkire et al. (2013) or the Poverty Gap Index (FGT_1) by Foster, Greer, and Thorbecke (1984), to measure relative intracouple inequality between the primary female and male in households with couples as primary members. For this index, when the individual deprivation score, c_i, is lower than or equal to the cutoff k, the $c_i'(k)$ replaces this value with the value of k. Formally, if $c_i'(k) > k$, $c_i'(k) = c_i$, but when $c_i'(k) \leq k$, $c_i'(k) = k = 0.333$. This censoring intends to limit the gap of women in relation to men so that changes in the deprivation scores of men that are not multidimensionally poor do not affect the index. This index classifies the households as lacking gender parity when the female is multidimensionally poor and her new censored deprivation score, $c_i'(k)$, is higher than the one of her partner.

The GGI measure calculation is the following:

$$GGI = H_{GGI} \times I_{GGI}, \tag{7}$$

where H_{GGI} is the percentage of women living in households with no gender parity, measured as the number of households classified as lacking gender parity, h, divided by the total of households with primary couples in their composition, z. The H_{GGI} computation is the following:

$$H_{GGI} = \frac{h}{z}\,. \tag{8}$$

And I_{GGI} is the average percentage gap between the censored deprivations of the women and men in a household in which there is no gender parity. The I_{GGI} calculation is the following:

$$I_{GGI} = \frac{1}{h}\sum_{j=1}^{h} \frac{c_j'(k)^M - c_j'(k)^W}{1 - c_j'(k)^M}, \tag{9}$$

where $c_j'(k)^W$ and $c_j'(k)^M$ are, respectively, the new censored deprivation scores of the primary female and the primary male (when they are partners) in the household j.

The second measure is the Fuzzy Gender Gap Index (FzGGI), which considers a household as having disadvantaged women when the poverty membership degree, m_i, of the primary male is lower than the primary female. For this index, the computation of the percentage of disadvantaged women is the following:

$$H_{FzGGI} = \frac{h^{fz}}{z}, \tag{10}$$

where h^{fz} is the number of households with disadvantaged women, and the average percentage gap between membership degrees of women and men in households with disadvantaged women (I_{FzGGI}) is the following:

$$I_{FzGGI} = \frac{1}{h^{fz}} \sum_{j=1}^{h^{fz}} \frac{m_j^{fz^M} - m_j^{fz^W}}{1 - m_j^{fz^M}}, \tag{11}$$

where $m_j^{fz^W}$ and $m_j^{fz^M}$ are, respectively, the poverty membership degree of the primary female and the primary male (when they are partners) in the household j.

Finally, the calculation of FzGGI is the product of the previous two measures:

$$FzGGI = H_{FzGGI} \times I_{FzGGI}. \tag{12}$$

Because the definitions of households lacking gender parity and disadvantaged women are different, the GGI and the FzGGI results are not comparable. The GGI restricts the analysis for multidimensionally poor women, while the FzGGI includes all the households with couples as primary members. The FzGGI's perspective is also relevant because intracouple gaps and inequalities also happen in non-poor households.

2.3 Indexes, dimensions, and indicators

This section details the indicators and supports them using the theoretical and empirical literature. The focus is on the dimensions of the ORI, as the dimensions of the SMPI are extensively discussed in the literature (see Alkire & Santos, 2010; and Anand & Sen, 1997).

Table 2 presents the structure of the two indexes, the AF method's cutoffs [4], and the indicators' weights. Each dimension includes a subjective indicator, which accounts for the self-understanding of the household heads about their household's situation in that dimension. The subjective indicators work as complements to the other indicators.

2.3.1 The Standard Multidimensional Poverty Index

2.3.1.1 Education

Beyond the many positive effects on socioeconomic development, education has an intrinsic importance that establishes the freedom and opportunities of people (Sen, 1999). This chapter measures the dimension of Education with two indicators: *School achievement* and *Education subjective*. The first is an individual-level indicator based on a similar measure proposed by Espinoza-Delgado and Klasen (2018). For the elderly (greater than or equal to 60 years old) or adults (between 16 and 59 years old), this measure counts the number of completed years of education in relation to the conclusion of the elementary school. For instance, if a person's education level is elementary school, the indicator is 0; if a person has three years of additional study after the completion of elementary school, the measure is 3; and if a person has three years left to complete the elementary school, the measure is -3. The same logic applies to adolescents (between 12 and 15 years) and children (between 4 and 11 years old), but, in these cases, the indicator calculates if the individual is on track to conclude the elementary school, giving a buffer of two years to account for the many reasons a student can be in delay.

The second indicator, *Education subjective,* illustrates the perception of household heads of the family's standard of living regarding education, ranging from good, satisfactory, and bad.

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[4] Some of the indicators and cutoffs are the same as in Tavares and Betti (2021).

2.3.1.2 Health and food security

Health is also a constituent part of development, as it has an intrinsic value (Sen, 1999), it is a basic capability, and a prerequisite for human development (Alkire & Santos, 2010). For this dimension, I propose three indicators: *Share of expenditure on food, Food Security Index*, and *Health subjective*. Ideally, health and food consumption data should be at the individual-level. However, health is one of the most difficult dimensions to measure, as most surveys do not offer data for all the household members (Alkire & Santos, 2010). The POF has information on individuals' weight and nutritional details, but they are available only for a small portion of the sample and for people greater than or equal to ten years old. Therefore, because it is not possible to calculate the indicators at the individual level for the whole population, the three indicators are on the household level.

The first indicator, *Share of expenditure of food,* is the percentage of the household consumption expenditure on food products. The *World Food Programme* (WFP) and others use this indicator to assess food insecurity and identify families vulnerable to shocks affecting food prices (see Lele et al., 2016; Rose, 2012). As for the second indicator, *Food Security Index,* the IBGE calculates it following the Brazilian Household Food Insecurity Measure Scale (EBIA). The calculation uses psychological factors (e.g., worry that the food will run out), food quality, food quantity available for adults and children, and hunger (e.g., when someone does not eat all they long because of lack of money) (see IBGE, 2020a). The resulting scale is the following: food security, light food insecurity, moderate food insecurity, and severe food insecurity. Finally, the third indicator, *Health subjective,* accounts for the household heads' perception on the standard of living in terms of health in their home (good, satisfactory, and bad).

2.3.1.3 Living standards

In this chapter, eight indicators represent the Living Standards dimension: *Housing, People-per-bedroom, Drinking water*, *Sanitation*, *Electricity, Assets*, *Cooking Fuel,* and *Housing subjective*. In combination, these indicators stand for acute poverty. Some of them are related to health and affect mostly women, as the indicators of drinking water, sanitation, and cooking fuel (Alkire & Santos, 2010).

Building individual-based indicators for the living standards dimension is both empirically and conceptually tricky for two main reasons (Vijaya et al., 2014). First, there is no individual-level data in most surveys. Second, we cannot know whether individuals within a household use the goods equally or if someone has control over them. Therefore, following other studies (Burchi et al., 2021; Espinosa-Delgado & Klasen, 2018; Vijaya et al., 2014), I built these variables at the household level assuming that they are semi-public goods with equal access among everyone within the household.

Regarding the indicators in this chapter, *Housing* accounts for the material used in the roof, walls, and floor. *People-per-bedroom* measures the number of people per permanent bedroom in the household. *Drinking water* considers the weekly frequency of water supply, the presence or absence of plumbed running water inside the household, and the kind of water source. *Sanitation* evaluates the number of indoor bathrooms with shower and toilet, the existence of at least one private bathroom (not shared with other households), and the kind of sewage disposal available in the household. *Electricity* analyses whether the household has access to electricity and the weekly frequency of this access. *Assets* evaluates if the households have the following items: computer, radio, TV refrigerator, bicycle, motorbike, and car or truck. *Cooking Fuel* examines the kind of cooking fuel used in the household. Finally, *Housing subjective* analyzes the perception of the household heads on living standards regarding housing in their home (good, satisfactory, or bad).

2.3.2 The Occupation-Resources Index

2.3.2.1 Occupation

The dimension "Occupation" works as a proxy measure of work and time quality, which are key aspects in gender and feminist economics analyses (see Berik & Kongar, 2021). This dimension includes four indicators: *Informality*, *Deprivation on employment, Commuting time,* and *Leisure subjective.*

The first indicator, *Informality,* is an important indicator in the Global South as it represents the situation of a big share of their workers. The consequence of high informality is that a large part of the population remains without access to the social security system. Moreover, informal workers face additional challenges because they tend to be not unionized, lack awareness of their rights, have dispersed activities, have irregular earnings, and get devaluated jobs (Kabeer, 2021). The indicator in this chapter is an individual-level measure that select some work categories considering the workers' accessibility to social security to have a proxy for informal occupation, as suggested by the IBGE (2020c). The selected categories are the following: auxiliary family workers; private-sector employees and domestic workers without a formal contract; and employers and self-employed workers who do not contribute to social security.

Regarding the treatment of ineligible subgroups, *Informality* considers children and adolescents as deprived if they work in illegal conditions[5] or if every adult in their household has an informal job. Elderlies are deprived when they have an informal job or no income because these two situations indicate that they have no access to the social security system and probably did not have this access during most of their career.

The second indicator, *Deprivation on employment,* is a complementary measure to informality as it includes other situations in which people may be vulnerable. This indicator is at the individual level, and it defines adults as deprived if they do not have a job and are not studying or if they are employed without pay and are not studying. Children and adolescents are deprived when working in illegal

[5] According to law number 10.097 of December 2000, adolescents between 14 and 16 years old are allowed to work as an apprentice, not exceeding six hours a day (8 hours if they have finished elementary school). Moreover, adolescents that have not finished elementary school must attend school.

conditions (the same as the *Informality* indicator) or when everyone in their household is deprived on employment. Elderlies are deprived when they have no source of income, which means that they are deprived on social protection. A limitation of this indicator is that the POF does not cover unpaid domestic work. This measure partially captures unpaid domestic work through the non-working status in the dataset, but it does not capture people working a "second shift," meaning people who have a paid job and are also responsible for unpaid domestic work. Therefore, this indicator underestimates the deprivations of women because they are usually responsible for unpaid domestic work in Brazil (Barbosa, 2018; Lavinas, 2016).

The third indicator, *Commuting time,* is an individual-level indicator that accounts for the total time to arrive at the main job from home. This variable matters because it exposes and represents the gender inequalities in the labor market, the access to transportation, the division of domestic responsibilities at home, and the self-identity (Hanson & Johnston, 1986; Pereira & Schwanen, 2015). Moreover, long commute time is associate with poverty (especially in metropolitan areas), as poor people tend to be more vulnerable to transport disadvantages (Lucas, 2021; Pereira & Schwanen, 2015). For children and adolescents, the measure is the average commuting time of the adults in their households. A limitation of this measure is that the survey only gives information on the commuting time of the main job, ignoring people working in multiple jobs.

The fourth indicator, *Leisure subjective,* shows the household head's perception of the family's standard of living regarding leisure (good, satisfactory, or bad). According to Barbosa (2018), men have more leisure time than women in Brazil. Therefore, to see how the subjective measure differs between women and men is important, as it can reflect disparities in the time available for leisure.

In this dimension, the only indicator that is not at the individual level is the *Leisure subjective,* as only the household heads have answered it in the survey. Moreover, the treatment of ineligible population for the indicators *Informality* and *Commuting time* does not include adults who do not work. In these cases, I treat them as non-deprived.

2.3.2.2 Resources

This dimension shows the economic situation of households and individuals, and the access to financial products and private health insurance. Therefore, the indicators can also be interpreted as aspects of agency or degree of empowerment (see Alkire, 2007; and Mishra & Tripathi, 2011).

The dimension comprises six indicators: *Dependency ratio, Housing tenure, Financial access, Private insurance, Payment difficulties, and Financial subjective.* The first indicator, *Dependency ratio*, intends to capture the economic vulnerability of households that rely on few household members to sustain a large family. This indicator measures the household proportion of children, adolescents, and elderly with no income with respect to adults. *Dependency ratio* is at the household level, but for the characteristics of the indicator, we cannot have an individual-based version.

The second indicator, *Housing tenure,* accounts for the arrangements under which the household occupies the accommodation (own home, rented, ceded, or occupied). The third indicator, *Financial access,* counts the number of different financial products that the individual has access to. For children and adolescents, this measure is the total of financial product types in their household. These two indicators are important because they are related to forms of agency (Kabeer, 2021). *Housing tenure* can reflect the extent to which the person has control over the property and social vulnerability due to informal arrangements and informal settlement. *Financial access* is a proxy of control over income, which is a key determinant of whether a person can exercise choices and benefit from his/her efforts (Alkire et al., 2013).

The fourth indicator, Private insurance, shows if the person has private health insurance or not. This measure also reflects inequalities in access to resources because having private insurance in Brazil depends on accessibility, ability to afford costs, and whether the job offers private insurance as a benefit. Of the previous three indicators I presented, only *Housing tenure* is at the household level because it is a classification of the property ownership status.

The fifth indicator, *Payment difficulties*, calculates the number of payment difficulties a household had for one year due to financial difficulties. The sixth indicator, *Financial subjective*, considers the household heads' assessments about the difficulty to live until the end of the month with the family's income. The answers options are very easy, easy, some facility, some difficulty, difficult, very difficult. These two indicators are complementary, showing the economic vulnerability of households. Both indicators are at the household level because there is no data available at the individual level.

Table 2 - Multidimensional poverty indexes, dimensions, indicators, and cutoffs

Dimension	Indicator	In the AF method, the individuals are deprived if…	Level	Standard Weight	P-C Weight*
	STANDARD MPI				
Education	Schooling achievement	(Preschool children) they are not attending daycare, preschool, or primary school, and the head of their household has not completed lower secondary school. When infants are less than three years, the measure classifies them as not deprived. (Children and Adolescents) they are not on course to complete lower secondary school by the age of 17. (Adults and Elderly) they have not completed lower secondary school.	Individual	0.166	0.167
	Education subjective	the head of their household considers the family's standard of living in relation to education as bad.	Household	0.166	0.167
Health and Food Security	Share of expenditure on food	in their household, food represents 75% or more of the total consumption expenditure.	Household	0.111	0.120
	Food security index	their household have light food insecurity or more, according to the Brazilian Scale of Food Insecurity (EBIA).	Household	0.111	0.104
	Health subjective	the head of their household considers the family's standard of living in relation to health as bad.	Household	0.111	0.110

Dimension	Indicator	In the AF method, the individuals are deprived if…	Level	Standard Weight	P-C Weight*
Living Standards	Housing	in their household, the housing materials for at least one of the floor, roof, and walls are inadequate.	Household	0.041	0.037
	People-per-bedroom	in their household, there are three or more residents per permanent bedroom.	Household	0. 041	0.037
	Drinking water	in their household, the water frequency is not daily; or there is no indoor plumbed water; or the water does not come from the public distribution system.	Household	0. 041	0.033
	Sanitation	in their household, sanitation is not improved; or it is shared with other households; or the sewage disposal is not connected to the public system.	Household	0. 041	0.045
	Electricity	their household has no access to electricity.	Household	0. 041	0.045
	Cooking fuel	in their household, the cooking fuel is wood, oil, kerosene, or another liquid fuel.	Household	0. 041	0.041
	Assets	their household does not own a car or truck and does not own more than one of these assets: computer, radio, TV refrigerator, bicycle, or motorbike[1].	Household	0. 041	0.046
	Housing subjective	the head of their household considers the family's standard of living in relation to housing as bad.	Household	0. 041	0.049
OCCUPATION-RESOURCES INDEX					
Occupation	Informality	(Children and Adolescents) they are working in illegal conditions, or all adults in their household are deprived in this indicator. (Adults) they have an informal job. (Elderly) they have an informal job or have no income (pension, wage, financial earnings, transfers, except for conditional cash benefits).	Individual	0.125	0.099
	Deprivation on employment	(Children and Adolescents) they are working in illegal conditions, or all adults in their household are deprived in this indicator. (Adults) they do not have a job and are not studying, or are employed without pay and are not studying.	Individual	0.125	0.167

Dimension	Indicator	In the AF method, the individuals are deprived if…	Level	Standard Weight	P-C Weight*
		(Elderly) they have no income (pension, wage, financial earnings, transfers, except for conditional cash benefits).			
	Commuting time	(Children and Adolescents) the average commuting time of the adults in their household is larger than one hour. (Adults and Elderly) they spend more than one hour to arrive at her/his workplace from home.	Individual	0.125	0.134
	Leisure subjective	the head of their household considers the family's standard of living in relation to leisure as bad.	Household	0.125	0.100
Resources	Dependency ratio	in their household, the proportion of children and elderly without an income in relation to adults is bigger than two[2].	Household	0.083	0.080
	Housing tenure	they are renting their accommodation under a verbal rental contract, or they are living in a ceded house or occupied house, or the rent payment refers to the household in conjunction with a non-residential unit (store, workshop, and others).	Household	0. 083	0.108
	Financial access	(Children and Adolescents) all adults and elderly in their household are deprived in this indicator. (Adults and Elderly) they have no access to financial products (bank account, check pay, credit card, or saving account).	Individual	0. 083	0.089
	Private insurance	they have no access to private health insurance.	Individual	0. 083	0.076
	Payment difficulties	in their household, due to financial difficulties, they delayed one of the following payments more than two times in the last 12 months: rent, house installments, bills, or goods and services.	Household	0. 083	0.074
	Financial subjective	the head of their household considers that the family's income allows them to live until the end of the month with difficulty or a lot of difficulty.	Household	0. 083	0.073

Notes: *Prevalence-correlation weights. 1. Cars and trucks have double weight within the indicator. 2. If the household is composed only of elderly without an income with or without children/adolescents, I multiply the number of residents by two. In this way, these individuals will always be deprived in the AF method and have a double weight in the fuzzy approach.

2.3.3 Descriptive statistics

Table 3 presents the types of data and descriptive statistics for the indicators of the two indexes. As explained previously, I transform the continuous and ordinal indicators into binary variables for the AF method, while for the fuzzy approach, I use the indicators as continuous or ordinal when possible. In the binary indicators, zero means deprived, and one non-deprived. When the indicator is continuous or ordinal, it ranges from no deprivation to complete deprivation, except schooling achievement, assets, and financial access, which count the number of years of education, assets, and financial product types.

Table 3 – Data type, descriptive statistics, and score range

Indicators	Data type	Mean	Standard Errors*	Min	Max
Standard MPI					
Schooling achievement	Ordinal	0.630	0.0329	-12	12
Education subjective	Ordinal	1.508	0.0056	1	3
Share of expenditure on food	Continuous	0.157	0.0009	0	0.90
Food security index	Ordinal	1.599	0.0069	1	4
Health subjective	Ordinal	1.818	0.0064	1	3
Housing	Ordinal	1.027	0.0103	0	9
People-per-bedroom	Continuous	1.905	0.0074	0.3	13
Drinking water	Ordinal	0.606	0.0107	0	6
Sanitation	Ordinal	0.494	0.0064	0	4
Electricity	Ordinal	0.056	0.0031	0	4
Cooking fuel	Ordinal	0.010	0.0006	0	2
Assets	Ordinal	6.068	0.0340	0	27
Housing subjective	Ordinal	1.424	0.0051	1	3
Occupation-Resources Index					
Informality	Binary	0.773	0.0018	0	1
Deprivation on employment	Binary	0.850	0.0015	0	1
Commuting time	Ordinal	0.639	0.0049	0	4
Leisure subjective	Ordinal	1.990	0.0071	1	3
Dependency ratio	Continuous	0.465	0.0045	0	6
Housing tenure	Ordinal	1.891	0.0110	1	6
Financial access	Ordinal	1.204	0.0094	0	4
Private insurance	Binary	0.260	0.0040	0	1
Payment difficulties	Ordinal	0.720	0.0071	0	3
Financial subjective	Ordinal	3.083	0.0099	0	5

Note: *Linearized standard errors considering the survey design.

Because of the novelty of the ORI, I present the pairwise correlations among all indicators to understand their relations (Figure 1). The figure shows that the SMPI indicators (from 1 to 13) correlate positively, except *Schooling achievement* and *Assets* that have a positive correlation only with each other. As for the SMPI's indicators relationship with the ORI indicators (from 14 to 23), most have a negative but weak correlation, but a positive correlation with *Schooling achievement* and *Assets*. *Financial access* and *Private insurance* show relatively stronger negative correlations, especially with the food security index (the bigger it is, the worst is food security).

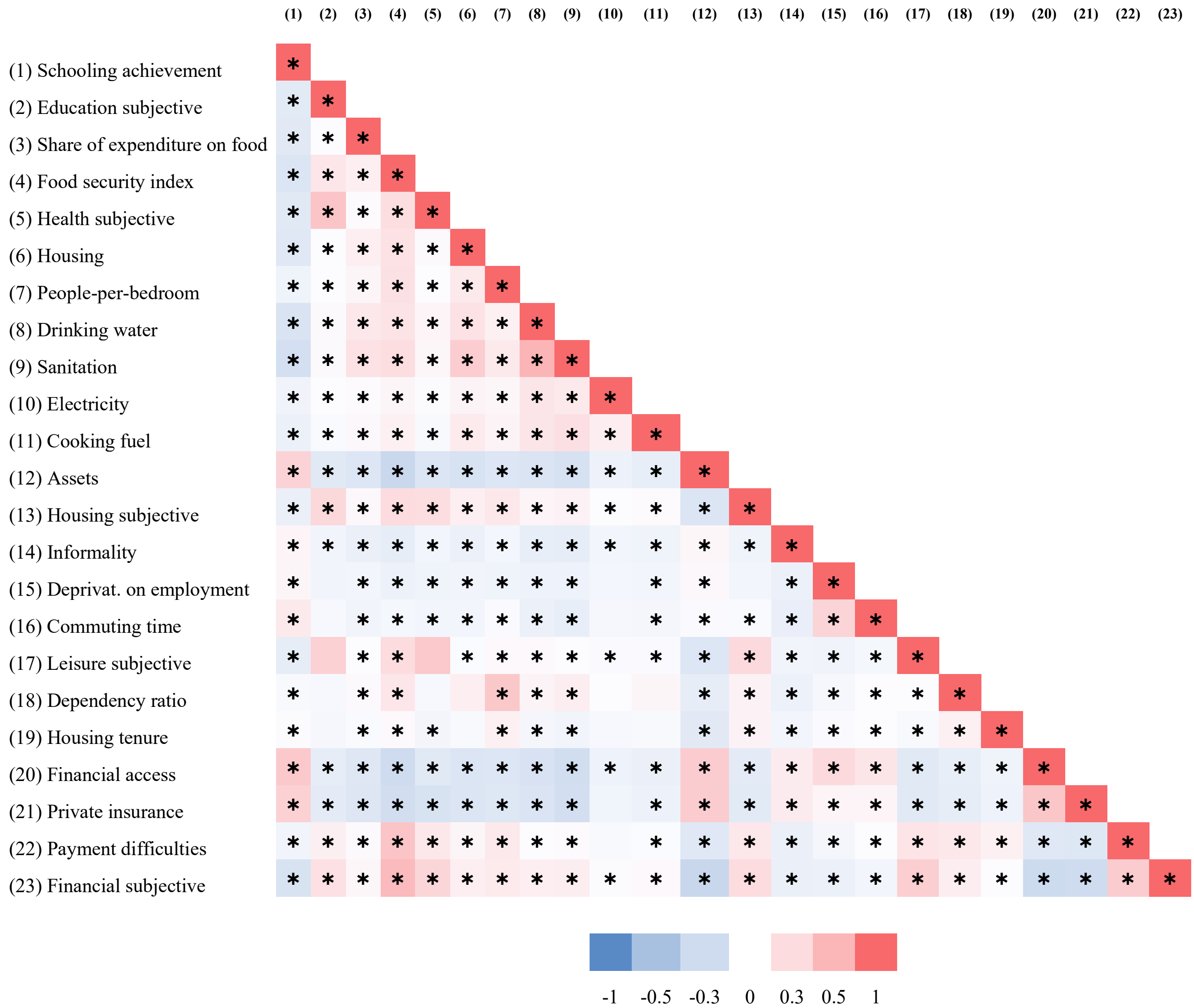

Figure 1 - Pearson correlation matrix of the indicators

Notes: Significance level: ∗ $p < 0.01$. For indicators 1, 12, 14, 15, 20, and 21, the larger they are, the less deprived an individual is. For the remaining indicators, the larger they are, the more deprived a person is.

Moreover, *Payment difficulties* and *Financial subjective* also have a relatively stronger positive correlation with *Food security index* than other indicators. These results suggest that a bad financial situation is related to food insecurity. The correlations of *Financial subjective* also reveal that people with fewer assets, financial access, private insurance, and more payment difficulties tend to classify their financial situation negatively. Another interesting outcome is the relations among the subjective indicators: they are all positively correlated, meaning that a person is inclined to have similar perceptions in all the subjective indicators.

2.4 Results

2.4.1 Estimations for the whole population: intrahousehold perspective

2.4.1.1 Multidimensional poverty

Before showing the results of the multidimensional poverty indexes, I present the indicators' percentage of deprivation by gender using the threshold defined for the AF approach (Table 4). According to the SMPI indicators, women are less deprived than men in education, especially in *Schooling achievement*. This advantage of women in education is in line with the literature on education in Brazil (see Beltrão & Alves, 2013; and Melo & Morandi, 2021). In the dimensions Food security and Health, women are slightly better off in the indicators *Share of expenditure on food* but are more deprived in the *Food security index* and *Health subjective*. As for the Living standards' indicators, women are less deprived in all of them.

In most of the ORI's indicators, women are at a disadvantage. In the indicator of deprivation on employment, for example, women have, on average, almost 11 percentual points (pp) more than men. Possible explanations for this result are the larger unemployment rate among women in 2018 and 2019 (IBGE, 2021) and that the indicator is capturing women that work exclusively in unpaid domestic duties. Moreover, women with children tend to look less for jobs in the labor market to focus on raising their children (Lavinas, Alves, & Nicoll, 2016).

In the indicators *Informality* and *Commuting time*, women are less deprived, in part because they have less participation in the labor market, and those indicators treat non-employed adults as non-deprived. The results also show that women are at a disadvantage on financial matters, as they are more deprived in *Financial access*, *Payment difficulties*, and *Financial subjective*.

Table 4 – Percentage of deprivation of males and females and gender differences by subgroups

Indicators	Deprived (%)						Female-Male Differences	
	Total	SE	Male	SE	Female	SE	Absolute	Relative
Standard MPI								
Schooling achievement	29.08	0.002	30.34	0.003	27.89	0.002	-2.45***	0.92
Education subjective	11.66	0.002	11.83	0.003	11.50	0.003	-0.33*	0.97
Share of expendit. on food	0.08	0.000	0.09	0.000	0.06	0.000	-0.03**	0.63
Food security index	40.98	0.004	40.83	0.004	41.13	0.004	0.30	1.01
Health subjective	26.45	0.003	26.17	0.004	26.72	0.004	0.55**	1.02
Housing	10.70	0.003	11.06	0.003	10.36	0.003	-0.70***	0.94
People-per-bedroom	12.71	0.003	12.89	0.003	12.54	0.003	-0.35**	0.97
Drinking water	30.19	0.004	30.98	0.004	29.45	0.004	-1.53***	0.95
Sanitation	39.10	0.004	40.35	0.005	37.93	0.004	-2.42***	0.94
Electricity	0.22	0.000	0.26	0.000	0.18	0.000	-0.08***	0.70
Cooking fuel	1.01	0.001	1.16	0.001	0.88	0.001	-0.28***	0.76
Assets	1.33	0.001	1.39	0.001	1.28	0.001	-0.11*	0.92
Housing subjective	7.66	0.002	7.72	0.002	7.60	0.002	-0.12	0.98
Occupation-Resources Index								
Informality	22.68	0.002	24.46	0.002	21.02	0.002	-3.44***	0.86
Depriv. on employment	14.98	0.001	9.32	0.002	20.28	0.002	10.97***	2.18
Commuting time	4.58	0.001	5.22	0.001	3.99	0.001	-1.23***	0.76
Leisure subjective	34.13	0.004	33.67	0.004	34.56	0.004	0.89***	1.03
Dependency ratio	3.73	0.001	3.48	0.002	3.96	0.002	0.48***	1.14
Housing tenure	18.14	0.003	18.38	0.003	17.93	0.003	0.45**	0.98
Financial access	38.26	0.003	37.84	0.003	38.66	0.003	0.82***	1.02
Private insurance	74.02	0.004	75.08	0.004	73.02	0.004	-2.07***	0.97
Payment difficulties	22.26	0.003	22.12	0.003	22.40	0.003	0.27	1.01
Financial subjective	35.32	0.004	34.95	0.004	35.66	0.004	0.71***	1.02

Notes: Linearized standard errors (SE) considering the survey design. Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

Table 5[6] presents the results by gender of the multidimensional poverty incidence[7] and fuzzy for the SMPI, including outcomes for subgroups. The fuzzy results range between 0 and 100, with 0 representing the minimum poverty degree, and 100 the maximum. For this index, we can observe that multidimensional poverty appears not to be feminized because men have larger poverty outcomes than women for most subgroups and the two methods. In total, men are between 2% and 7% poorer than women.

[6] In this section, the outcomes of the category "Undeclared" in the subgroup Color/Ethnicity do not receive any comments, as the POF do not inform why a person is classified as undeclared.
[7] Table 12 in the appendix presents the intensity of poverty (A) among subgroups.

However, individuals living in female-headed households are considerably worse off than those in male-headed households (although the female-male differences are smaller). Moreover, the results for single women and women living in households with no couples as primary members (i.e., adults without children and adults with children[8]) are unclear because each method produces a different result, or the outcomes are not statistically significant. The categories with the largest relative differences are Single without children, Couple with children, and Male-headed for the incidence; and Single with children, Couple without children, and Male-headed for the fuzzy results.

What is clearer from the results is the considerable inequality within subgroups (i.e., Household Headship, Age Groups, Family Composition, Region, Color/Ethnicity, and Area Type). Elderly and family compositions that include elderlies are multidimensionally poorer than most people in other categories within the Age and Family Composition subgroups. The North and Northeast regions are in some specifications about twice multidimensionally poorer than other regions. Rural areas also are in a much worse situation compared to urban areas. Finally, color/ethnicity also matters, as Black, Brown, and Indigenous people are at least eight pp multidimensionally poorer than White and Asian people.

Table 6 shows the multidimensional poverty results for the ORI[9]. Compared to the SMPI's results, the estimations reveal a different scenario, as multidimensional poverty is higher among women in most subgroups. According to the total results, women are between 5% and 7% multidimensionally poorer than men. Interestingly, women are in a better situation than men in female-headed households, and, in the fuzzy results, women are less multidimensionally poor in female-headed houses than in male-headed houses. Considering both methods, the categories that women are in most

[8] In this section, "children" include both children and adolescents.
[9] Table 13 in the appendix shows the poverty intensity (A) by subgroups.

relative disadvantage with respect to men of the same group are Asian, Elderly, Elderly(ies), and Male-headed.

Table 5 - Multidimensional poverty estimations and gender differences for the Standard MPI by subgroup

	Standard MPI									
	H (%)			Differences		Fuzzy			Differences	
Variables	Total	Male	Female	Absolute	Relative	Total	Male	Female	Absolute	Relative
Total	18.03	18.75	17.35	-1.40***	0.93	18.03	18.25	17.82	-0.44***	0.98
Household Headship										
Male-headed	16.66	17.69	15.44	-2.25***	0.87	16.70	17.15	16.17	-0.97***	0.94
Female-headed	20.07	20.88	19.52	-1.36***	0.94	20.01	20.48	19.69	-0.79***	0.96
Age Groups										
Child	12.21	12.88	11.49	-1.39***	0.89	18.21	18.54	17.87	-0.67*	0.96
Adult	18.27	19.41	17.21	-2.19***	0.89	17.04	17.35	16.75	-0.6***	0.97
Elderly	25.41	25.70	25.18	-0.52	0.98	21.81	21.81	21.81	0.00	1.00
Family Composition										
Single without children[1]	17.62	18.93	15.80	-3.13**	0.83	17.86	18.24	17.34	-0.90	0.95
Single with children[1]	15.89	15.29	16.22	0.93	1.06	20.00	21.22	19.33	-1.88*	0.91
Couple without children[2]	14.69	15.59	13.71	-1.88***	0.88	14.91	15.43	14.34	-1.09***	0.93
Couple with children[2]	16.66	17.78	15.51	-2.27***	0.87	16.85	17.23	16.45	-0.78***	0.95
Adults without children[3]	15.85	15.62	16.04	0.42	1.03	17.40	17.16	17.59	0.43	1.03
Adults with children[3]	22.08	22.07	22.08	0.02	1.00	22.38	21.78	22.79	1.01	1.05
Elderly(ies)[4]	22.25	23.32	21.44	-1.88***	0.92	20.92	21.60	20.42	-1.19**	0.94
Elderly(ies) and adult(s)[5]	21.06	21.84	20.38	-1.46***	0.93	20.08	20.51	19.71	-0.79***	0.96
Region										
North	31.88	33.76	29.98	-3.78***	0.89	27.27	28.00	26.53	-1.47***	0.95
Northeast	27.53	28.90	26.25	-2.65	0.91	24.29	24.89	23.74	-1.14***	0.95
Center-west	12.62	12.88	12.38	-0.50	0.96	15.25	15.24	15.27	0.03	1.00
Southeast	9.06	8.88	9.24	0.35***	1.04	10.01	9.80	10.21	0.40*	1.04
South	15.23	15.85	14.63	-1.23***	0.92	15.64	15.77	15.52	-0.25	0.98
Color/Ethnicity										
White	11.64	11.91	11.40	-0.51***	0.96	13.28	13.31	13.25	-0.07	1.00
Black	22.82	24.02	21.60	-2.42	0.90	22.14	22.28	22.00	-0.29	0.99
Asian	6.89	6.94	6.85	-0.10***	0.99	8.11	7.29	8.70	1.41	1.19
Brown	23.32	24.08	22.59	-1.49	0.94	21.88	22.11	21.66	-0.44*	0.98
Indigenous	22.15	21.87	22.40	0.54***	1.02	21.99	21.37	22.56	1.18	1.06
Undeclared	29.27	36.66	21.54	-15.12***	0.59	22.67	26.82	18.33	-8.49*	0.68
Area type										
Urban	14.62	14.91	14.36	-0.55***	0.96	16.54	16.57	16.51	-0.07	1.00
Rural	37.73	39.24	36.11	-3.13***	0.92	26.66	27.23	26.04	-1.18***	0.96

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Fuzzy outcomes represent degrees of poverty. Standard errors are available under request. 1. "Single" refers to adults only. 2. Only adult couples, and with or without other adults in the household. 3. No couples as primary members of the household. 4. With or without children. 5. At least one adult and with or without children.

Regarding the inequality within subgroups, Region, Color/Ethnicity, and Area type have a similar pattern as in the SMPI: the categories with worse deprivations are the North and Northeast regions; the Black, Brown, and Indigenous; and the Rural areas. Within the Age Groups and Family

Composition, in contrast to the SMPI results, Elderlies are among the less multidimensionally poor. In the Age Groups, Adults is the category with worse outcomes, and in the Family Composition, Single with children and Adults with children are more disadvantaged.

Table 6 - Multidimensional poverty estimations and gender differences for the Occupation-Resources Index by subgroup

	Occupation-Resources Index									
	H (%)			Differences		Fuzzy			Differences	
Variables	Total	Male	Female	Absolute	Relative	Total	Male	Female	Absolute	Relative
Total	33.49	32.26	34.66	2.40***	1.07	33.49	32.65	34.29	1.64***	1.05
Household Headship										
Male-headed	30.97	27.95	34.54	6.59***	1.24	31.77	29.52	34.41	4.89***	1.17
Female-headed	37.23	40.90	34.79	-6.11***	0.85	36.06	38.92	34.15	-4.77***	0.88
Age Groups										
Child	30.43	30.73	30.11	-0.61	0.98	30.23	30.45	29.99	-0.46	0.98
Adult	37.36	35.89	38.74	2.86***	1.08	36.72	35.59	37.78	2.19***	1.06
Elderly	22.05	18.58	24.80	6.22***	1.33	24.97	23.16	26.40	3.24***	1.14
Family Composition										
Single without children[1]	30.65	32.67	27.85	-4.81**	0.85	30.57	32.01	28.58	-3.43**	0.89
Single with children[1]	58.92	62.00	57.22	-4.78**	0.92	46.74	48.97	45.50	-3.46**	0.93
Couple without children[2]	30.35	29.09	31.73	2.64***	1.09	31.24	30.32	32.26	1.94***	1.06
Couple with children[2]	34.85	33.18	36.56	3.38***	1.10	34.40	32.98	35.87	2.89***	1.09
Adults without children[3]	35.92	37.19	34.93	-2.26	0.94	35.95	37.51	34.74	-2.77***	0.93
Adults with children[3]	48.12	47.08	48.82	1.74	1.04	44.53	43.32	45.34	2.02***	1.05
Elderly(ies)[4]	18.00	15.22	20.09	4.87***	1.32	21.55	20.41	22.40	1.99***	1.10
Elderly(ies) and adult(s)[5]	31.29	30.91	31.63	0.72	1.02	32.68	32.62	32.74	0.12	1.00
Region										
North	42.28	41.81	42.75	0.94	1.02	39.97	39.33	40.61	1.28***	1.03
Northeast	42.77	42.30	43.20	0.9**	1.02	41.16	40.76	41.53	0.78***	1.02
Center-west	30.08	28.23	31.77	3.54***	1.13	30.81	29.67	31.86	2.19***	1.07
Southeast	20.73	19.25	22.14	2.9***	1.15	23.53	22.51	24.50	2***	1.09
South	33.28	31.89	34.61	2.72***	1.09	32.36	31.42	33.27	1.85***	1.06
Color/Ethnicity										
White	25.23	23.81	26.52	2.71***	1.11	26.72	25.97	27.39	1.42***	1.05
Black	40.24	38.86	41.64	2.78***	1.07	39.26	38.17	40.36	2.19***	1.06
Asian	21.48	14.06	26.71	12.65***	1.90	22.31	18.79	24.78	5.99**	1.32
Brown	40.23	38.94	41.47	2.53***	1.06	39.00	37.87	40.08	2.21***	1.06
Indigenous	36.97	34.18	39.51	5.33	1.16	35.77	33.52	37.82	4.31	1.13
Undeclared	41.40	44.65	38.00	-6.65	0.85	39.28	40.76	37.73	-3.02	0.93
Area type										
Urban	31.46	30.09	32.71	2.62***	1.09	31.76	30.84	32.60	1.77***	1.06
Rural	45.28	43.81	46.87	3.06***	1.07	43.53	42.31	44.86	2.55***	1.06

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Fuzzy outcomes represent degrees of poverty. Standard errors are available under request. 1. "Single" refers to adults only. 2. Only adult couples, and with or without other adults in the household. 3. No couples as primary members of the household. 4. With or without children. 5. At least one adult and with or without children.

2.4.1.2 Inequality among the poor

I now present the inequality among the multidimensionally poor for both the SMPI and ORI. Table 7 shows the SMPI outcomes by subgroup. For this index, most categories reveal that inequality among the poor is higher for men with respect to women. In total, the inequality among multidimensionally poor, I_q, is 5% higher for men. The Indigenous population, Adults without children, and Single with children are the categories with the largest relative differences disfavoring men.

Regarding the fuzzy inequality estimations, I_{fz}, the outcomes are similar to those of the I_q, as men present higher inequality in most subgroups. The total fuzzy inequality is 6% larger for men with respect to women. The categories with the highest gender relative disparities are Indigenous (disfavoring women), Southeast (disfavoring women), and Asian (disfavoring men).

In both approaches, the North and Northeast have the highest inequalities among the Regions, Black and Brown have the largest inequalities among the Color/Ethnicity subgroup, Rural areas have greater inequality than Urban areas, and Elderly has the highest inequality among the Age Groups. The SMPI inequality results, combined with the outcomes from the previous subsection, reveal that the poorest categories in these subgroups also have the highest inequalities among the poor.

Table 8 shows the results of the ORI by subgroups. The outcomes reveal that inequality among the poor is higher among women in most subgroups, although the differences are statistically significant only in three categories. The total Iq for women is 2 % larger with respect to men. The largest relative gender differences in inequality are among Indigenous (disfavoring men)., Asian (disfavoring men), and South (disfavoring women). Within subgroups, the category Female-headed has higher inequality than Male-headed, Elderly has the largest inequality among the Age Groups, Single with children has the highest inequality in the Family Composition subgroup, the Northeast has the greatest inequality among the Regions, Asian has the largest inequality among the subgroup Color/Ethnicity, and Rural areas have large inequality than Urban areas.

Table 7- Inequality among the multidimensionally poor and gender differences for the Standard MPI by subgroup

	Standard MPI									
	I_q			Differences		I_{fz}			Differences	
Variables	Total	Male	Female	Absolute	Relative	Total	Male	Female	Absolute	Relative
Total	0.0233	0.0239	0.0226	-0.0013***	0.95	0.0193	0.0199	0.0186	-0.0012***	0.94
Household Headship										
Male-headed	0.0236	0.0243	0.0226	-0.0017***	0.93	0.0174	0.0185	0.0161	-0.0024***	0.87
Female-headed	0.0229	0.0233	0.0226	-0.0007	0.97	0.0221	0.0228	0.0216	-0.0012	0.95
Age Groups										
Child	0.0184	0.0188	0.0180	-0.0008	0.96	0.0172	0.0173	0.0171	-0.0002	0.99
Adult	0.0241	0.0247	0.0234	-0.0013**	0.95	0.0182	0.0191	0.0173	-0.0017***	0.91
Elderly	0.0242	0.0255	0.0232	-0.0023***	0.91	0.0267	0.0281	0.0257	-0.0024*	0.91
Family Composition										
Single without children[1]	0.0322	0.0337	0.0298	-0.0038	0.89	0.0243	0.0259	0.0220	-0.0039	0.85
Single with children[1]	0.0235	0.0265	0.0220	-0.0045	0.83	0.0238	0.0267	0.0222	-0.0044	0.83
Couple without children[2]	0.0227	0.0233	0.0220	-0.0013	0.95	0.0155	0.0167	0.0142	-0.0025***	0.85
Couple with children[2]	0.0225	0.0227	0.0223	-0.0004	0.98	0.0164	0.0170	0.0157	-0.0014**	0.92
Adults without children[3]	0.0256	0.0289	0.0231	-0.0058**	0.80	0.0222	0.0230	0.0215	-0.0015	0.94
Adults with children[3]	0.0207	0.0206	0.0207	0.0001	1.00	0.0239	0.0227	0.0247	0.0021	1.09
Elderly(ies)[4]	0.0240	0.0252	0.0231	-0.0021**	0.92	0.0248	0.0273	0.0230	-0.0043***	0.84
Elderly(ies) and adult(s)[5]	0.0237	0.0243	0.0231	-0.0012*	0.95	0.0221	0.0228	0.0214	-0.0013	0.94
Region										
North	0.0289	0.0302	0.0274	-0.0028***	0.91	0.0395	0.0427	0.0364	-0.0063***	0.85
Northeast	0.0246	0.0254	0.0238	-0.0016***	0.94	0.0305	0.0323	0.0289	-0.0034***	0.89
Center-west	0.0198	0.0197	0.0200	0.0002	1.01	0.0131	0.0129	0.0133	0.0004	1.03
Southeast	0.0189	0.0193	0.0186	-0.0007	0.96	0.0072	0.0065	0.0079	0.0014*	1.21
South	0.0216	0.0221	0.0211	-0.001	0.95	0.0126	0.0126	0.0126	0.000	1.00
Color/Ethnicity										
White	0.0206	0.0208	0.0204	-0.0005	0.98	0.0112	0.0116	0.0109	-0.0007	0.94
Black	0.0260	0.0261	0.0259	-0.0002	0.99	0.0278	0.0282	0.0274	-0.0008	0.97
Asian	0.0225	0.0205	0.0240	0.0034	1.17	0.0064	0.0074	0.0057	-0.0017	0.77
Brown	0.0240	0.0249	0.0231	-0.0018***	0.93	0.0253	0.0258	0.0248	-0.0011	0.96
Indigenous	0.0158	0.0174	0.0144	-0.0030	0.83	0.0244	0.0200	0.0284	0.0084*	1.42
Undeclared	0.0211	0.0242	0.0157	-0.0085**	0.65	0.0312	0.0505	0.0110	-0.0395***	0.22
Area type										
Urban	0.0211	0.0214	0.0208	-0.0006	0.97	0.0157	0.0158	0.0157	-0.0001	0.99
Rural	0.0280	0.0290	0.0270	-0.0020***	0.93	0.0396	0.0417	0.0372	-0.0045***	0.89

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are available under request. 1"Single" refers to adults only. 2. Only adult couples, and with or without other adults in the household. 3. No couples as primary members of the household. 4. With or without children. 5. At least one adult and with or without children.

Table 8 – Inequality among the multidimensionally poor and gender differences for the Occupation-Resources Index by subgroup

	Occupation-Resources Index									
	I_q			Differences		I_{fz}			Differences	
Variables	Total	Male	Female	Absolute	Relative	Total	Male	Female	Absolute	Relative
Total	0.0232	0.0230	0.0234	0.0004	1.02	0.0438	0.0398	0.0476	0.0079***	1.20
Household Headship										
Male-headed	0.0222	0.0219	0.0226	0.0007	1.03	0.0414	0.0336	0.0506	0.0170***	1.51
Female-headed	0.0244	0.0245	0.0243	-0.0002	0.99	0.0474	0.0521	0.0443	-0.0079***	0.85
Age Groups										
Child	0.0247	0.0246	0.0249	0.0003	1.01	0.0276	0.0291	0.0259	-0.0032***	0.89
Adult	0.0220	0.0219	0.0220	0.0002	1.01	0.0497	0.0452	0.0539	0.0088***	1.19
Elderly	0.0287	0.0281	0.0291	0.0010	1.03	0.0432	0.0334	0.0508	0.0174***	1.52
Family Composition										
Single without children[1]	0.0205	0.0205	0.0204	-0.0002	0.99	0.0375	0.0395	0.0347	-0.0048	0.88
Single with children[1]	0.0455	0.0479	0.0440	-0.0039	0.92	0.0852	0.0981	0.0780	-0.0201***	0.80
Couple without children[2]	0.0201	0.0207	0.0196	-0.0010	0.95	0.0388	0.0353	0.0426	0.0073***	1.21
Couple with children[2]	0.0226	0.0228	0.0223	-0.0005	0.98	0.0430	0.0387	0.0474	0.0087***	1.22
Adults without children[3]	0.0225	0.0220	0.0229	0.0009	1.04	0.0483	0.0494	0.0475	-0.0020	0.96
Adults with children[3]	0.0217	0.0223	0.0213	-0.001	0.95	0.0556	0.0518	0.0581	0.0062	1.12
Elderly(ies)[4]	0.0259	0.0257	0.0260	0.0003	1.01	0.0330	0.0254	0.0387	0.0132***	1.52
Elderly(ies) and adult(s)[5]	0.0217	0.0207	0.0227	0.0020**	1.09	0.0438	0.0392	0.0479	0.0086***	1.22
Region										
North	0.0228	0.0227	0.0230	0.0003	1.01	0.0497	0.0473	0.0521	0.0048***	1.10
Northeast	0.0240	0.0239	0.0242	0.0003	1.01	0.0547	0.0509	0.0582	0.0073***	1.14
Center-west	0.0226	0.0225	0.0226	0.0001	1.00	0.0412	0.0365	0.0456	0.0091***	1.25
Southeast	0.0231	0.0226	0.0236	0.0010	1.05	0.0288	0.0254	0.0321	0.0067***	1.26
South	0.0232	0.0220	0.0242	0.0022*	1.10	0.0407	0.0362	0.0450	0.0088***	1.24
Color/Ethnicity										
White	0.0216	0.0210	0.0221	0.0011*	1.05	0.0335	0.0294	0.0373	0.0079***	1.27
Black	0.0256	0.0257	0.0255	-0.0003	0.99	0.0555	0.0524	0.0587	0.0064**	1.12
Asian	0.0286	0.0312	0.0276	-0.0036	0.88	0.0421	0.0369	0.0458	0.0089	1.24
Brown	0.0237	0.0235	0.0238	0.0003	1.01	0.0512	0.0466	0.0557	0.0092***	1.20
Indigenous	0.0209	0.0230	0.0192	-0.0038	0.84	0.0429	0.0420	0.0437	0.0016	1.04
Undeclared	0.0200	0.0198	0.0203	0.0005	1.02	0.0585	0.0633	0.0535	-0.0097	0.85
Area type										
Urban	0.0233	0.0233	0.0234	0.0001	1.01	0.0412	0.0375	0.0446	0.0071***	1.19
Rural	0.0227	0.0220	0.0234	0.0014**	1.06	0.0589	0.0516	0.0667	0.0151***	1.29

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are available under request. 1. "Single" refers to adults only. 2. Only adult couples, and with or without other adults in the household. 3. No couples as primary members of the household. 4. With or without children. 5. At least one adult and with or without children.

For the fuzzy inequality results, in most subgroups, women are at a disadvantage. This time the disparities are more pronounced, and most differences are statistically significant. According to the total result, inequality is 20% larger for women. The relative differences in inequality are largest among Male headed, Elderly, and Elderly(ies), all of them with women at a disadvantage.

The inequalities within subgroups for the fuzzy inequality are similar to those of the multidimensional poverty outcomes. Among the Age Groups and Family composition, Adults and Single with children have the highest inequalities; among the Regions, the north and northeast have the largest inequality; among the Color/Ethnicity, the Black, Brown, and Indigenous have the greatest inequality; and among the Area type, Rural has the highest inequality.

2.4.2 Estimations for household heads: interhousehold perspective

In this subsection, the focus is on household heads, providing an individual-based interhousehold perspective. As discussed in previous sections, restricting the data to household heads allows us to estimate more indicators at the individual level because they answered all the survey questions. Different from the whole population perspective, the outcomes for the interhousehold perspective show that women are multidimensionally poorer with respect to men in most subgroups in both the SMPI and ORI.

The SMPI outcomes (Table 9) show that, in total, female heads are between 10% and 15% multidimensionally poorer than male heads. For both approaches (H and Fuzzy), Indigenous, Asian, Southeast, and Adults with children appear among the categories with the largest relative differences disfavoring women. The patterns of inequalities within subgroups are similar to those from the whole population perspective (see Table 5), with the difference that in the subgroup of Family Composition, Adults with children has the worst position.

Table 9 - Household head's multidimensional poverty estimations and gender differences for the Standard MPI by subgroup

	Standard MPI									
	H (%)			Differences		Fuzzy			Differences	
Variables	Total	Male	Female	Absolute	Relative	Total	Male	Female	Absolute	Relative
Total	21.39	20.53	22.60	2.07***	1.10	18.52	17.43	20.03	2.61***	1.15
Household Headship										
Male-headed[1]	-	-	-	-	-	-	-	-	-	-
Female-headed[1]	-	-	-	-	-	-	-	-	-	-
Age Groups										
Child[1]	-	-	-	-	-	-	-	-	-	-
Adult	19.69	18.94	20.81	1.87***	1.10	17.07	16.04	18.63	2.6***	1.16
Elderly	25.68	25.04	26.41	1.37	1.05	22.14	21.38	23.01	1.63***	1.08
Family Composition										
Single without children[2]	17.62	18.93	15.80	-3.13**	0.83	17.86	18.24	17.34	-0.90	0.95
Single with children[2]	20.71	20.68	20.72	0.04	1.00	19.11	16.35	19.46	3.11	1.19
Couple without children[3]	16.75	16.64	17.10	0.46	1.03	15.57	15.50	15.78	0.28	1.02
Couple with children[3]	21.10	20.40	23.05	2.65***	1.13	16.49	15.95	18.02	2.07***	1.13
Adults without children[4]	18.38	15.13	19.57	4.43**	1.29	17.99	14.94	19.11	4.17***	1.28
Adults with children[4]	28.22	36.39	27.34	-9.06**	0.75	22.50	19.05	22.87	3.82*	1.20
Elderly(ies)[5]	23.33	23.83	22.80	-1.03	0.96	21.37	21.38	21.35	-0.03	1.00
Elderly(ies) and adult(s)[6]	25.53	24.27	26.90	2.64**	1.11	21.46	20.11	22.93	2.82***	1.14
Region										
North	37.65	39.74	34.78	-4.96***	0.88	27.82	28.40	27.02	-1.37	0.95
Northeast	34.44	34.17	34.77	0.6	1.02	26.00	25.29	26.86	1.57***	1.06
Center-west	15.03	13.93	16.68	2.75***	1.20	15.65	14.32	17.65	3.33***	1.23
Southeast	11.00	9.85	12.54	2.69***	1.27	10.67	9.50	12.23	2.73***	1.29
South	19.11	19.17	19.01	-0.16	0.99	16.52	16.16	17.10	0.94	1.06
Color/Ethnicity										
White	13.78	13.10	14.75	1.65**	1.13	13.26	12.25	14.73	2.47***	1.20
Black	26.12	25.85	26.46	0.61	1.02	23.02	21.93	24.38	2.46**	1.11
Asian	7.13	6.20	8.53	2.33	1.38	8.64	6.33	12.08	5.75**	1.91
Brown	28.15	27.22	29.44	2.22***	1.08	22.83	21.88	24.14	2.26***	1.10
Indigenous	24.08	21.78	27.49	5.71	1.26	21.96	19.49	25.61	6.12	1.31
Undeclared	25.04	17.21	32.87	15.65	1.91	17.04	14.69	19.39	4.69	1.32
Area type										
Urban	17.19	15.38	19.51	4.13***	1.27	16.92	15.40	18.89	3.49***	1.23
Rural	47.74	46.71	50.05	3.34***	1.07	28.49	27.75	30.16	2.41***	1.09

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Fuzzy outcomes represent degrees of poverty. Standard errors are available under request. 1. Results are not applied for these categories because the data is restricted only to household heads. 2. "Single" refers to adults only. 3. Only adult couples, and with or without other adults in the household. 4. No couples as primary members of the household. 5. With or without children. 6. At least one adult and with or without children.

Table 10 - Household head's multidimensional poverty estimations and gender differences for the Occupation-Resources Index by subgroup

	Occupation-Resources Index									
	H (%)			Differences		Fuzzy			Differences	
Variables	Total	Male	Female	Absolute	Relative	Total	Male	Female	Absolute	Relative
Total	27.98	25.67	31.19	5.52***	1.21	29.44	27.79	31.74	3.96***	1.14
Household Headship										
Male-headed[1]	-	-	-	-	-	-	-	-	-	-
Female-headed[1]	-	-	-	-	-	-	-	-	-	-
Age Groups										
Child[1]	-	-	-	-	-	-	-	-	-	-
Adult	33.01	29.61	38.14	8.53***	1.29	32.96	30.43	36.79	6.35***	1.21
Elderly	15.33	14.44	16.34	1.9**	1.13	20.58	20.24	20.97	0.74	1.04
Family Composition										
Single without children[2]	30.65	32.67	27.85	-4.81**	0.85	30.57	32.01	28.58	-3.43**	0.89
Single with children[2]	50.91	36.50	52.72	16.22***	1.44	42.46	35.70	43.31	7.61***	1.21
Couple without children[3]	25.94	24.64	29.99	5.35***	1.22	27.54	26.51	30.76	4.24***	1.16
Couple with children[3]	34.22	32.12	40.14	8.02***	1.25	34.25	32.49	39.21	6.72***	1.21
Adults without children[4]	32.25	25.88	34.59	8.71***	1.34	32.36	27.88	34.01	6.13***	1.22
Adults with children[4]	47.76	37.80	48.84	11.04**	1.29	45.91	39.78	46.57	6.79**	1.17
Elderly(ies)[5]	12.57	11.79	13.39	1.6	1.14	18.27	18.32	18.22	-0.1	0.99
Elderly(ies) and adult(s)[6]	21.64	19.65	23.81	4.16***	1.21	25.34	23.85	26.96	3.1***	1.13
Region										
North	39.33	38.97	39.83	0.86	1.02	38.67	38.26	39.22	0.95	1.02
Northeast	37.42	35.17	40.13	4.96***	1.14	37.80	36.65	39.19	2.55***	1.07
Center-west	24.42	22.15	27.83	5.67***	1.26	26.36	24.60	29.00	4.4***	1.18
Southeast	16.76	13.81	20.73	6.92***	1.50	20.30	18.16	23.18	5.02***	1.28
South	28.17	27.11	29.85	2.74*	1.10	28.44	27.65	29.70	2.05*	1.07
Color/Ethnicity										
White	19.53	17.96	21.80	3.84***	1.21	22.29	21.24	23.81	2.58***	1.12
Black	34.39	31.93	37.46	5.53***	1.17	35.37	33.52	37.68	4.16***	1.12
Asian	14.45	8.81	22.84	14.03***	2.59	15.10	12.90	18.37	5.47*	1.42
Brown	35.12	32.44	38.80	6.35***	1.20	35.38	33.40	38.09	4.69***	1.14
Indigenous	32.30	26.41	41.00	14.59*	1.55	35.14	31.86	39.99	8.13	1.26
Undeclared	28.34	28.68	28.00	-0.68	0.98	29.27	29.49	29.05	-0.44	0.99
Area type										
Urban	26.31	23.35	30.14	6.79***	1.29	27.84	25.63	30.69	5.06***	1.20
Rural	38.44	37.51	40.53	3.01**	1.08	39.48	38.75	41.13	2.38***	1.06

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Fuzzy outcomes represent degrees of poverty. Standard errors are available under request. 1. Results are not applied for these categories because the data is restricted only to household heads. 2. "Single" refers to adults only. 3. Only adult couples, and with or without other adults in the household. 4. No couples as primary members of the household. 5. With or without children. 6. At least one adult and with or without children.

As for the ORI outcomes (Table 10), in total, multidimensional poverty for women is between 14% and 21% higher than for men. Similar to the SMPI, in both approaches, the Asian, Indigenous, and Southeast categories have the highest relative differences disfavoring women. As for the inequality within subgroups, the patterns are also similar to those for the whole population (see Table

6), as Adults, Single with children, Adults with children, North and Northeast, Black, Brown and Indigenous, and Rural are at a disadvantage within their subgroups. In the household head perspective, we can observe that female household heads with children, especially single (both living with or without other adults), have the worst outcomes and the highest absolute disparities within the Family Composition subgroup in the ORI.

The similarity of patterns of inequality within subgroups in both perspectives (whole population and household heads) and both approaches (incidence and fuzzy) is evidence of the robustness of the analysis. Moreover, as I previously noted, this similarity confirms the persistent disadvantage of some categories, especially for the North and Northeast regions, the Black, Brown, and Indigenous populations, and Rural areas.

2.4.3 Estimations for couples: intracouple perspective

This subsection focuses on the outcomes of the primary female with respect to her partner (for adult- or elderly-heterosexual-couples living in the same household). Because social norms significantly contribute to decisions within households, especially between couples (Bertrand, Kamenica, & Pan, 2015; Codazzi, Pero, & Sant'Anna, 2018), the intracouple perspective allows us to go deeper into the intrahousehold analysis. Figure 2 and Figure 3 show the female-male difference in means by intervals of deprivation scores and membership degrees for the SMPI and ORI, respectively. The aim is to analyze the intracouple disparities for people with low/moderate deprivation or membership degree (interval from 0 to 0.333), moderate/high deprivation or membership degree (interval from 0.333 to 0.666), and high/very high deprivation or membership degree (interval from 0.666 to 1).

For the SMPI (Figure 2), the outcomes correspond to disparities in *School achievement* because this is the only indicator at the individual level (in household-level indicators, primary females and their partners have the same values). The graphics reveal that only for the low/moderate interval the outcomes are statistically significantly different from zero, and, in this interval, these outcomes are negative, which means that women have higher School achievement than their partners (largely if women are the head of the household). As for the ORI results (Figure 3), in most intervals, women are at a disadvantage when their partners are the household head (male-headed), and women are at an advantage when they are the household head (female-headed).

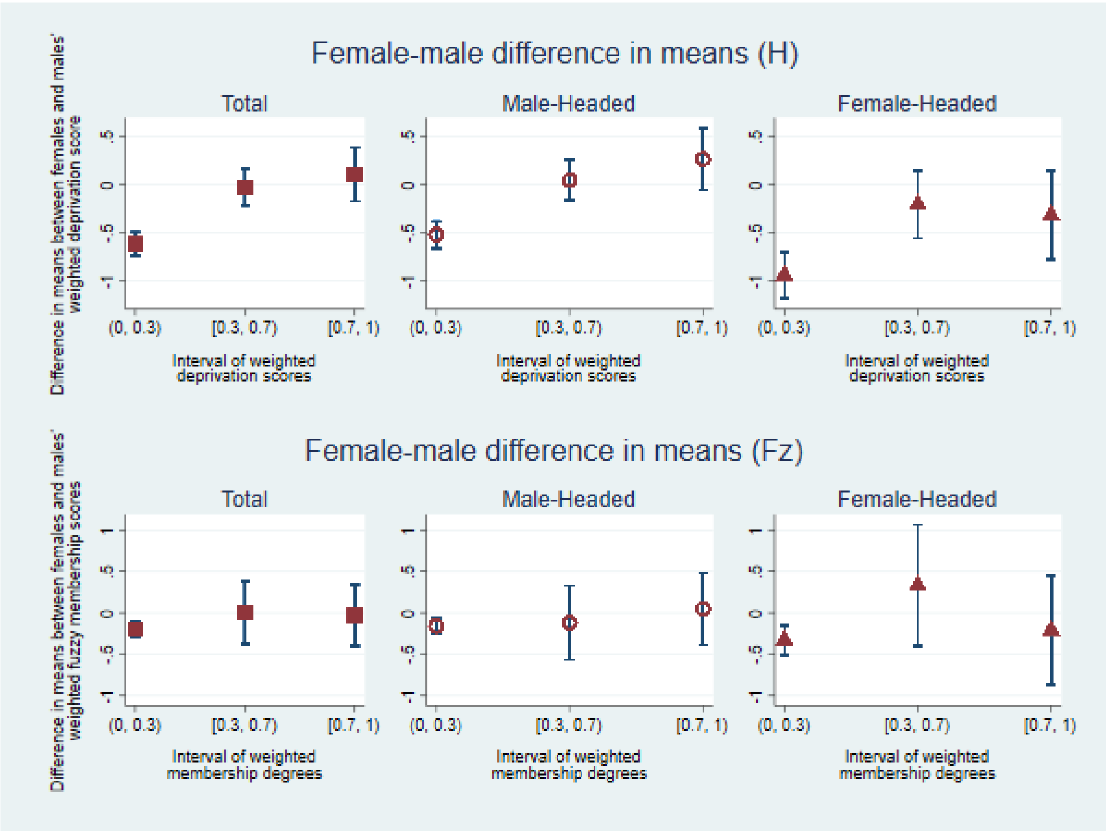

Figure 2 - Female-male difference in means for the Standard MPI by intervals of weighted deprivation scores and fuzzy membership degrees

Note: Capped spikes for T-test confidence intervals (upper and lower 95% confidence limits).

To further understand the intracouple gender gaps in households, Table 11 shows the results for the Gender Gap Index (GGI), the Fuzzy Gender Gap Index (Fz_{GGI}), and their components. For the SMPI outcomes, the total share of women lacking gender parity, H_{GGI}, is 2%, with an average gap of 24 pp. These results increase when women are the household head. As for the fuzzy estimations, which account for all the households regardless of poverty status, the total share of households with women in disadvantage, H_{FzGGI}, is 27%, but the average gap is smaller than the previous results (6 pp). For the fuzzy approach, the share of women at a disadvantage is smaller in female-headed households than in male-headed households, but the average gap is larger for female-headed households.

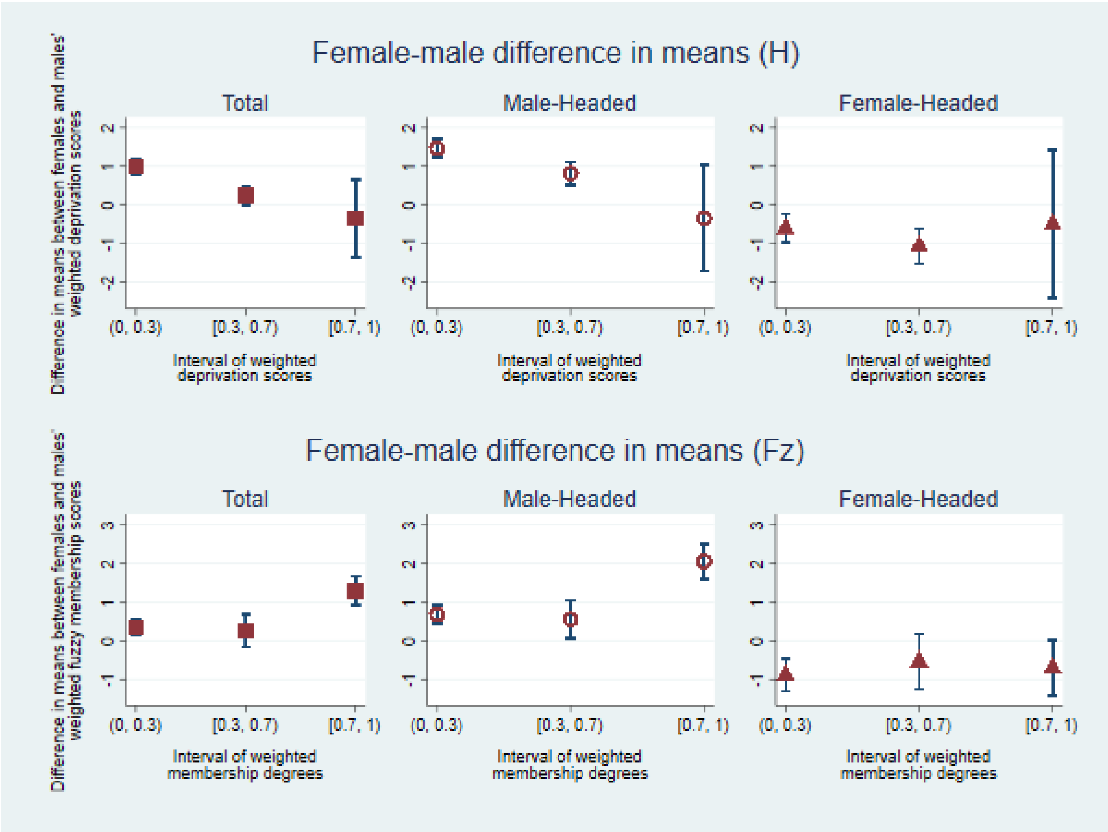

Figure 3 - Female-male difference in means for the Occupation-Resources Index by intervals of weighted deprivation scores and fuzzy membership degrees
Note: Capped spikes for T-test confidence intervals (upper and lower 95% confidence limits).

Regarding the ORI outcomes, the total share of women lacking gender parity is 22%, with an average gap of 23%. For the fuzzy approach, the total share of women at a disadvantage is 56%, and the average gender gap is 33 pp. Interestingly, the outcomes for women are considerably better when they are the household head. For instance, the GGI is 3% in female-headed households, while 6% in male-headed households, and 5% in total. This pattern is even more apparent in the fuzzy results, as the FzGGI is 12% in female-headed households, while 21% in male-headed households, and 18% in total.

Table 11 – Intracouple gender gap measures for the Standard MPI and the Occupation-Resources Index

Measures	Standard MPI			Occupation-Resources Index		
	Total	Male-headed	Female-headed	Total	Male-headed	Female-headed
Share of women lacking gender parity (H_{GGI})[1]	2.59%	2.53%	2.78%	22.41%	24.87%	15.10%
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Average female-male gender gap (I_{GGI})	23.86%	23.84%	23.92%	23.32%	23.86%	20.70%
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Gender gap index (GGI)	0.0061	0.0059	0.0065	0.0521	0.0591	0.0311
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of disadvantaged women (H_{FzGGI})[2]	26.92%	28.43%	22.46%	55.51%	61.23%	38.54%
	(0.003)	(0.004)	(0.006)	(0.004)	(0.005)	(0.007)
Average female-male fuzzy gender gap (I_{FzGGI})	6.16%	5.93%	7.05%	33.30%	33.84%	30.76%
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.007)
Fuzzy Gender gap index (FzGGI)	0.0164	0.0167	0.0157	0.1841	0.2064	0.1181
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Linearized standard errors considering the survey design in round brackets. 1. When the female is multidimensionally poor and her new censored deprivation score is higher than the one of her partner (for more details see the Subsection 2.2.4). 2. When the poverty membership degree of the primary female is higher than her partner (for more details see the Subsection 2.2.4).

2.5 Conclusion remarks

Individual-based estimations are essential to understand gender differences in multidimensional poverty. This chapter contributes to the literature on multidimensional poverty measurement by applying and proposing procedures to improve individual-level estimations considering the limitations of household surveys. This analysis focuses on Brazil and the main findings are the following.

If we look only to the SMPI for the whole population, poverty appears not to be feminized, as men are poorer than women in most subgroups. However, if we look to other perspectives and the ORI, women are mostly at a disadvantage. In the ORI estimation, women are worse off in all the perspectives (whole population, household head, and couples) in most subgroups. In the interhousehold perspective, female household heads are poorer in most subgroups in both the indexes (SMPI and ORI). These results suggest that women are worse off than men in terms of employment and time quality, economic security, and access to resources – which are crucial aspects of agency or degree of empowerment.

Moreover, in most specifications, individuals living in female-headed households are poorer than those living in male-headed households, but in female-headed households, women are at an advantage compared to men, or at least the disparity decreases. In the intracouple ORI gender gap estimations, the outcomes considerably improve when women are the household head.

The results also reveal a clear pattern in the inequality within subgroups. In most specifications, the categories North and Northeast regions, the Black, Brown, and Indigenous populations, and Rural areas show a persistent disadvantage in their subgroups, confirming the usual geographical and racial inequalities in Brazil. In fact, Tavares and Betti (2021) demonstrate that these same populations have the worst conditions in terms of monetary and multidimensional poverty within the context of the COVID-19 pandemic in Brazil.

The previous outcomes reveal the importance of considering different subgroups and indexes in multidimensional poverty analysis. Yet, this study represents one step in individual and gender analysis, as further improvements are possible. The main limitation of this study is the scarce availability of individual-level indicators in the Brazilian household budget survey, especially of health indicators. Consequently, the indexes here are not entirely at the individual level, but they are a mix of individual and household level indicators, which can bias the gender differences analysis. In addition, to build individual-level indicators for the whole population, this study relies on assumptions about the impact of adults' deprivations on children living in the same household.

To improve multidimensional poverty analysis and gender analysis, new rounds of the Brazilian household budget survey (POF) should include more individual-level variables. Moreover, the health section should consider the whole sample (not a subsample), and the work section should include unpaid domestic work. Even if this research would benefit from more availability of individual-level data, the procedures I propose here reduce limitations.

As policy implications, this study suggests that social policies should concern the situation of women, especially in the dimensions of Occupation and Resources, and considering the geographical and racial inequalities. However, interventions in this sense must always ensure that it does not create further disadvantages such as increasing female workload or reinforcing gender roles. Another aspect that should receive further research and policy consideration is understanding why people living in female-headed households are poorer than male-headed households and why gender disparities disfavoring women are higher in male-headed households.

Moreover, by proposing individual-based indicators, this study does not imply that households are a place where a group of autonomous individuals lives together, but, usually, they are a place of cooperation, care, sharing, and financial benefits due to economies of scale in production and consumption (Doss, 2021). Therefore, policies should also contemplate collective forms of agency, realize that care is central to our society and economy, and secure universal access and gender-balanced responsibilities to care.

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Appendix

Table 12 – Poverty intensity (A) estimations for the Standard MPI and gender differences by subgroup

	Standard MPI				
	A (%)			Differences	
Variables	Total	Male	Female	Absolute	Relative
Total	44.56	44.65	44.48	-0.17*	1.00
Household Headship					
Male headed	44.51	44.65	44.32	-0.33***	0.99
Female headed	44.62	44.64	44.62	-0.02	1.00
Age Groups					
Child	43.25	43.46	43.01	-0.45*	0.99
Adult	44.70	44.75	44.66	-0.09	1.00
Elderly	45.05	45.31	44.85	-0.47**	0.99
Family Composition					
Single without children	46.22	46.18	46.29	0.1	1.00
Single with children	44.79	44.86	44.76	-0.1	1.00
Couple without children[1]	44.47	44.65	44.25	-0.41**	0.99
Couple with children[1]	44.08	44.12	44.03	-0.09	1.00
Adults without children[2]	45.30	46.27	44.57	-1.69***	0.96
Adults with children[2]	44.27	43.70	44.65	0.95**	1.02
Elderly(ies) [3]	45.12	45.42	44.88	-0.54*	0.99
Elderly(ies) and adult(s)[4]	44.84	44.95	44.73	-0.21	1.00
Region					
N	45.71	45.99	45.38	-0.61	0.99
NE	44.64	44.71	44.57	-0.14	1.00
CO	44.29	44.34	44.24	-0.11*	1.00
SE	43.02	42.71	43.31	0.6	1.01
S	44.35	44.30	44.40	0.1***	1.00
Color/Ethnicity					
White	43.87	43.97	43.77	-0.2	1.00
Black	45.26	45.11	45.44	0.33	1.01
Asian	43.22	42.58	43.68	1.1	1.03
Brown	44.76	44.86	44.66	-0.2	1.00
Indigenous	44.08	44.25	43.92	-0.33***	0.99
Undeclared	44.09	45.70	41.24	-4.46***	0.90
Area type					
Urban	44.50	44.55	44.46	-0.09**	1.00
Rural	44.70	44.84	44.53	-0.31***	0.99

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are available under request. 1. With or without other adults in the household. 2. No couples as primary members of the household. 3. With or without children. 4. At least one adult and with or without children.

Table 13 - Poverty intensity (A) estimations for the Occupation-Resources Index and gender differences by subgroup

	Occupation-Resources Index				
	A (%)			Differences	
Variables	Total	Male	Female	Absolute	Relative
Total	44.10	44.04	44.14	0.1	1.00
Household Headship					
Male headed	43.74	43.50	43.97	0.47***	1.01
Female headed	44.53	44.78	44.34	-0.45***	0.99
Age Groups					
Child	43.32	43.43	43.20	-0.24	0.99
Adult	44.28	44.23	44.33	0.09	1.00
Elderly	44.34	44.06	44.50	0.43	1.01
Family Composition					
Single without children	43.70	43.71	43.69	-0.02	1.00
Single with children	49.21	50.10	48.68	-1.42**	0.97
Couple without children[1]	43.42	43.50	43.35	-0.16	1.00
Couple with children[1]	43.90	43.90	43.91	0.01	1.00
Adults without children[2]	44.51	44.80	44.26	-0.54	0.99
Adults with children[2]	44.35	44.15	44.47	0.32	1.01
Elderly(ies) [3]	43.68	43.42	43.83	0.41	1.01
Elderly(ies) and adult(s)[4]	43.64	43.49	43.77	0.28	1.01
Region					
N	44.25	44.27	44.24	-0.04	1.00
NE	44.66	44.62	44.71	0.09	1.00
CO	43.95	43.92	43.97	0.06	1.00
SE	42.87	42.62	43.08	0.45*	1.01
S	43.45	43.20	43.67	0.47*	1.01
Color/Ethnicity					
White	43.39	43.35	43.43	0.07	1.00
Black	45.04	45.08	45.01	-0.08	1.00
Asian	45.24	48.30	44.11	-4.19*	0.91
Brown	44.30	44.18	44.41	0.24*	1.01
Indigenous	44.38	43.68	44.94	1.26	1.03
Undeclared	44.20	44.64	43.66	-0.99	0.98
Area type					
Urban	44.03	44.00	44.05	0.05	1.00
Rural	44.36	44.17	44.56	0.38**	1.01

Notes: Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are available under request. 1. With or without other adults in the household. 2. No couples as primary members of the household. 3. With or without children. 4. At least one adult and with or without children.

Chapter 3

Leaving no one behind in the labor market: a fuzzy multidimensional analysis of vulnerability in Brazil

Abstract

With the purpose of leaving no one behind, this chapter proposes two fuzzy labor market vulnerability indexes (LMVI) that include people inside and outside the labor market. The first is an individual-based index to analyze to which extent a person is vulnerable in terms of the capacity of achieving full potential in work and career, finding and seizing employment opportunities, and having a decent job. The second index is a household-based measure to evaluate the share of vulnerable members in the labor market in each household. The intention of the second index is to understand if vulnerable people or people outside the labor force (e.g., dependents) can have support from members of their household that are working and are not vulnerable. Using the Continuous National Household Sample Survey (PNADC), the study applies the LMVIs to the Brazilian context and compares 2016 and 2019. The outcomes reveal that the average degree of vulnerability was high and had a slow change between the years. Although education levels improved, precarity and other labor deprivations did not make progress in the period. Within subgroups, the most vulnerable are people from rural areas, from the north and northeast states, Black, Brown, Indigenous people, and young adults, which corroborates the usual inequalities patterns in Brazil.

Keywords: Multidimensional indicators · Labor market · Vulnerability · Fuzzy-set approach · Latin America · Brazil

3.1 Introduction

Brazil has made significant progress in improving labor market conditions in the first decade of the 20th Century. The favorable trend ended with the economic and political crisis beginning in 2014, and a considerable challenge persists in terms of decreasing the levels of informality and precarity, producing decent employment positions, and improving income levels. The current pandemic deepened the labor market crisis by increasing precarity and pushing many people outside the labor force (Al Masri, Flamini, & Toscani, 2021). These circumstances reinforce the importance of good quality and broad information on the labor market. Multidimensional studies have been advancing in this sense, especially with analysis on the quality of employment, which depicts the situation of overlapping deprivations of employed people (see Sehnbruch, 2020; and González et al., 2021).

However, unemployed and people outside the labor force are also subject to vulnerability - often to a greater extent than employed persons. Therefore, including them in labor market analysis is essential, especially when studying global south countries.

Given this gap in the multidimensional labor market indicators literature, this chapter aims to propose two labor market vulnerability indexes (LMVI) that include people inside and outside the labor market. The first is an individual-based index to analyze to which extent a person is vulnerable in terms of the capacity of achieving full potential in work and career, finding and seizing employment opportunities, and having a decent work. Adopting individual-level indicators is the most appropriate way to estimate labor-market-related outcomes because each person has a different condition regarding employment[16]. The second index is a household-based measure to evaluate the share of vulnerable members in each household. Because the individual's occupation situation directly impacts his/her family members, the intention of the second index is to understand if people that are vulnerable or outside the labor force (e.g., dependents) can have support from members of their household that are working and are not vulnerable.

To accomplish the study's object, I built the indexes with three dimensions: education, employment, and income. Consequently, these indexes are inserted in a wider context along with social indicators and sustainable development analyses. Within the Sustainable Development Goals (SDG), the study contributes to the following goals: Goal 8 to "promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all," Goal 1 to "end poverty in all its forms everywhere," and Goal 4 to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all" (see ILO, 2018). Moreover, I selected the variables based on consolidated indicators of international labor statistics such as the Key

[16] For other advantages of adopting an individual-based index, see Chapter 2.

Indicators of the Labour Market (KILM)[17] and the Decent Work indicators both from the International Labour Organization (ILO), the OECD's Job Quality Framework, and the IBGE's labor statistics[18] (ILO, 2018; ILO, 2016; Hijzen, & Menyhert, 2016; IBGE,2020).

However, instead of only presenting separated indicators in a dashboard format, this chapter presents the indicators both in a dashboard approach and as a single measure in multidimensional composite indexes. In this way, we take advantage of seeing details of changes in the indicators in the dashboard approach, as well as observe, in the multidimensional indexes, people's vulnerability based on their deprivations - which may happen at the same time (e.g., a person may be simultaneously deprived in the dimensions of education, employment, and income).

To estimate these multidimensional indexes, I use the fuzzy set approach proposed by Betti et al. (2015). The social indicators literature based on the fuzzy set theory focuses mostly on poverty, but it is expanding to other applications on socioeconomic conditions (see Betti and Lemmi, 2021). An advantage of the fuzzy approach is to present the results in a continuous form, which, in the context of this chapter, we can interpret as degrees of vulnerability in the labor market. The fact that the fuzzy measure here is relative, accounts for the possibility that vulnerability is not detached from the people's perception of labor market conditions. Economic, cultural, and social contexts influence the decisions of searching for work, accepting jobs in lower conditions than expected, bargaining for higher wages, and continuing or starting to study (Freire & Saboia, 2021; Gyes & Szekér, 2013; Aina et al., 2021; Nussbaum, 2001, p. 283-290). For instance, people with the perception that it is too hard to find a job may give up searching, remaining vulnerable in the labor market.

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[17] The KILM was a publication of 18 country-level indicators related to the labor market. It was published every two years since 1999, but the ILO has discontinued its publication in 2016. The indexes of this chapter encompass 13 of the 18 KILM indicators (see ILO, 2016).

[18] OECD refers to the Organization for Economic Co-operation and Development, and IBGE to the Brazilian Institute of Geography and Statistics.

As mentioned above, in the last years, the literature on labor market indicators had a significant advance in measuring the job quality[19]. Multilateral international organizations have been the protagonists in proposing indicators to capture the complexity of the labor markets (ILO, 2016; ILO, 2018; ILO, 2013; OECD, 2014; IDB, 2017). The different studies use various indicators that cover people inside and outside the labor force, as well as micro and macro variables. But critics point out that most of the institutional studies use a dashboard of indicators, which makes it difficult for policymakers to identify vulnerable people among the numerous indicators, and that often the required data are not available in global south countries (Sehnbruck et al., 2020; Gonzáles et al., 2021).

Multidimensional analyses were able to reduce these problems by developing synthetic and intuitive measures (Huneeus et al., 2015; Sehnbruck et al., 2020; Gonzáles et al., 2021; IDB, 2017). However, by not including people outside the labor force, they do not capture a part of the complexity of the labor market. For example, they disregard people who would like to have paid work and have no option but to dedicate themselves to unpaid care and domestic work, or people considered too young or old to get a job. By not considering these people, one disproportionally leaves women behind in the analysis, as they are the majority in unpaid care and domestic work and often delay their career plans because of maternity. Moreover, these studies do not consider vulnerability at the household level and, consequently, do not contemplate how members can support one another.

In sum, the main contributions of the chapter are twofold. First, it proposes two fuzzy metrics that capture labor market vulnerabilities in a more general way. Second, it proposes a new household-based measure that captures the vulnerability achieving all the members within a family – and we can interpret this measure as extreme vulnerability. Scholars can find the indicators proposed here in many labor market household surveys of global south countries, which facilitate replicability.

[19] For a review of the quality of employment literature, see Burchell et al. (2015).

Another advantage of the indexes is that they can be used as independent variables in econometric analysis to analyze broader impacts in the labor market.

The remaining content of this chapter proceeds as follows. Section 3.2 describes the data and the fuzzy method. Section 3.3 explains how I constructed the indexes. Section 3.4 shows the results, and Section 3.5 concludes.

3.2 Data and Methodology

3.2.1 Data

This chapter uses the Continuous National Household Sample Survey (PNADC) for 2016 and 2019. The Brazilian Institute of Geography and Statistics (IBGE) launched the PNADC in October 2011 but, at that time, offered a restricted set of labor market indicators. The survey started to provide additional socio-economic topics in 2016, replacing the Brazilian National Household Sample Survey (PNAD) and the Monthly Employment Survey (PME).

The PNADC aims to monitor the evolution of the country's labor force and socio-economic characteristics. The data is available for major regions, federation units (states), metropolitan areas, and state capitals. In this survey, the IBGE interviews the selected households for five consecutive trimesters, releasing monthly, quarterly, and annual information. The annual disclosures are the only ones that provide detailed socio-economics topics, which the survey collects in the first and fifth interviews.

This chapter uses the data from the annual disclosure of the fifth interview because this round has additional work-related information, such as other forms of work and child labor. The survey sample size is 447,334 observations (about 108,384 per quarter) in 2016 and 433,535 observations (about 111,834 per quarter) in 2019. Moreover, the PNADC employs a multi-stage stratified sampling design, which requires caution when calculating standard errors. That is why I use linearized standard errors considering the survey design.

For this article, in the individual-based analysis, I restrict the sample to adults (between 18 and 65 years old) in the labor force, potential labor force, and outside the potential labor force but that would like to have a job. I call this selected sample the "expanded labor force." Usually, labor market analyses consider only the labor force and the potential labor force. However, these analyses do not consider people that would like to have a job but, for some reason, are not available and not looking for a job. In the household-based analysis, in addition to the expanded labor force, I keep in the sample all the members of households that have at least one person in the expanded labor force. Figure 1 details the population selected for this chapter and shows how the selected sample figures in the usual labor market classification.

The resulting samples of the household and individual analyses consist, respectively, of 396,894 and 214,838 observations in 2016, and 382,575 and 215,340 observations in 2019. When restricting the sample, I correct the population strata accounting for the survey design.

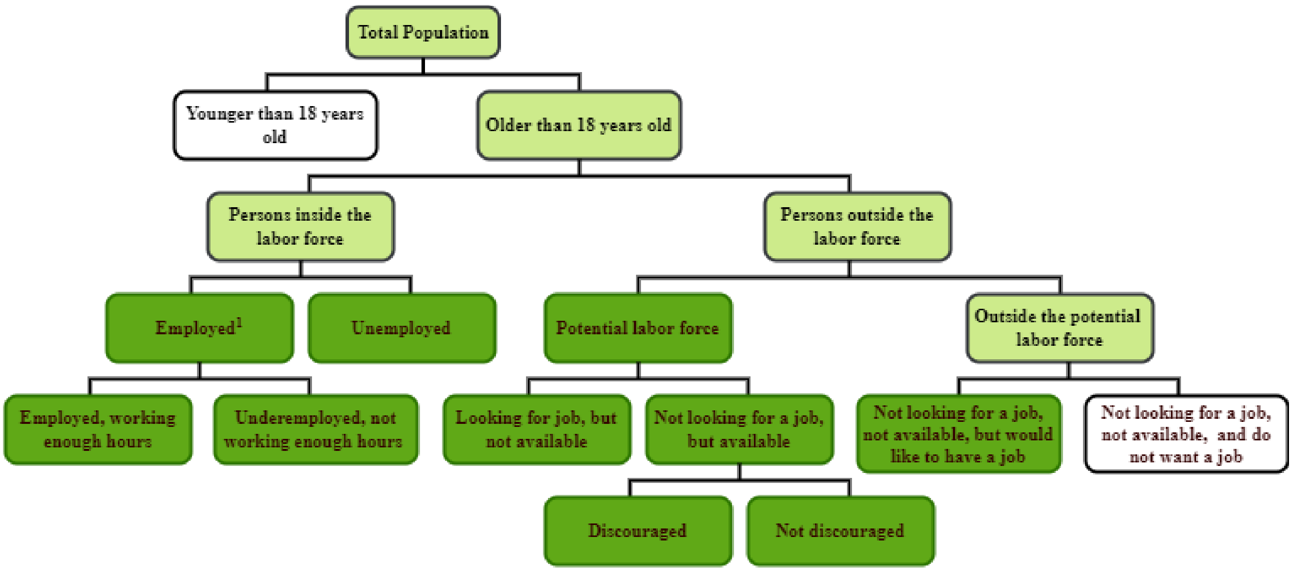

Figure 1 – Labor market classification and selected population
Notes: Adapted from IBGE (2021). Light green rounded rectangles represent subgroups that are partially in the expanded labor force; dark green rounded rectangles represent subgroups that are totally part of the expanded labor force; and white rounded rectangles represent subgroups that are not part of the expanded labor force. 1. Refers to employees, employers, self-employed, domestic workers, and unpaid auxiliary family workers. See Table 3 for the description of the other categories.

This chapter uses and compares cross-sections of two units of time. Therefore, I also present the population's demographic characteristics for each year (Table A1, Appendix), as variations in vulnerability and deprivations may be in part due to changes in household composition and age structure.

3.2.2 The fuzzy set approach

Traditional multidimensional methods usually rely on cutoffs to estimate indicators, resulting in binary outcomes (e.g., poor or non-poor; vulnerable or non-vulnerable). Alternatively, the fuzzy set approach for multidimensional analysis can transform binary outcomes into a continuous measure, which implies that every individual belongs to a fuzzy set group (e.g., poverty, vulnerability) to some degree that ranges between zero and 100 [0, 100].

This chapter applies the fuzzy method to measure labor market vulnerability at the individual and household level, interpreting the results as degrees of vulnerability. To calculate the degrees of vulnerability for each individual i, I use the following membership function as proposed by Betti et al. (2015):

$$m_i = \left(\frac{\sum_\gamma w_\gamma \mid X_\gamma > X_i}{\sum_\gamma w_\gamma \mid X_\gamma > X_1}\right)^{\alpha-1} \left(\frac{\sum_\gamma w_\gamma X_\gamma \mid X_\gamma > X_i}{\sum_\gamma w_\gamma X_\gamma \mid X_\gamma > X_1}\right). \tag{1}$$

where w_γ is the individual sample weight ranked by γ ($\gamma = 1. \dots . n$), X is the deprivation score of each dimension, and α is a parameter to set the outcome to a reference. In this study, the α is set to keep the mean of the fuzzy index equal to the incidence (*H*) as estimated in the Alkire-Foster (AF) method[20].

In the AF method, the definition of the incidence, or headcount ratio, H, is the following:

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[20] For a comprehensive explanation of the AF method, see Alkire et al. (2015).

$$H = \frac{q}{n}\,, \tag{2}$$

where q is the number of multidimensionally vulnerable, and n is the number of the total population. This estimation classifies people as vulnerable when they have the weighted sum of deprivations (their deprivation scores) higher than a defined threshold. Following the literature that uses the AF (Sehnbruch et al., 2021; Alkire, Oldiges, & Kanagaratnam, 2021; OPHI and UNDP, 2021), I set the weights equally among the three dimensions and the vulnerability threshold as one-third of weighted deprivations.

The justification for setting the weights equally among the dimensions in the fuzzy estimation and *H* calculation are the following. First, considering the vulnerability threshold of one-third when estimating *H*, if a person is deprived in one of the dimensions, the algorithm will define he/she as vulnerable. In this way, I consider that being deprived in one of the dimensions is already enough to be vulnerable in the labor market. Second, because the chapter compares two points in time, keeping the same dimension weights for the two years is more appropriate to make comparisons and avoid violations of desired multidimensional-analysis properties (see Dutta, Nogales, & Yalonetzky, 2021). Table *1* presents the deprivation thresholds and the indicator's weights.

3.3 Constructing the Labor Market Vulnerability Indexes (LMVI)

As this chapter proposes a new perspective on labor market indicators, this subsection shows the relevance of each dimension and indicator in relation to the labor market and explains the details of each indicator's construction.

Table *1*Table presents the details of the individual-based index. This index estimates the vulnerability degree of each adult from the expanded labor force. The household-based index has fuzzy indicators that represent how much a family is vulnerable by calculating, from the individual-based indicators, the share of deprived people in the household (see Table 2). Because people in the labor force usually support their family members outside the labor force, the higher the indicator, the greater the vulnerability[21]. In their maximum value, the indicators show that no one in the household support those deprived or outside the expanded labor force (e.g., dependents).

Finally, although the indexes convey a great deal of information, they only have three dimensions: education, employment, and income. I chose the variables avoiding indicators that could also capture people who are not vulnerable or indicators that may produce mixed outcomes. For example, excess of hours can define as vulnerable high earner individuals that choose to work extra hours; and time employed in the same job (as a proxy for employment stability) can set as non-vulnerable individuals working many years in the same job but in precarious conditions or as vulnerable individuals that changed job for a better position. Table 1 and Table 2 summarize the structure of the individual and household indexes, respectively. The following subsections details each of the three dimensions.

Table 1 – Individual-based Labor Market Vulnerability Index structure

Dimension	**Indicators**	**Description**	**In the AF method, people are deprived if.,.**	**Weight**
Education	School achievement	Number of completed years of education in relation to the conclusion of the high school.	they have not completed high school.	0.333
Employment	Deprivation on employment[1]	0 if the individual has an informal job, or is unemployed, underemployed, discouraged, employed without pay, looking for a job but not available, not looking for a job but available, not looking for a job and not available but would like to work, work excessive hours with underpayment or in unpaid works (i.e., homework, care, and own consumption); 1 otherwise[2].	they fit in one of the categories in the description.	0.333
Income	Household dependency ratio	Number of people without income per household member in each household.	3/4 of the members in their household have no income.	0.166
	Income	Total income from all sources.	they earn less than one minimum wage[3].	0.166

Notes: 1. For more details of this indicator, see Table 3. 2. For people that are not looking for a job and are not available, I consider as deprived only those that cannot work or/and search for a job because they have unpaid domestic and care responsibilities or are too young or old (in this analysis, they are always between 18 and 65 years old). 3. The national minimum wage was R$880.00 in 2016 and R$998.00 in 2019. To account for possible mistakes in the declaration, I approximated the threshold as R$875.00 in 2016, and R$995.00 in 2019

[21] Except for the *Income* indicator, in which individuals are less vulnerable when total household income per capita increases.

Table 2 - Household-based Labor Market Vulnerability Index structure

Dimension	Indicators	Description	In the AF method, based in the individual-based deprivations, people are deprived if	Weight
Education	School achievement	In the household, the share of members in the expanded labor force deprived in the correspondent individual-based indicator (if there are any children or adolescents outside school, the indicator considers everyone in this household as deprived).	everyone from the expanded labor force in their household is deprived.	0.333
Employment	Deprivation on employment	In the household, the share of members in the expanded labor force deprived in the correspondent individual-based indicator (if there are any children or adolescents in child labor, the indicator considers everyone in this household as deprived).	everyone from the expanded labor force in their household is deprived	0.333
Income	Household dependency ratio	Number of people without income per household member in each household.	3/4 of the members in their household have no income.	0.166
	Income	Total household income per capita from all sources.	their total household income per capita is less than 1/2 of the minimum wage.	0.166

3.3.1 Education

Education is a constituent component of development, influencing what people can achieve, opportunities, and freedom (Sen. 1999). For this reason, education indicators are prevalent in multidimensional socioeconomic indexes, such as the OPHI/UNDP Global Multidimensional Poverty Index and the Human Development Index (HDI), and its importance is a consensus among scholars and society in general.

In the labor market context, the many links between education and access to decent and productive work also make this dimension indispensable. For instance, studies associate a higher level of education to better conditions of employment, improved opportunities, greater salaries, and protection from labor vulnerabilities (Card, 1999; Harmon, Oosterbeek, & Walker, 2003; Diris & Vliet, 2022). Therefore, education is not only one of the best indicators for skill level, but it is also crucial to examine a persons' capability in general.

This study computes the dimension of education with a measure of *School achievement*. The calculation is based on the school achievement indicators of Espinoza-Delgado and Klasen (2018) and of Chapter 2, expanding and adapting it for the labor vulnerability context. The individual-based indicator counts the number of years of education in relation to high school completion, which, according to the Constitution of Brazil, is the basic level for self-development, full citizenship, and professional formation. Therefore, ranging from -12 and 12, the indicator is 0 if a person has completed the secondary education, it is higher than zero according to the additional years in relation to the secondary education, or it is smaller than zero corresponding to the years left to complete secondary education.

The household-based *School achievement* indicator estimates the share of individuals from the expanded labor force that have not completed the secondary education in each household[22]. The idea is that a household having only persons without secondary education implies that everyone in that household will probably have difficulties finding decent work and, consequently, supporting their family. Moreover, the household-based education indicator classifies all people as deprived in households with one or more children outside school. This classification is because children's school dropout may reflect the family socioeconomic and labor status (Duryea, Lam, & Levison, 2007) and may affect the work prospects of these children (Mussida, Sciulli, & Signorelli, 2019).

3.3.2 Employment

Employment is one of the main channels affecting individual capabilities in global south countries because it is the source to cover the basic needs of families and determines if an individual is entitled to social security benefits (Sehnbruch, 2008). In Brazil and many peripheral countries, most of the working population does not have a formal job, which means that they are not protected or covered in cases of poor working conditions, parental necessities, economic crisis, unemployment shocks, health problems, and they are probably not contributing to a pension. The quality of employment also

[22] As described in subsection 3.2.1, the household-based indicators include only households with at least one person in the expanded labor force.

directly affects other social indicators (ILO, 2018). Therefore, having a job is not enough condition that guarantees socioeconomic security and wellbeing, but aspects of employment such as fair remuneration, proper work conditions, stability, and protection of rights are also essential (González et al., 2021; Hijzen & Menyhert, 2016; Sehnbruch et al., 2021).

Clearly, underemployed, unemployed, and people outside the labor force are also subject to vulnerability - often to a greater extent than employed persons. People in these situations can be vulnerable in the following four ways. First, they may have low income or no source of income if they had no access to social security. Besides all the problems that come with low income, this condition makes finding a job even harder as there is a cost to keep looking for a job and to get qualified. Second, because they probably are not insured by the social security system, they may not be shielded from economic and health shocks and will likely have difficulties getting retirement benefits. Third, they may be discouraged or have difficulty finding a job, thus not achieving their career objectives because of lack of opportunity, qualification, or experience. In these cases, there may be a shortage of labor market policies to incentive the labor demand of employers and labor qualification. Fourth, they may be involuntarily not available or/and not searching for a job because they work on unpaid domestic work and care. This condition shows a deprivation of capabilities and functioning, especially affecting women, and that the state is failing to facilitate and encourage work by providing measures such as increasing public provision of daycare services, enabling flexible working hours, and promoting an equal share of domestic and care work between men and women within households (Espino & Santos, 2021).

In an attempt to capture the vulnerabilities for both the people in and outside the labor force, I measure this dimension with the indicator *Deprivation on employment*, which comprises the following deprivation situations: informality, employment without pay, underemployed, excessive hours of work with underpayment or in unpaid works, unemployed, discouraged, looking for a job but not available, not looking for a job but available, and not looking for a job and not available but would like to work. Table 3 describes these subcategories in detail.

Table 3 – Details of the subcategories in the indicator "Deprivation on employment"

Indicators	Subcategories	Description
Deprivation on employment	Informality	Workers in the private sector without a formal contract; or domestic workers without a formal contract; or employer without registration formal registration; or self-employed without formal registration; or Auxiliary family worker.
	Employment without pay	Unpaid workers helping a member of the household or a relative.
	Underemployed	Workers working less than 40 hours who would like to work more hours and are available for it.
	Excessive working hours with underpayment or in unpaid works[1]	Workers working more than 44 hours per week earning less than the hourly wage of a person who works 44 hours for a minimum wage[2]; or working more than 44 hours per week without pay in domestic work, care, or own consumption.
	Unemployed	People who are not working and took active measures to find a job and are available to work.
	Discouraged	People who would like to work and are available but did not look for a job because they think they would not find one[3].
	Looking for a job but not available	People looking for a job but not available because they must dedicate themselves to domestic and care work or are considered too young or too old to get a job.
	Not looking for a job but available	People who are available but are not looking for a job because must dedicate themselves to domestic and care work.
	Not looking for a job and not available but would like to work	People who would like to work but are not looking for a job and are not available because they must dedicate themselves to domestic and care work or are considered too young or too old to get a job.

Notes: Subcategories based on the IBGE classifications (see IBGE (2021), and Figure 1). 1. I only include those with underpayment or unpaid to represent people who work for excess hours out of necessity. 2. The national minimum wage was R$880.00 in 2016 and R$998.00 in 2019. 3. They think they cannot find a job because they did not find a job in their locality, did not find an adequate job, are considered too young or old, or they do not have experience or qualifications.

The necessity of having a single indicator containing different employment-related subcategories is because they represent mutually exclusive situations. For example, a person cannot be unemployed and work excessive hours with underpayment at the same time. Therefore, by having one indicator for each subcategory, if one person fits in one of the categories, the dimension would classify him/her as deprived in that indicator and non-deprived in all the other indicators. This problem of ineligible population would diminish the weight of the variables within the dimension, which can produce misleading conclusions. Instead, in the individual-based index, *Deprivation on employment* assigns people as deprived if they fit in one of the subcategories described in Table 3 and as non-deprived otherwise.

In the household-based index, the indicator *Deprivation on employment* calculates the share of deprived people in the expanded labor force within each household. Employed people can help other household members with economic support and, in some cases, even finding a job. Additionally, this index classifies everybody in the household as deprived when the household has one or more children in child labor. This classification is because child labor affects child's education, health, and prospects (Kassouf, 2007), and it is an indication of the negative labor status of their family (Duryea, Lam, & Levison, 2007).

3.3.3 Income

Income is necessary to satisfy many needs. It is even more critical in countries such as Brazil, where the state fails to provide essential services (e.g., education, health, housing), and many people need to turn to the private sector to satisfy their demands, reinforcing the commodification of fundamental rights (Lavinas, 2013).

Specifically in relation to the labor market, the links between labor and income are many. Wage represents the main income source of families in Brazil (IBGE, 2021), reflects employment conditions, and is a proxy for standard of living. Moreover, total income affects the job prospects of individuals, as it is a resource to access better basic education[23] and to cover the costs of job searching or starting a new enterprise. Income also influences the costs of opportunities between studying and the need to make a living in low-skilled jobs and determines if a person is entitled to credit with reasonable conditions (Dymski, 2007). Therefore, including income-related indicators in the

[23] In Brazil, private schools typically have better education performance than public schools (Moraes & Belluzzo, 2014).

multidimensional indexes has numerous advantages, also working as a complement for the other dimensions (Santos and Villatoro, 2016).

This dimension contains two indicators: *Household dependency ratio* and *Income*. In the individual-based index, the first indicator measures the share of people without income in each household. The second indicator reveals the total income from wages and all sources. The reason to include all sources is twofold. First, income from other sources than wages may influence the decision to work and the kind of job a person is susceptible to accepting. Second, by only including wages, the indicator would assign a zero income to all the people without a job, even if a person is outside the labor force and have a high income from other sources. Together, these two indicators indicate to which extent individuals have resources to ensure a basic standard of living conditions, develop capabilities in the labor market, and financially support or be supported by the members of their household.

In the household-based index, the *Household dependency ratio* is the same as in the individual-based index, and the *Income* indicator is the total household income per capita. More than in the individual-based index, the dimension here represents how much family members can support each other financially, and to which extent families are vulnerable to income shocks.

3.4 Results

3.4.1 Changes in multidimensional vulnerability

This subsection presents the fuzzy vulnerability estimations of the individual-based index and the household-based index for 2016 and 2019. Additionally, I analyze the changes in outcomes by subgroups. Table *4* shows the fuzzy outcomes (FZ), standard errors (SE), absolute changes, and relative changes. Here I set the fuzzy outcomes to range between 0 and 100, with 0 indicating the minimum vulnerability degree, and 100 the maximum.

As mentioned in the introduction, the economic context during the period of this study was not favorable for the Brazilian labor market. Brazil had two consecutive years of economic recession in 2015 and 2016, and the economic recovery was limited, with an average economic growth rate of 1.5% in 2017, 2018, and 2019 (Saboia et al., 2021). Moreover, other components such as the labor reform in 2017, the limited growth of the real minimum wage beginning in 2017[24], and the reduced investment in most social policy sectors[25], likely contributed to increasing the vulnerability in the labor market, especially of low-skilled workers (Saboia et al., 2021; Krein et al., 2018).

In general, the outcomes confirm this negative trend, as they show that vulnerability was high and did not have large changes between 2016 and 2019. In the individual-based index, the total result increased from 64.5 in 2016 to 65.3 in 2019. In the gender subgroup, women had on average less vulnerability than men in 2016 but had a higher increase of vulnerability from 2016 to 2019. Among the color/ethnicity subgroup, Asian people had the lowest vulnerability but the highest increase from 2016 to 2019, reducing the gap to the other groups. Brown people had the highest vulnerability in 2016, and Indigenous people became the most vulnerable in 2019. Comparing the age subgroups, young adults (between 18 and 25 years old) had the highest vulnerability and the largest increase in vulnerability between the two years.

Looking at geographical divisions, people living in rural areas are much more vulnerable than in urban areas. The vulnerability degree is more than 80 for the rural subgroup, the highest level of all subgroups. Among the states, the ones in the north and northeast have the highest vulnerability, such as Maranhão (MA), Para (PA), Piauí (PI), and Alagoas (AL). In contrast, the federal district (DF) and the states in the south and southeast have the lowest vulnerability degrees, as, for instance, Santa

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[24] For details about the labor reform and the criteria for setting and adjusting the minimum wage in Brazil, see Saboia et al. (2021).

[25] Vieira (2020) shows that from social security, public pension, health, culture, agriculture development, education, housing, sanitation, work and income, and urbanism, only the first tree had a real growth in spending between 2013 and 2019.

Catarina (SC), São Paulo (SP), and Rio de Janeiro (RJ). In any case, the degree of vulnerability is consistently above 50, and most absolute changes were not statistically significant.

In the household-based analysis, most outcomes slightly decreased between 2016 and 2019. The total outcome reduced from 53.1 in 2016 to 52 in 2019. Considering that some of the HH's indicators capture families in which everyone is deprived, what I can also consider as extreme vulnerability, these outcomes are very high. Still, the household-based results show that fewer families were in extreme vulnerability in 2019.

Comparing women and men, we can see that both subgroups had almost the same degree of vulnerability in 2016, but women had a lower decrease in vulnerability from 2016 to 2019. In the color/ethnicity subgroup, Indigenous people were those with higher vulnerability in both years, whereas Asian people were those with smaller vulnerability, even if they were the only subgroup with an increase in vulnerability between the two years. In the age groups, the vulnerability differences among them are smaller than the individual-based results, with young people again with the largest vulnerability in the labor market. Among the area type and states subgroups, the patterns are similar to those from the individual-based index. Households in rural areas have the greatest vulnerability degree, around 70 in both years, and the northern and northeastern states are also those with the highest vulnerability.

Alternatively, to better understand the change patterns among the states, Figure 2 and Figure 3 exhibit the association of the degree of vulnerability in 2016 and the changes between 2016 and 2019 for the individual- and household-based indexes, respectively. In the individual-based outcomes (Figure 2), states with the lowest vulnerability degrees in 2016 are associated with increases in vulnerability in 2019, and states with the largest vulnerability degrees in 2016 are associated with decreases in vulnerability between the years, although the decreases were never superior to 2 vulnerability degree points. In the household-based index results (Figure 3), there is no clear correlation: almost all states had a small decrease from 2016 to 2019.

Table 4 - Changes in degree of vulnerability between 2016 and 2019

	Individual-based						Household-based					
	2016		2019				2016		2019			
Variables	FZ	SE	FZ	SE	Abs. Change	Rel. Change	FZ	SE	FZ	SE	Abs. Change	Rel. Change
Total	64.98	0.002	65.32	0.002	0.35	1.01	53.07	0.002	51.95	0.002	-1.12***	0.98
Gender												
Women	63.41	0.002	64.20	0.002	0.79***	1.01	53.06	0.002	52.07	0.002	-0.99***	0.98
Men	66.29	0.002	66.32	0.002	0.04	1.00	53.07	0.002	51.82	0.002	-1.25***	0.98
Color/Ethnicity												
White	57.42	0.003	58.25	0.002	0.83**	1.01	47.11	0.002	46.18	0.002	-0.92***	0.98
Asian	49.52	0.016	57.23	0.016	7.72***	1.16	44.13	0.018	46.28	0.016	2.15	1.05
Black	70.19	0.003	69.31	0.003	-0.88*	0.99	54.44	0.005	53.35	0.004	-1.09*	0.98
Brown	71.57	0.002	70.94	0.002	-0.63***	0.99	58.43	0.002	56.75	0.002	-1.68***	0.97
Indigenous	70.94	0.021	73.50	0.015	2.56	1.04	62.11	0.020	60.63	0.018	-1.48	0.98
Age												
18 - 25	68.45	0.002	69.82	0.002	1.37***	1.02	50.02	0.002	49.99	0.003	-0.03	1.00
26 - 35	61.16	0.002	61.96	0.003	0.80**	1.01	49.43	0.002	48.51	0.003	-0.92***	0.98
36 - 65	65.62	0.002	65.30	0.002	-0.319	1.00	48.11	0.002	47.14	0.002	-0.98***	0.98
Area type												
Urban	62.23	0.002	62.75	0.002	0.51*	1.01	50.11	0.002	49.12	0.002	-0.99***	0.98
Rural	83.36	0.002	83.11	0.002	-0.25	1.00	70.54	0.003	69.46	0.003	-1.08***	0.98
States												
RO	69.97	0.008	68.81	0.008	-1.16	0.98	58.45	0.009	56.12	0.009	-2.33*	0.96
AC	70.45	0.010	72.52	0.008	2.07	1.03	64.54	0.011	63.23	0.009	-1.31	0.98
AM	73.74	0.007	74.65	0.007	0.91	1.01	66.19	0.007	65.15	0.007	-1.04	0.98
RR	66.73	0.014	68.20	0.014	1.47	1.02	60.12	0.012	58.90	0.013	-1.23	0.98
PA	77.09	0.006	75.89	0.006	-1.20	0.98	66.29	0.006	65.25	0.006	-1.04	0.98
AP	70.61	0.017	70.77	0.012	0.16	1.00	66.10	0.015	60.85	0.015	-5.25**	0.92
TO	67.95	0.010	67.86	0.009	-0.10	1.00	57.95	0.009	55.61	0.011	-2.34*	0.96
MA	79.79	0.004	78.77	0.004	-1.02*	0.99	70.42	0.005	68.99	0.005	-1.43**	0.98
PI	76.18	0.008	75.89	0.008	-0.29	1.00	63.75	0.010	62.44	0.009	-1.31	0.98
CE	74.09	0.005	73.27	0.005	-0.83	0.99	62.86	0.005	60.74	0.006	-2.12***	0.97
RN	71.05	0.009	71.84	0.012	0.79	1.01	58.77	0.009	58.47	0.012	-0.30	0.99
PB	73.29	0.007	73.23	0.009	-0.06	1.00	61.76	0.008	60.55	0.009	-1.21	0.98
PE	71.80	0.008	71.24	0.008	-0.56	0.99	63.13	0.007	60.12	0.008	-3.02***	0.95
AL	75.36	0.007	74.44	0.007	-0.92	0.99	64.57	0.006	63.79	0.007	-0.77	0.99
SE	73.86	0.011	73.99	0.009	0.13	1.00	62.86	0.009	61.64	0.009	-1.22	0.98
BA	74.23	0.006	75.00	0.006	0.77	1.01	62.32	0.006	62.13	0.007	-0.19	1.00
MG	65.50	0.006	65.45	0.005	-0.05	1.00	50.27	0.005	48.84	0.005	-1.43**	0.97
ES	64.85	0.007	64.94	0.007	0.09	1.00	53.17	0.006	50.51	0.007	-2.66***	0.95
RJ	61.02	0.005	61.84	0.005	0.82	1.01	49.82	0.004	49.82	0.004	0.01	1.00
SP	57.28	0.005	59.18	0.005	1.90**	1.03	44.83	0.005	44.80	0.005	-0.03	1.00
PR	60.35	0.005	60.66	0.005	0.31	1.01	46.59	0.005	45.41	0.005	-1.18	0.97
SC	55.79	0.005	55.16	0.005	-0.63	0.99	41.09	0.005	38.31	0.005	-2.79***	0.93
RS	59.15	0.005	58.76	0.006	-0.39	0.99	44.13	0.006	42.74	0.006	-1.38	0.97
MS	64.27	0.007	62.92	0.008	-1.35	0.98	47.88	0.008	46.41	0.008	-1.47	0.97
MT	64.69	0.007	63.23	0.007	-1.46	0.98	50.90	0.008	48.50	0.007	-2.40**	0.95
GO	65.20	0.006	64.00	0.006	-1.20	0.98	51.49	0.006	48.54	0.006	-2.95***	0.94
DF	53.75	0.011	55.67	0.011	1.92	1.04	45.70	0.008	43.94	0.008	-1.76	0.96

Notes: Linearized standard errors (SE) considering the survey design. Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01. FZ refers to the average fuzzy estimations. For state abbreviations, see *Table A2* in the Appendix.

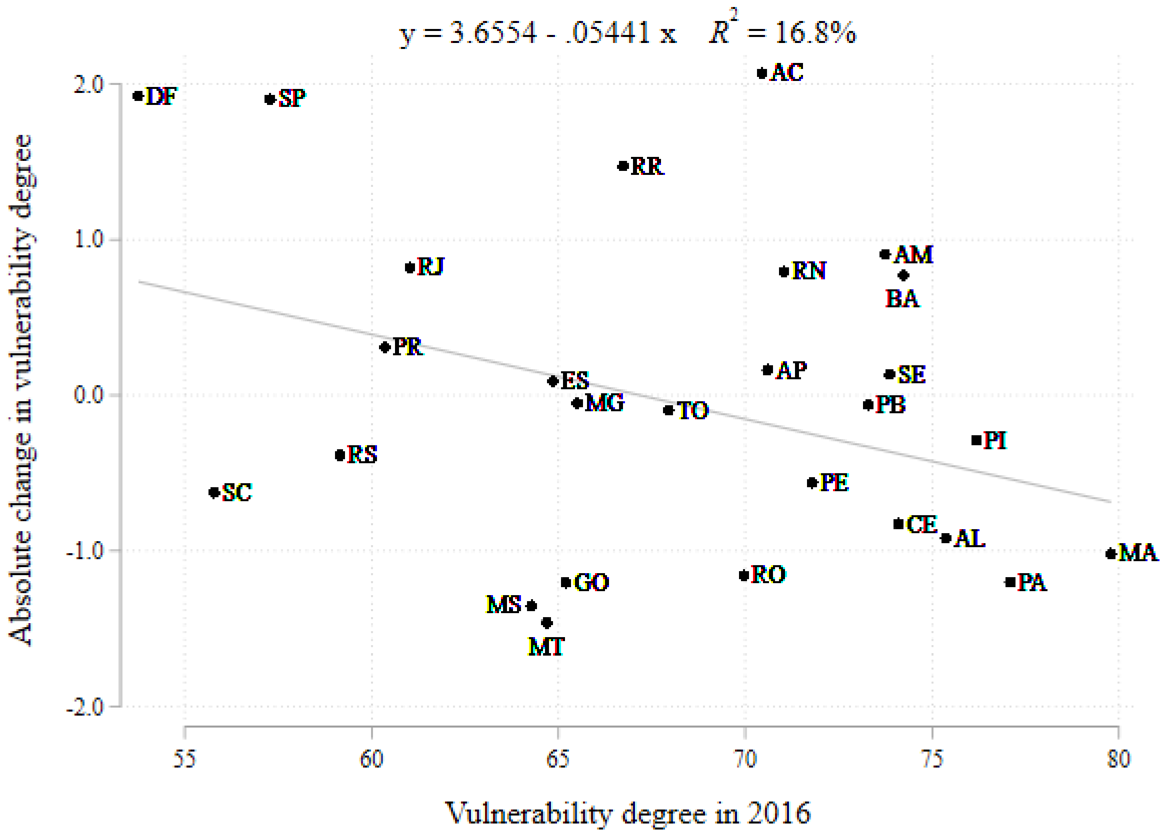

Figure 2 - Changes in vulnerability degrees by state in the individual-based index

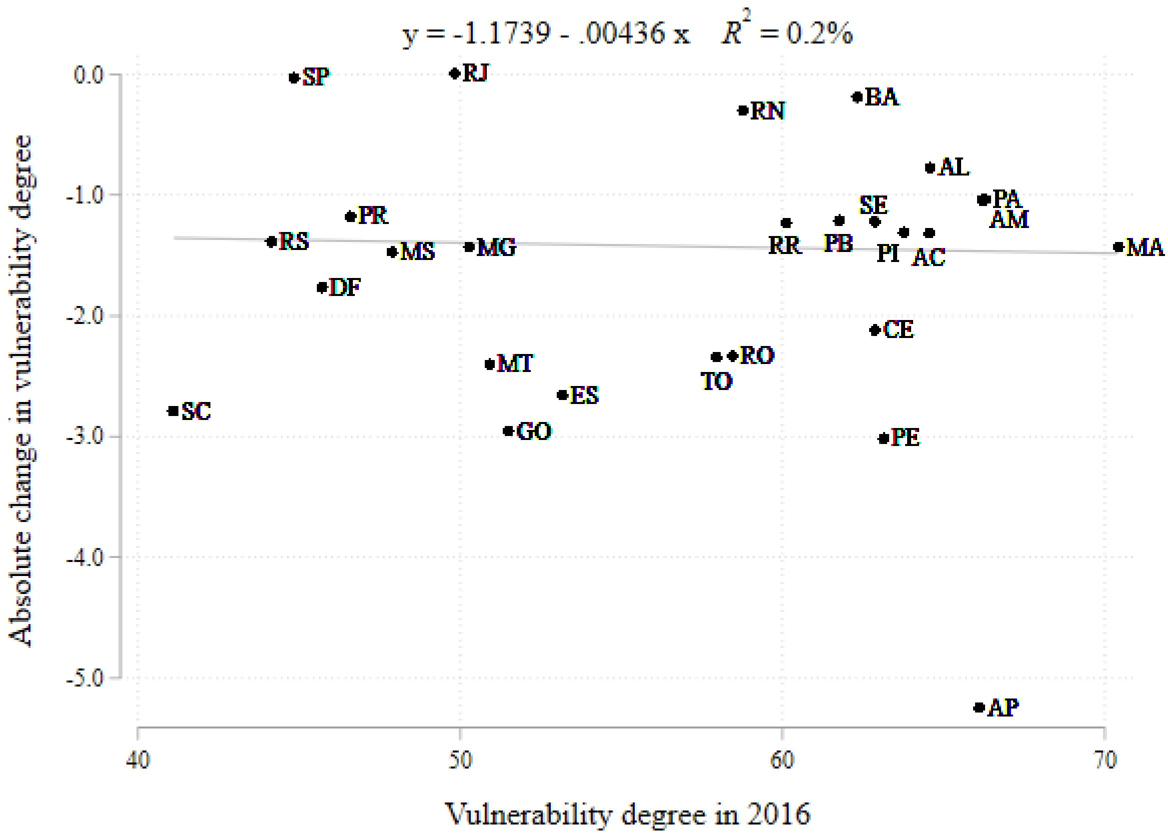

Figure 3 - Changes in vulnerability degrees by state in the household-based index

3.4.2 Changes in deprivations by indicator and subcategories

This subsection analyzes changes in the indicators and their subcategories between 2016 and 2019. The analysis is complementary to the previous subsection as it shows the results in a dashboard format as an alternative for the composite indexes. Table 5 presents the indicator's outcomes for the Individual-based Index, and Table 6 for the Household-based Index. These tables detail the indicators by showing their mean, deprivation scores, and changes between 2016 and 2019.

In Table 5, the *School achievement* is the only indicator that improved between 2016 and 2019. The average years of education additional to high school increased from 1.6 years to 2.2 years, and the deprivation scores decreased from 43.8% to 39.8%. For the *Deprivation on employment*, the table has only deprivation shares because the indicators and their subcategories are binary. These deprivation shares increased in all subcategories except in the employed without pay. The *Household dependency ratio* reveals that the share of people without income in each household was almost stable in the period, although the deprivation score increased 0.45 pp. Finally, the I*ncome* indicator shows that the total income increased slightly.

Taking these outcomes together, I observe that three patterns stand out. First, education improvements appear to be resilient to economic stagnation and decreased public spending. Second, even if, on average, the education level increased, this was not reflected in employment improvements, as employment precarity and other labor market deprivations increased in the period. There was an expansion not only in informality, excessive working hours with underpayment or without pay, and underemployment, but also in unemployment, discouraged people, and people without the possibility to search or/and start a new job. Third, the fact that other sources increased proportionally more than wages is also an indication of labor market precarity.

Table 5 - Changes by indicator in the Individual-based Index between 2016 and 2019

Indicators and Subcategories	**Mean**		**Abs.**	**Rel.**	**Depriv. (%)**		**Abs.**	**Rel.**
	2016	**2019**	**Change**	**Change**	**2016**	**2019**	**Change**	**Change**
School achievement								
Total	1.606	2.154	0.548***	1.341	43.83	39.75	-4.08***	0.91
Deprivation on employment[1]								
Total	-	-	-	-	49.55	52.74	3.19***	1.06
Informality	-	-	-	-	37.84	40.02	2.18***	1.06
Employment without pay	-	-	-	-	1.43	1.28	-0.15***	0.90
Underemployed	-	-	-	-	4.30	6.01	1.71***	1.40
Work excessive hours with underpayment or in unpaid works	-	-	-	-	14.43	15.00	0.56***	1.04
Unemployed	-	-	-	-	10.14	10.87	0.73***	1.07
Discouraged	-	-	-	-	2.55	3.68	1.13***	1.44
Looking for a job but not available	-	-	-	-	0.11	0.11	0.00	0.99
Not looking for a job but available	-	-	-	-	0.64	0.82	0.18***	1.28
Not looking for a job and not available but would like to work	-	-	-	-	0.75	0.81	0.06	1.08
Household dependency ratio								
Total	0.351	0.351	0.000	1.000	8.97	9.42	0.45**	1.05
Income[2]								
Total	2005.62	2049.58	43.96	1.022	31.60	34.06	2.46***	1.08
Wage	1870.13	1896.63	26.49	1.014	-	-	-	-
Other sources[3]	135.49	152.96	17.47	1.129	-	-	-	-

Notes: Depriv. (%) refers to deprivation scores of each subcategory with respect to the expanded labor force. 1.The results are only available for the deprivation share because the subcategories are binary indicators. 2. Monthly real individual income in November 2019 Brazilian Reals. 3. Other sources subcategory includes social programs, pension and unemployment benefits, rental income, financial earnings, and scholarships.

In Table 6, *School achievement* and *Income* improved between 2016 and 2019. Within the former indicator, the household average share of people in the expanded labor force with less than secondary education decreased from 47.5% to 42.9 %, and the share of households with all its expanded labor force deprived in education decreased 5 pp. As part of the *School achievement* in the household-based Index, children outside school also decreased. The household average number of children outside school reduced from 0.04 to 0.03, and the share of households with children outside school fell from 3.7% to 2.7%. As for the *Income* indicator, the total household per capita income increased 86.19 Brazilian Reals (BRL), 55.01 BRL of which came from the household wage income per capita. The *Income*'s total deprivation share practically remained stable.

Like in the individual-based index, the *Deprivation on employment* indicator worsened. The household total share of deprived people in the expanded labor force expanded from 51.2% to 54.2%, and the share of households that have all the expanded labor force deprived increased 2.2 pp.

However, one positive outcome is that households with at least one child or adolescent in child labor decreased from 5.2% to 4.1%. Finally, even if the mean of the *Household dependency ratio* slightly decreased, its deprivation score marginally increased.

Therefore, we can observe that more families are in extreme deprivation in most employment-related indicators, which indicates that the labor market became more precarious in the period. Considering that the *Household dependency ratio* slightly decreased and the household income per capita raised, families probably have more members who can help financially. However, the rise was not large, especially if we consider that *Deprivation on employment* worsened in the period.

Table 6 - Changes by indicator in the Household-based Index between 2016 and 2019

Indicators and Subcategories	**Mean**		**Abs.**	**Rel.**	**Depriv. (%)**		**Abs.**	**Rel.**
	2016	**2019**	**Change**	**Change**	**2016**	**2019**	**Change**	**Change**
School achievement								
Total	0.475	0.429	-0.046***	0.903	35.88	30.87	-5.01***	0.86
Children outside school[1]	0.040	0.029	-0.011***	0.733	3.65	2.74	-0.91***	0.75
Deprivation on employment[2]								
Total	0.512	0.542	0.030***	1.058	36.68	38.88	2.20***	1.06
Informality	0.325	0.327	0.002	1.007	-	-	-	-
Employment without pay	0.013	0.012	-0.001***	0.892	-	-	-	-
Underemployed	0.045	0.061	0.017***	1.376	-	-	-	-
Work excessive hours with underpayment or in unpaid works	0.153	0.157	0.004*	1.025	-	-	-	-
Unemployed	0.100	0.109	0.009***	1.092	-	-	-	-
Discouraged	0.026	0.039	0.013***	1.499	-	-	-	-
Looking for a job but not available	0.001	0.001	0.000	1.071	-	-	-	-
Not looking for a job but available	0.007	0.009	0.002***	1.286	-	-	-	-
Not looking for a job and not available but would like to work	0.009	0.010	0.001**	1.118	-	-	-	-
Child labor[3]	0.052	0.041	-0.01***	0.799	-	-	-	-
Household dependency ratio								
Total	0.415	0.411	-0.005**	0.989	13.20	13.42	0.22	1.02
Income[4]								
Total	1318.15	1404.34	86.19***	1.065	29.66	29.26	-0.41	0.99
Wage	1065.72	1120.73	55.01**	1.052	-	-	-	-
Other sources	214.21	243.88	29.67***	1.139	-	-	-	-

Notes: Depriv. (%) refers to deprivation scores of each subcategory regarding households with at least one person in the expanded labor force. 1. Household average number of children and adolescents outside school. 2. Only the Mean results are available because I count all the subcategories to calculate the deprivation scores of households with all their expanded labor force deprived. 3. Household average number of children and adolescents in child labor condition as defined by IBGE (2019). 4 Monthly real household income per capita in November 2019 Brazilian Reals.

3.4.3 Determinants of multidimensional vulnerability

To complement the previous analyzes, I now estimate the Fractional Logit Model (Papke & Wooldridge, 1996) to examinate potential demographic and geographic determinants of vulnerability. This model is appropriate when the dependent variable ranges between 0 and 1 [0,1], which is the case of the fuzzy vulnerability degree. The intention here is not to find causality but to get some evidence on the links among the variables and show a simple example of how studies can use the vulnerability indexes. Table 7 presents the regression outcomes separately for each year and pooled. I also include interactions between gender and color/ethnicity, and, in the pooled regression, interaction with years to see if the differences between the years are statistically significant.

For both years, the outcomes are consistent with those of subsection 3.4.1. For instance: Black, Brown, and Indigenous people have a stronger positive link with vulnerability degree compared to White and Asian people; in relation to urban areas, rural areas have a stronger positive association with vulnerability; and, except for the Northeastern region, all the other regions have a weaker link to vulnerability with respect to the Northern region. Moreover, even if females have a smaller association to vulnerability than males, female household heads have a higher link to vulnerability.

Regarding the interaction between gender and color/ethnicity, no group has statistically significant coefficients. Concerning the interaction with years, they show that compared to White people, the association to vulnerability decreased between the years for the Black and Brown people. On the other hand, the link to vulnerability increased for Asian people compared to White, but Asian people still have a smaller coefficient than White. For male-headed households, the vulnerability is even smaller in relation to female-headed households in 2019. Finally, the link to vulnerability was reduced for the age variable and increased for the household size.

Table 7 - Fractional Logistic Regression outcomes

y = Fuzzy vulnerability degree Variables	2016	SE	2019	SE	Pooled	SE
Gender (base = Male)						
Female	-0.0817	0.0104***	-0.0653	0.0116***	-0.0817	0.0104***
Color/ethnicity (base =White)						
Black	0.4369	0.0224***	0.3663	0.0198***	0.4369	0.0224***
Asian	-0.3609	0.0874***	-0.0795	0.0775	-0.3609	0.0874***
Brown	0.4503	0.0141***	0.3900	0.0137***	0.4503	0.0141***
Indigenous	0.3483	0.0941***	0.4080	0.0942***	0.3483	0.0941***
Not declared	2.4159	0.4796***	-0.3650	0.4422	2.4159	0.4796***
Household head gender (base = Female)						
Male household head	-0.0789	0.0104***	-0.1208	0.0097***	-0.0789	0.0104***
Age	-0.0499	0.0022***	-0.0598	0.0021***	-0.0499	0.0022***
Squared age	0.0007	0.0000***	0.0008	0.0000***	0.0007	0.0000***
Regions (base = North)						
Northeastern	0.0990	0.0213***	0.0928	0.0209***	0.0990	0.0213***
Central-western	-0.2740	0.0203***	-0.2434	0.0207***	-0.2740	0.0203***
Southeastern	-0.2689	0.0222***	-0.3087	0.0218***	-0.2689	0.0222***
Southern	-0.2751	0.0237***	-0.2962	0.0230***	-0.2751	0.0237***
Area type (base = Urban)						
Rural	0.9522	0.0160***	0.9327	0.0149***	0.9522	0.0160***
Household size	0.2341	0.0099***	0.2779	0.0118***	0.2341	0.0099***
Squared household size	-0.0058	0.0011***	-0.0103	0.0014***	-0.0058	0.0011***
Interactions (Gender x Color/ethnicity)						
Female x Black	0.0260	0.0273	0.0301	0.0249	0.0260	0.0273
Female x Asian	0.1116	0.1131	-0.0260	0.0971	0.1116	0.1131
Female x Brown	-0.0111	0.0145	-0.0010	0.0160	-0.0111	0.0145
Female x Indigenous	0.0480	0.1340	0.0165	0.1074	0.0480	0.1340
Female x Not declared	-1.0201	0.9028	0.0267	0.5916	-1.0201	0.9028
Year (base = 2016)					0.1758	0.0662***
Interaction with years (base =2016)						
2019 x Female					0.0165	0.0156
2019 x Black					-0.0706	0.0299**
2019 x Asian					0.2814	0.1169**
2019 x Brown					-0.0602	0.0196***
2019 x Indigenous					0.0596	0.1331
2019 x Not declared					-2.7809	0.6523***
2019 x Male household head					-0.0419	0.0142***
2019 x Age					-0.0099	0.0031***
2019 x Squared age					0.0001	0.0000***
2019 x Northeastern					-0.0062	0.0299
2019 x Central-western					0.0306	0.0290
2019 x Southeastern					-0.0398	0.0311
2019 x Southern					-0.0212	0.0330
2019 x Rural					-0.0196	0.0219
2019 x Household size					0.0438	0.0154***
2019 x Squared household size					-0.0045	0.0018**
2019 x Female x Black					0.0040	0.0369
2019 x Female x Asian					-0.1377	0.1491
2019 x Female x Brown					0.0100	0.0216
2019 x Female x Indigenous					-0.0315	0.1717
2019 x Female x Not declared					1.0468	1.0794
Constant	0.5690	0.0490***	0.7448	0.0445***	0.5690	0.0490***
Observations	214,837		215,339		430,176	
F test	559.7		539.6		537.2	

Notes: Linearized standard errors (SE) considering the survey design. Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

3.5 Conclusion remarks

This chapter represents the first effort to create aggregated multidimensional vulnerability measures that consider people inside and outside the labor market. One of the innovations is the household-based index, which creates fuzzy indicators that represent how much a family is vulnerable depending on the share of deprived people within households. The study applies the LMVIs to the Brazilian context and compares the results between 2016 and 2019

The period covered in this chapter had large transformations in the labor market due to economic and political crises and ineffective public policies. The outcomes here confirm this unfavorable development, as they reveal that the average degree of vulnerability was high and had a slow change between the years. In effect, the deprivation score considering all the indicators and their subcategories is higher than looking only to informality or unemployment alone. This means that precarity and labor underutilization situations did not improve in the period.

More specifically, in the individual-based index, vulnerability increased in most subgroups, or they had statistically non-significant changes. Whereas in the household-based index, the vulnerability slightly decreased for most subgroups, which indicates that fewer families have most of their members in the expanded labor force deprived. However, the changes were slow for most subgroups, especially if we consider that the deprivation on employment dimension worsened in the period.

Although the vulnerability is high in general, the outcomes and changes are heterogeneous between and within subgroups. What is common between the two indexes is that, within subgroups, the most vulnerable are people from rural areas, from the north and northeast states, Black, Brown, and Indigenous people, and young adults. These outcomes confirm the usual inequalities patterns in Brazil, as I also show in Chapter 1 and Chapter 2.

Other conclusions when looking at the dashboard of indicators are the following. Compared to the other dimensions, education appears to be resilient to a period of economic stagnation and reduction in education public spending. Moreover, even if education levels improved, this was not reflected on employment indicators, as precarity and other labor market deprivations increased in the period. Lastly, the fact that the rise in other sources of income is proportionally higher compared to wages also indicates labor market precarity.

Finally, in the same way as the dimensions of multidimensional poverty analysis, the dimensions of the LMVIs represent different established policy debates. Although it is not possible and not in the chapter's scope to cover each of these dimensions in detail, one of the main usefulness of the proposed indexes is that they identify which subgroups have labor-market overlapping deprivations and which subgroups have families in extreme vulnerability. Therefore, they can also be helpful for policy purposes, as policy-makers can define priorities more effectively and analyze if public policies have been successful. Moreover, studies can also apply the indexes to estimate policy impacts on the labor market in a broader way. In that sense, an important contribution of the indexes is that they do not leave people behind, as they include people inside and outside the labor market. Particularly, the indexes do not leave women behind because they involve people that would like to work but cannot search for or/and start a paid job because they must dedicate themselves to unpaid domestic and care work or are considered too young or old to get a job.

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Appendix

Table A1- Demographic characteristics per year

	Population share (%)					
	2016			2019		
	Total	Individual	Household	Total	Individual	Household
Gender						
Women	51.69	45.62	50.95	51.99	47.08	51.32
Men	48.31	54.38	49.05	48.01	52.92	48.68
Color/Ethnicity						
White	44.68	44.90	44.05	42.66	42.29	41.97
Asian	0.53	0.56	0.52	0.63	0.66	0.60
Black	7.66	8.55	7.75	9.12	10.24	9.30
Brown	46.87	45.74	47.42	47.23	46.44	47.76
Indigenous	0.25	0.25	0.26	0.35	0.37	0.36
Age						
18 - 25	12.26	18.94	13.36	12.03	18.79	13.20
26 - 35	15.30	26.48	16.74	14.42	24.74	15.88
36 - 65	37.51	54.57	38.11	38.85	56.48	39.82
Area type						
Urban	85.18	87.02	85.54	85.68	87.34	86.11
Rural	14.82	12.98	14.46	14.32	12.66	13.89
States						
RO	0.83	0.80	0.85	0.84	0.80	0.85
AC	0.41	0.35	0.42	0.41	0.37	0.42
AM	1.86	1.74	1.96	1.90	1.82	2.01
RR	0.23	0.21	0.24	0.26	0.26	0.27
PA	4.05	3.88	4.21	4.09	3.80	4.25
AP	0.39	0.34	0.40	0.40	0.38	0.42
TO	0.74	0.68	0.74	0.74	0.68	0.73
MA	3.38	2.93	3.38	3.36	2.95	3.38
PI	1.59	1.55	1.59	1.56	1.55	1.58
CE	4.38	4.03	4.33	4.36	4.16	4.34
RN	1.67	1.61	1.67	1.67	1.63	1.68
PB	1.92	1.78	1.88	1.91	1.74	1.86
PE	4.56	4.12	4.46	4.53	4.18	4.42
AL	1.61	1.35	1.53	1.59	1.32	1.50
SE	1.09	1.05	1.09	1.10	1.05	1.10
BA	7.17	7.29	7.23	7.09	7.03	7.03
MG	10.15	10.62	10.17	10.10	10.43	10.12
ES	1.89	1.90	1.89	1.92	1.97	1.93
RJ	8.29	7.99	8.02	8.24	8.06	8.06
SP	21.88	23.16	22.12	21.92	23.33	22.15
PR	5.46	5.64	5.46	5.45	5.51	5.42
SC	3.36	3.44	3.29	3.41	3.50	3.33
RS	5.48	5.77	5.37	5.42	5.47	5.22
MS	1.28	1.32	1.31	1.29	1.33	1.32
MT	1.62	1.58	1.63	1.64	1.67	1.67
GO	3.29	3.37	3.32	3.35	3.44	3.40
DF	1.41	1.50	1.45	1.44	1.57	1.50

Notes: For state abbreviations, see *Table A2*.

Table A2 – Regions, and State abbreviations

Regions	States
Northern	RO = Rondônia; AC = Acre; AM = Amazonas; RR = Roraima; PA = Pará; AP = Amapá; TO = Tocantins.
Northeastern	MA = Maranhão; PI = Piauí; CE = Ceará; RN = Rio Grande do Norte; PB = Paraíba; PE = Pernambuco; AL = Alagoas; SE = Sergipe; BA = Bahia.
Southeastern	MG = Minas Gerais; ES = Espírito Santo; RJ = Rio de Janeiro; SP = São Paulo.
Southern	PR = Paraná; SC = Santa Catarina; RS = Rio Grande do Sul.
Central-western	MS = Mato Grosso do Sul; MT = Mato Grosso; GO = Goiás; DF = Distrito Federal