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Evolution and inequalities in depression prevalence and the treatment gap in Brazil: a decomposition analysis

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1. Introduction

The global burden of disease attributable to mental disorders has risen in the last decades. Mental disorders currently account for approximately 14.6% of the years lived with disability (YLDs) globally, more than one third of them due to depressive disorders (IHME, 2021). However, prioritizing mental health is a challenge for healthcare systems. On average, countries spend only 1.7% of their health budget on mental health services and those funds are largely spent on specialized mental hospitals without connections with routine healthcare platforms (Patel et al., 2018; Ridley et al., 2020). In low- and middle-income countries, estimates suggest that between 79 and 93% of people with depression do not receive care (Esponda et al., 2020). To face this issue, the World Health Organization launched a "Special Initiative for Mental Health" aimed at expanding health coverage for common mental disorders, including depression, as a step for achieving universal health coverage (WHO, 2019).

In Brazil, the burden of disease attributable to mental disorders is also high –7.5% of disability-adjusted life years are due to mental disorders, the fourth largest share in the Americas (IHME, 2021). Results from a nationally representative survey estimated that the prevalence of depression was 7.9% of the population aged 18 years or older in 2013 and that less than a quarter of depressed individuals received any treatment (Lopes et al., 2016). Existing evidence suggests that there are racial inequalities in depression prevalence and in the treatment gap for depression in Brazil (Faisal-Cury et al., 2021; Smolen & Araújo, 2017; Stopa et al., 2015).

The goal of this paper was three-fold. First, we assessed the evolution of the prevalence of depression and the treatment gap for depression between 2013 and 2019 using two waves of a national representative survey. Depression prevalence was assessed using scores from the PHQ-9 instrument, a standard instrument extensively used for screening and diagnosis of depression, which allowed us to approximate the true prevalence of depression (Kroenke et al., 2001; Levis et al., 2019). The treatment gap was defined as the share of depressed individuals that do not receive any kind of treatment (Kohn et al., 2004, 2018; Patel et al., 2016; Werlen et al., 2020). Second, we assessed socioeconomic and racial inequalities in depression prevalence and the treatment gap. Socioeconomic inequalities were analyzed looking at the gradients according to income quintiles. For depression, we also plotted the concentration curve and computed the Erreygers-corrected version of the concentration index. Racial inequalities were assessed by estimating depression prevalence and the treatment gap according to racial self-identification.

Finally, we applied decomposition methods to identify the driving factors behind trends and inequalities in depression prevalence and the treatment gap. To decompose the evolution of depression prevalence and the treatment gap between 2013 and 2019, we applied the Oaxaca-Blinder method for decomposing differences in means between groups (O'Donnell et al., 2007). A method for decomposing the concentration index was used to assess the factors driving health inequalities in depression prevalence, this method has extensively been used to analyze health-related inequalities (Erreygers, 2009; Van Doorslaer & Van Ourti, 2011). Differences in the treatment gap between white and brown/mixed or black individuals were also decomposed using the Oaxaca Blinder method.

Brazil is an important setting for evaluating the evolution of and inequalities in depression prevalence and the treatment gap. On the one hand, socio-economic inequalities are large, and it is one of the most unequal countries in the world with a GINI index of 53.4 in 2019 (World Bank, 2021). Racial inequalities are also stark. In 2018, 32.9% of black or brown/mixed[1] individuals had incomes below the US$5.5/day poverty line and 8.8% below the US$1.9/poverty line. Among white individuals, those shares were 15.4% and 3.6%, respectively. Racial inequalities are pervasive –for example, illiteracy and homicide rates are significantly larger among black or brown/mixed individuals than among whites (IBGE, 2019). Additionally, the period of our analysis coincides with major economic recession in Brazil, signed by a fall in GDP per capita and increased unemployment rate. During this period, increases unemployment rates were associated with higher mortality among black or brown/mixed race individuals, but not among white individuals (Hone et al., 2019).

On the other hand, Brazil has a national health service that provides publicly funded and free at the point of care services at all levels of care. A central piece of Brazil's national health service are primary healthcare programs, which have been expanded nationally through the deployment of Family Health Teams since the mid-1990s. FHTs currently cover over 60% of the population and have been shown to be related to improved population health (Bastos et al., 2017; Bhalotra et al., 2020; Hone et al., 2020; Rocha & Soares, 2010) and reduced health inequalities (Hone et al., 2017). While in the 2000s there have been initiatives to expand services provided by the national health service, including mental healthcare (Athié et al., 2016; Soares & de Oliveira, 2016), access to specialized care remains a major challenge in the public sector, with long waiting lines (Castro et al., 2019). There is also a sizable private healthcare sector in Brazil, where approximately one quarter of the population, mostly higher-income and formally employed individuals in urban centers, are covered by private health insurance schemes (Paim et al., 2011).

This study contributes to the literature on socioeconomic and racial inequalities in health and healthcare access in Brazil. Existing evidence suggest they exist in different areas: infant mortality (Garcia & Santana, 2011), obesity (Triaca et al., 2020), multimorbidity and associated healthcare (Hone et al., 2021), catastrophic health expenditure (Boing et al., 2014), reproductive and maternal health interventions (França et al., 2016), and healthcare utilization (Barbosa & Cookson, 2019; Mullachery et al., 2016). While there are studies documenting inequalities in depression prevalence and the treatment gap (Lopes et al., 2016; Smolen & Araújo, 2017; Stopa et al., 2015), ours is the first, to the best of our knowledge, to quantify the contribution of the driving factors behind the evolution and behind different forms of inequalities in mental health in Brazil. In that sense, our work also contributes to the literature on the drivers of inequalities in mental health and access to related healthcare services in low- and middle-income countries (Evans-Lacko et al., 2018; Srivastava et al., 2021).

2. Materials and Methods

2.1. Data

We used data from the 2013 and 2019 waves of the National Health Survey (PNS), a nationally representative household-based survey conducted by the Brazilian Institute of Geography and Statistics (IBGE) in partnership with the Ministry of Health. The survey includes a wide array of socioeconomic characteristics and information on the utilization of healthcare services for all members of sampled households. For a randomly selected household member (at least 18 years old in 2013 and at least 15 years old in 2019), the survey collects in-depth information on health, including self-perception of health status, lifestyle and diagnosis and treatment of chronic diseases. The survey sample was designed to be representative at the national level, major regions (South, South-East, North, North-East, and Center-West), the 27 states, state capitals and their metropolitan areas, and rural and urban areas. The sampling design is clustered in three stages. Census tracts or groups of census tracts are the primary sampling units, households are the second stage sampling units and

[1] Racial inequalities are usually analyzed grouping brown/mixed and black individuals. The same is done by most affirmative action policies in Brazil.

adult members in the households are the third stage sampling units. Microdata made available by the IBGE includes all information needed to account for the sampling design, including weights adjusted for non-response rates and population projections (IBGE, 2014, 2020).

The detailed individual questionnaire answered by a selected household member includes the Brazilian version of the PHQ-9, a standard instrument extensively used for screening and diagnosis of depression. The PHQ-9 questionnaire asks the individual how often over the last 2 weeks he/she has been bothered by the symptoms of depression defined by the DSM-IV. Each can be answered as “not at all” (score: 0), “less than half the days” (score: 1), “more than half the days” (score: 2), or “nearly every day” (score: 3). Total score for each individual is computed by adding the score of each item and indicates the severity of depression (0-4 none, 5-9 mild, 10-14 moderate, 15-19 moderately severe, 20-27 severe) (Kroenke et al., 2001; Levis et al., 2019). The PNS also includes information on the following questions: “Has a medical doctor or other health professional (such as a psychiatrist or a psychologist) ever diagnosed you with depression?” (Yes; no); and “Do you frequently visit a medical doctor or healthcare service for depression or only when you have a problem?” (Yes; only when I have a problem; never).

We kept data on individual answers to the PHQ-9 questionnaire, diagnosis, and treatment of depression. Additionally, we kept variables that remained unchanged between the two waves of the PNS: family income per capita, sex, race, age, highest educational level achieved, area of residence, state of residence, economic activity status, employment status, number of residents in the household, number of rooms in the household, partner lives in the same household, registration with a family health team (FHT) –i.e., Brazil’s main provider of public primary healthcare–, frequency of home visits received from any member of a FHT in the last 12 months, variables indicating previous medical diagnosis for different non-mental chronic conditions (hypertension, other heart conditions, stroke, asthma, rheumatoid arthritis, chronic back pain, work-related musculoskeletal disorders, diabetes, hypercholesterolemia, cancer, chronic pulmonary diseases, chronic kidney diseases, other chronic diseases), consumption of tobacco products, any physical activity in the last 3 months, number of days of physical activity per week, frequency of alcohol consumption, and frequency of participation in the last 12 months for each of the following activities: sport or artistic group activities, associations (neighbors associations, social movements, academic centers or other), volunteering, and religious services or activities (excluding baptisms, weddings and burials).

We also kept variables that demanded minor adjustments to be compatible between the two waves of the PNS because of slight differences in definition and/or answer categories. Holder of any private health insurance, number of family members the individual can count on, number of friends the individual can count on, and characteristics of the household: predominant material of the roof, predominant material of the walls, predominant material of the floor, sewerage system, number of toilets, and number of rooms. Additionally, we kept the variable identifying the availability of an internet connection in the household, even though its definition changed between the two waves –i.e., it asked if “the residents have access to internet in the household” in 2013 and if “any resident has access to internet in the household through a computer, tablet, cellphone, television or any other device” in 2019. The definition of variables identifying victimization changed substantially between the two waves and it was not possible to make them compatible. Therefore, we only kept for 2019 variables identifying exposure in the last 12 months to different acts of psychological, physical, and sexual violence.

Finally, we obtained data on the evolution of consumer price index from IBGE to compute family per capita income in constant terms. After dropping observations with missing data or younger than 18 years old we were left with a sample of 60,188 observations from 2013 and 88,500 observations from 2019.

2.2. Variables

2.2.1. Depression and treatment gap for depression

First, we computed the score of the PHQ-9 questionnaire for all individuals. We identified all observations with a total score ≥ 10 as depressed. This cut-off is frequently used in research, as it is considered a sign of clinically relevant symptoms of depression, and a study set in Brazil found that the PHQ-9 had a sensitivity of 72.5% and a specificity of 88.9% for diagnosing depression when using this cut-off (Levis et al., 2019; Santos et al., 2013). All depressed individuals that had either never been diagnosed with depression by a healthcare professional or that were diagnosed but never visit a healthcare service for depression were identified as falling in the treatment gap –i.e., the treatment gap variable indicates persons that present symptoms compatible with depression and do not have any contact with healthcare services related to this condition (Kohn et al., 2004, 2018).

2.2.2. Other measures

Using selected variables from PNS detailed above, we computed covariates that can be grouped in five blocks of contributing factors for the decomposition analysis: socio-demographical, socio-economic, social support, healthcare services, and risk factors.

Socio-demographical covariates included were: a binary variable indicating if the individual is female, age categorized in age groups (18-24, 25-34, 35-44, 45-54, 55-64, 65 or more), education (none, incomplete elementary, complete elementary school, incomplete secondary, complete secondary, incomplete higher, complete higher), race (white, black, Asian, mixed/brown, native), a binary variable indicating if the household is in an urban area and region of residence (North, North-East, Center-West, South-East, South). Socio-economic covariates related with income, employment and housing conditions included were: employment status (inactive, unemployed, employed), a binary variable proxy of the UN-Habitat (2016) definition of slum dwelling –according to predominant construction materials, toilet presence, sewerage system and number of residents per room–, internet connection in the household, log of household income per capita in 2019 Brazilian reais and income quintile[2]. Social support covariates included were: a binary variable indicating support from any family member and/or friend, cohabitation (alone, with partner, with other person), and participation in group, social and/or community activities (never, less than monthly, at least once per month). Covariates related to healthcare services included were: a binary variable indicating if the individual holds any private health insurance and a variable detailing if the person is registered with a FHT (No/Does not know, Yes and did not receive any home visit from a member of the FHT in the last 12 months, Yes and was visited by at least once in the last 12 months). Covariates related to risk factors were: a binary variable indicating medical diagnosis of at least one non-mental NCD, a binary variable indicating if the individual ever smokes tobacco products, physical activity (no, less than weekly, once or twice a week, three or more times per week), alcohol consumption (never, less than weekly, once a week, twice or more per week) and a binary variable indicating exposure to an episode of psychological, physical or sexual violence in the previous 12 months (only for 2019).

2.3. Statistical analysis

2.3.1. Descriptive and regression analysis

First, we computed the prevalence of depression and treatment gap for depression in 2013 and 2019 for the whole sample and according to household income per capita quintile and to race. We also computed the mean for all covariates in both years.

Second, we assessed the association between all covariates and depression and between all covariates and the treatment gap using linear probability models of the following form:

$$H_g = X\beta_g + \epsilon_g$$

[2] Income quintile was used for the analysis of socioeconomic and racial inequalities in 2019 and the log of family income per capita was used for the analysis of the evolution of depression and the treatment gap between 2013 and 2019.

Where *H* is one of the variables of interest (being depressed or being untreated, conditional on being depressed), X is a matrix of covariates which includes a constant term and covariates described above (with the exception of exposure to violence), β is a vector of coefficients and ϵ is an error term with conditional mean zero –i.e., $E\left[\epsilon_g \middle| X = 0\right]$. The subscript *g* indicates that the observation belongs to a certain group (for example, year of the PNS). The models were repeated separately for depression and for the treatment gap for *g = 2013* and for *g = 2019*. In this case, the log of the household income per capita was used as the income variable. These results were also used for the Oaxaca-Blinder decomposition to investigate the driving factors of the evolution of the prevalence of depression and the treatment gap for depression between 2013 and 2019 (see below).

2.3.2. Oaxaca Blinder decomposition

The Oaxaca-Blinder decomposition technique was originally designed for analyzing wage-differentials between gender and race groups (Blinder, 1973; Oaxaca, 1973), and can be applied to study differences in the mean of health-related outcome between groups (O'Donnell et al., 2007). The technique is widely used to analyze factors associated with differences in health outcomes or access to health care between groups or their evolution between different points in time (e.g., Brydsten et al., 2018; Brzezinski, 2019).

Assuming that the probability of being depressed or being untreated (conditional on being depressed) can be explained through linear models as the one described above, separable in observable and unobservable characteristics, letting D_B be a binary variable that indicates belonging to group B (for example, having been surveyed in 2019 or self-identifying as black or brown/mixed), and taking the expectations over X, the mean difference between individuals belonging to group B and individuals belonging to another group A (for example, having been surveyed in 2013 or self-identifying as white) can be expressed as:

$$\begin{aligned}\Delta_{\overline{H}} &= E[H_B|D_B = 1] - E[H_A|D_B = 0] \\ &= E[X|D_B = 1]\beta_B - E[X|D_B = 0]\,\beta_A\end{aligned}$$

To perform a decomposition, a counterfactual is needed. It is possible to adopt the prevalence of depression or the depression treatment gap that would have been observed in the sample of individuals belonging to group B if the coefficients linking individual characteristics to those variables would have been equal to the coefficients in the sample of individuals belonging to group A –i.e., $[X|D_B = 1]\beta_A$. For example, when performing a decomposition to analyze the drivers of the evolution of the prevalence of depression, the prevalence of depression that would have been observed in the sample surveyed in 2019 if the coefficients linking individual characteristics to depression had remained unchanged can be used as a counterfactual. Adding and subtracting that counterfactual and replacing the expected values of the covariates by the sample averages $\overline{X}_g$, the decomposition can be estimated as:

$$\Delta_{\overline{H}} = \overline{X}_B\left(\widehat{\beta_B} - \widehat{\beta_A}\right) + \left(\overline{X}_B - \overline{X}_A\right)\widehat{\beta_A} = \Delta^{U}_{\overline{H}} + \Delta^{E}_{\overline{H}}$$

The first term in the decomposition equation, $\Delta^{U}_{\overline{H}}$, is the "unexplained" (also: coefficient, discrimination, or price effect) part of the difference in the mean. The second term, $\Delta^{E}_{\overline{H}}$, is the "explained" (also: endowments, composition, or quantity effect) part of the difference. So, the Oaxaca-Blinder decomposition allows us to analyze which part of the differences in the prevalence of depression and the depression treatment gap is linked to mean characteristics of individuals according to group belonging –for example, differences in observable characteristics between 2013 and 2019– and what part is attributable to differences in the coefficients that link those characteristics to depression prevalence and the depression treatment gap. Additionally, it is possible to compute the detailed decomposition to estimate the contribution of the k^{th} covariate to the explained and unexplained component:

$$\Delta_{\overline{H}}^{U} = \left(\widehat{\beta_{B;0}} - \widehat{\beta_{A;0}}\right) + \sum_{k=1}^{M} \overline{X}_{B;k}\left(\widehat{\beta_{B;k}} - \widehat{\beta_{A;k}}\right)$$

$$\Delta_{\overline{H}}^{E} = \sum_{k=1}^{M} \left(\overline{X}_{B;k} - \overline{X}_{A;k}\right)\widehat{\beta_{A;k}}$$

We first estimated decompositions of this kind to analyze the factors associated with the evolution of the prevalence of depression and the treatment gap for depression between 2013 and 2019 using the coefficients obtained from the regressions described above.

Additionally, restricting the analysis to 2019 data and individuals self-identified as white, black or mixed/brown, we estimated Oaxaca-Blinder decompositions of racial differences in the treatment gap for depression between white individuals (group A) and mixed/brown or black individuals (group B). Mixed/brown and black individuals were grouped as is common practice when analyzing racial inequalities in Brazil (IBGE, 2019). For the analysis of racial differences, linear probability models were estimated as described above, but with two differences: the household income per capita quintile was used as the income variable and a variable indicating if the individual had suffered any violent episode in the previous 12 months was added.

The inclusion of categorical covariates with more than two categories (for example, region of residence or educational level in our analysis) generates challenges for the interpretation of individual contributions to the "explained" and "unexplained" parts of the composition. For the "explained" part, the contribution of each individual category varies with the choice of the omitted group, but the contribution of the categorical variable as a whole remains unchanged. However, for the unexplained part, changing the base category for categorical variables not only alters the results for the single binary variable associated with each non-omitted category but also changes the contribution of the categorical variable as a whole. This is because it is not possible to distinguish the part of the decomposition attributed to group membership (i.e., the difference in intercepts: $\widehat{\beta_{B;0}} - \widehat{\beta_{A;0}}$) from the part generated for differences in the coefficient of the omitted or base category. While normalization methods to solve this problem have been proposed, they make the result for each category not readily interpretable because there is no clear reference group (Fortin et al., 2011). We therefore decided not to apply those normalization methods and restrict our analysis of detailed contributions of each factor to the explained part of the decomposition.

2.3.3. The Concentration Index and its decomposition

Understanding inequalities across the income distribution is also relevant for understanding socio-economic inequalities in mental health. To achieve that goal, we plotted the concentration curve for the prevalence of depression in 2019 and computed the associated Erreygers-corrected concentration index (Erreygers, 2009; Van Doorslaer & Van Ourti, 2011).

Concentration curves plot the cumulative percentage of a health variable (depression prevalence) against the cumulative percentage of the population ranked by living standards (household income per capita). The concentration index is a summary measure of the information depicted in a concentration curve that equals twice the area between the concentration curve and equality line. It can be computed as:

$$C(h) = \frac{1}{n}\sum_{i=1}^{n}\left[\left(\frac{h_i}{\overline{h}}\right)\left(2R_i^y - 1\right)\right]$$

Where $C(h)$ is the concentration index of variable h (depression or depression treatment gap), h_i is the value of h for individual i, $\overline{h}$ is the mean of h in the sample, n is the sample size, and $R_i^y = n^{-1}(i - 0.5)$ is the fractional rank of individual i ordering the sample according to family income per capita (y) from the lowest to the highest value. The concentration index is a relative inequality measure, and it is possible to show that $0.75 \times C(h)$ equals the proportion of total health that should be redistributed from the richest half to the poorest part of the population to reduce $C(h)$ to 0 (perfect equality). The generalized concentration index is an analogous measure used to measure absolute inequality, and it is defined as $GC(h) = \overline{h} \times C(h)$.

For unbounded ratio-scale variables, the bounds of $C(h)$ are $n^{-1}(1-n)$ and $n^{-1}(n-1)$. So, for sufficiently large samples, $C(h)$ lies between -1 and 1. Negative values signal higher concentrations of variable h in the poorest half of the population and positive values in the richest half. If h is a bounded variable, the bounds of the concentration index depend on its mean ($\overline{h}$) (Erreygers, 2009; Kjellsson & Gerdtham, 2013). We therefore used a corrected version of the concentration index proposed by Erreygers (2009), which solves this problem. The Erreygers-corrected concentration index can be computed as:

$$E(h) = \left(\frac{4\overline{h}}{h_{max} - h_{min}}\right) C(h)$$

It is possible to decompose the concentration index to measure the contribution of individual factors to income-related inequalities in health (Van Doorslaer & Van Ourti, 2011). Supposing a linear model of the following form linking the health variable h (depression or the depression treatment gap) to observed contributing factors:

$$\frac{\mathrm{h_i} - \mathrm{h_{min}}}{\mathrm{h_{max}} - \mathrm{h_{min}}} = \beta_0 + \sum_{j=1}^{K} \beta_j x_{ji} + e_i$$

The Erreygers-corrected concentration index can be written as:

$$E(h) = 4\left[\sum_{j=1}^{K} \beta_j GC(x_j) + GC(e_i)\right]$$

Thus, the contribution of each factor x_j is given by the product of the sensitivity of heath with respect to that factor, β_j, and the degree of income-related inequality in the distribution of that factor $GC(x_j) = \overline{x_j} \times C(x_j)$. We used this decomposition technique to assess the factors contributing to socio-economic inequalities in the prevalence of depression in 2019. Covariates x_j included were the same ones used in the regression analysis described above, but with two differences: household income per capita quintile was used as the income variable and the variable indicating if the individual had suffered any violent episode in the previous 12 months was added. All coefficients β_j were estimated using a Linear Probability Model.

3. Results

3.1. Descriptive and regression analysis

Table 1 shows the mean for all variables used in the analysis of the evolution of depression prevalence and the treatment gap for depression, as well as the difference between 2013 and 2019. Results show that the prevalence of depression among the population aged 18 or older increased 2.9 percentage points (p.p.), from 7.9% (95%CI: 7.5%-8.3%) in 2013 to 10.8% (95%CI: 10.4%-11.2%) in 2019. The treatment gap –i.e., the share of individuals with depression that do not receive any treatment– decreased from 76.1% (95%CI: 74% - 78.1%) to 71.2% (95%CI: 69.5%-72.8%).

Table 1 – Summary statistics

Variable	2013 (n = 60,188)		2019 (n = 88,500)	
	Mean	95%CI	Mean	95%CI
Depression	0.079	0.075 - 0.083	0.108	0.104 - 0.112
Treatment gap	0.761	0.740 - 0.781	0.712	0.695 - 0.728
Female	0.529	0.529 - 0.529	0.532	0.532 - 0.532
Age				
18-24	0.159	0.159 - 0.159	0.139	0.139 - 0.139
25-34	0.217	0.213 - 0.220	0.181	0.178 - 0.184
35-44	0.192	0.187 - 0.197	0.202	0.198 - 0.207
45-54	0.175	0.171 - 0.179	0.178	0.175 - 0.182
55-64	0.134	0.130 - 0.139	0.150	0.147 - 0.154
65 or older	0.123	0.120 - 0.126	0.149	0.147 - 0.151
Race				
White	0.476	0.468 - 0.483	0.433	0.426 - 0.440
Black	0.091	0.087 - 0.096	0.115	0.111 - 0.119
Asian	0.009	0.008 - 0.011	0.009	0.008 - 0.010
Browns/Mixed	0.420	0.412 - 0.427	0.438	0.431 - 0.445
Indigenous	0.004	0.003 - 0.005	0.005	0.004 - 0.006
Education				
None	0.137	0.132 - 0.142	0.061	0.058 - 0.064
Basic incomplete	0.253	0.246 - 0.260	0.287	0.281 - 0.293
Basic complete	0.099	0.095 - 0.104	0.078	0.075 - 0.081
Secondary incomplete	0.056	0.053 - 0.059	0.067	0.064 - 0.070
Secondary complete	0.281	0.275 - 0.287	0.298	0.292 - 0.304
Higher incomplete	0.047	0.044 - 0.050	0.051	0.048 - 0.054
Higher complete	0.127	0.120 - 0.134	0.158	0.152 - 0.165
Urban	0.862	0.858 - 0.866	0.862	0.858 - 0.865
Region				
North	0.075	0.075 - 0.075	0.078	0.078 - 0.078
North-East	0.265	0.265 - 0.265	0.265	0.265 - 0.265
South-East	0.439	0.439 - 0.439	0.434	0.434 - 0.434
South	0.148	0.148 - 0.148	0.147	0.147 - 0.147
Center-West	0.074	0.074 - 0.074	0.076	0.076 - 0.076
Slum proxy	0.188	0.179 - 0.197	0.151	0.145 - 0.158
Internet	0.489	0.481 - 0.498	0.846	0.842 - 0.850
Employment status				
Inactive	0.351	0.345 - 0.357	0.335	0.330 - 0.340
Unemployed	0.034	0.032 - 0.037	0.053	0.050 - 0.056
Employed	0.615	0.608 - 0.621	0.613	0.607 - 0.618
Log family income per capita (R$ 2019)	6.857	6.836 - 6.879	6.836	6.818 - 6.854
Support of family and/or friends	0.935	0.931 - 0.939	0.981	0.980 - 0.983
Lives with				
Alone	0.067	0.064 - 0.069	0.075	0.073 - 0.077
Partner	0.613	0.606 - 0.619	0.614	0.609 - 0.619
Other person	0.320	0.314 - 0.327	0.311	0.306 - 0.316
Participation in group, social and/or community activities				
Never	0.224	0.218 - 0.231	0.167	0.163 - 0.172
Less than monthly	0.198	0.192 - 0.204	0.189	0.184 - 0.194
At least once per month	0.577	0.569 - 0.585	0.644	0.638 - 0.650
Health insurance	0.302	0.293 - 0.310	0.296	0.289 - 0.304
Registered with Family Health Team				
No / Does not know	0.455	0.443 - 0.468	0.385	0.374 - 0.396
Yes, and no home visits in last 12 months	0.096	0.090 - 0.103	0.144	0.138 - 0.150
Yes, and at least one home visit in last 12 months	0.448	0.436 - 0.461	0.471	0.461 - 0.481
Diagnosis of non-mental NCD	0.486	0.479 - 0.494	0.544	0.538 - 0.550
Tobacco	0.146	0.142 - 0.151	0.126	0.122 - 0.130
Physical activity				
No	0.685	0.677 - 0.692	0.580	0.573 - 0.586
Yes, less than weekly	0.011	0.009 - 0.012	0.015	0.014 - 0.017
Yes, once or twice a week	0.117	0.112 - 0.122	0.147	0.142 - 0.151
Yes, three or more times per week	0.187	0.181 - 0.193	0.258	0.252 - 0.264
Alcohol				
Never	0.596	0.589 - 0.604	0.578	0.572 - 0.584
Yes, less than weekly	0.164	0.159 - 0.170	0.158	0.154 - 0.162

Yes, once a week	0.108	0.104 - 0.113	0.118	0.114 - 0.122
Yes, twice or more per week	0.131	0.126 - 0.136	0.146	0.142 - 0.150

Note: the table shows means and 95% confidence intervals for all variables used in the decomposition analysis of the evolution of the prevalence of depression and the treatment gap for depression.

Looking at socio-demographic characteristics, it is possible to see that the Brazilian population got older and more educated. The pattern of racial self-identification also changed –the share of individuals self-identified as white decreased 4.3 p.p., while the share of individuals self-identified as black and brown/mixed increased 2.4 p.p. and 1.8 p.p., respectively.

Socio-economic and housing conditions also presented relevant trends between the two years of analysis. Notably, family income per capita remained stagnant and the share of the adult population that was unemployed increased from 3.4% (95%CI: 3.2%-3.7%) in 2013 to 5.3% (95%CI: 5%-5.6%) in 2019. However, there was a decrease in the share of individuals living under deficient housing conditions and an increase in the share of individuals with access to internet connections.

Variables related with social support also presented relevant changes. The share of individuals that declare that can count with any family member or friend increased from 93.5% (95%CI: 93.1%-93.9%) to 98.1% (95%CI: 98%-98.3%) and the share of individuals that participate in group, social and/or community activities at least once per month increased from 57.7% (95%CI: 56.9%-58.5%) to 64.4% (63.8%-65%). There was also a significant increase in the share of individuals living alone, from 6.7% (95%CI: 6.4-6.9) to 7.5% (95%CI: 7.3-7.7).

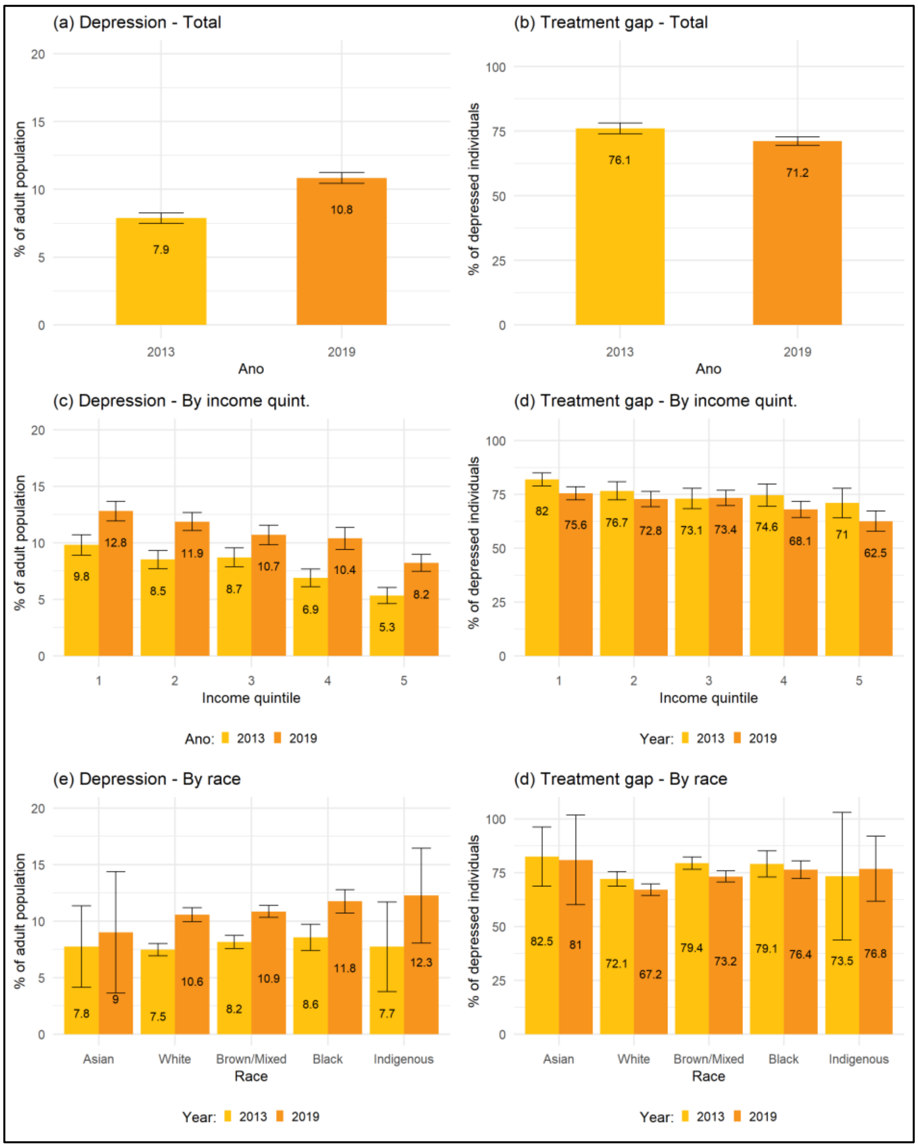
Looking at variables related with healthcare services, it is possible to see an expansion in the share of individuals registered with FHTs. There were no significant changes in the share of individuals that reported holding a private health insurance.

There were significant changes in most variables related with risk factors. The share of individuals with diagnosis of any non-mental NCD and alcohol consumption increased. However, the share of individuals that smoke tobacco products fell and physical activity increased –for example, the share of individuals that exercise at least three times per week increased from 18.7% (95%CI: 18.1%-19.3%) to 25.8% (25.2%-26.4%).

Figure 1 shows the evolution of depression prevalence and the treatment gap for depression between 2013 and 2019 for the whole population of individuals aged 18 or older, according to income quintile and according to race. It is worth noting that the trend of large increases in depression prevalence and less impressive reductions in the treatment gap between 2013 and 2019 can be seen for all quintiles of the income distribution (panels c and d) and for all three main race groups –brown/mixed, white, and black (panels e and f).

The socio-economic gradient in depression prevalence is more pronounced than the gradient in the treatment gap. For example, while the prevalence of depression was 56% higher among individuals in the lowest income quintile than among individuals in the highest income quintile in 2019 –12.8% (95%CI: 12%-13.7%) vs. 8.2% (95%CI: 7.5%-9%)–, the treatment gap was 20.8% higher –75.6% (95%CI: 72.6%-78.6%) vs. 62.5% (95%CI: 57.8%-67.3%). While there are not significant differences in depression prevalence according to racial self-identification, the treatment gap was smaller in 2019 for individuals self-identified as white –67.2% (95%CI: 64.5%-69.8%)– than for individuals self-identified as brown/mixed –73.2 (95%CI: 70.7-75.8)– or as blacks –76.4% (95%CI: 72.3%-80.5%).

Figure 1 – Prevalence of Depression and Treatment Gap, 2013 – 2019 (Total, by income quintile and by race)

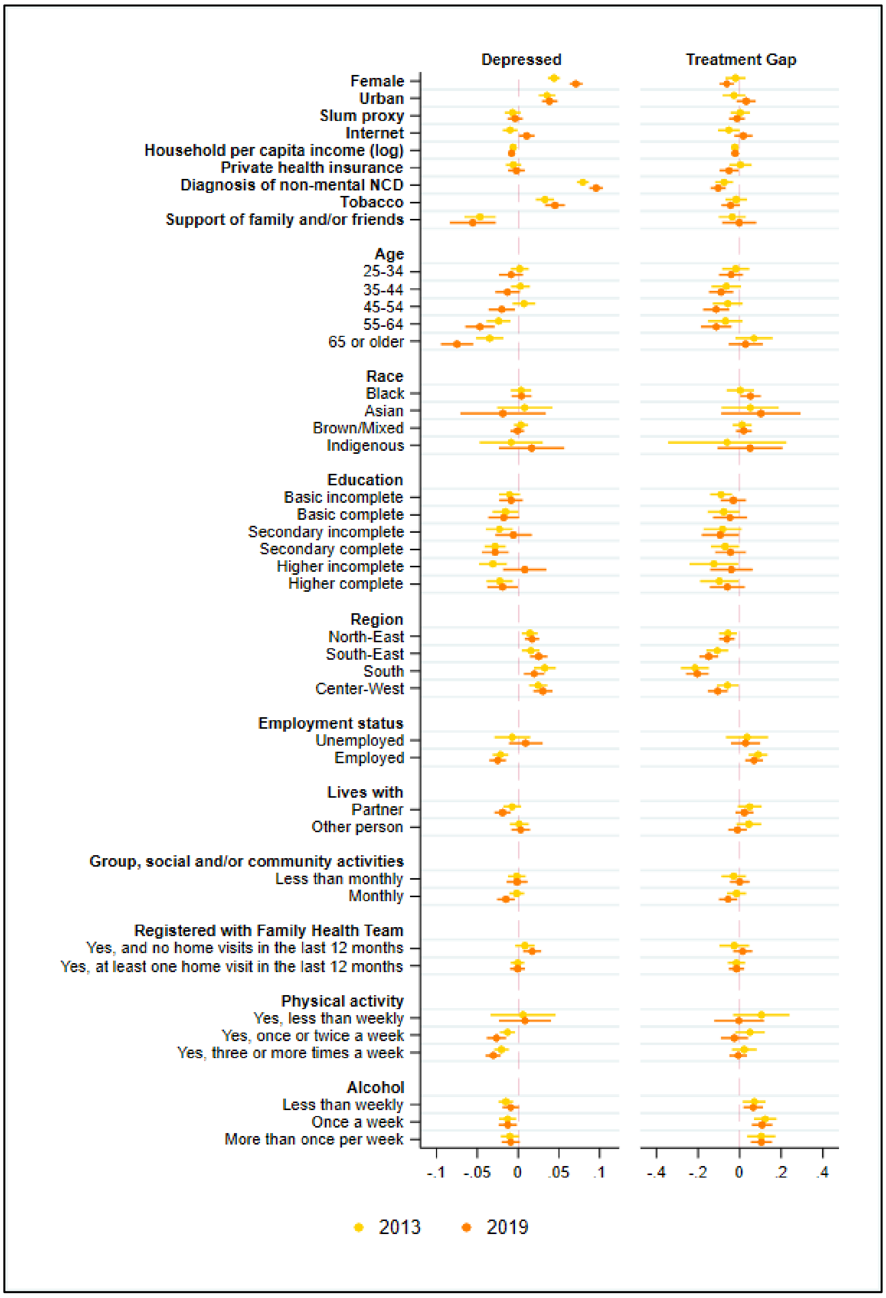


Note: the figure shows the evolution of the prevalence of depression (panel a) and the treatment gap for depression (panel b) in Brazil in 2013 and 2019. Panels c and d show the same results, but according to income quintile, and panels e and f according to racial self-identification. The error bars display the 95% confidence intervals.

Figure 2 shows the association between all covariates included in the analysis and the probability of being depressed and falling in the treatment gap –conditional on being depressed. Detailed coefficients are included in table A1 in the Appendix. Factors more strongly positively associated with the probability of being depressed in 2019 were being female –0.071 (95%CI: 0.063-0.079)–, having been diagnosed with any non-mental NCD –0.096 (95%CI: 0.087-0.104)–, living in an urban area –0.039 (95%CI: 0.029-0.048)–, and smoking tobacco –0.045 (95%CI: 0.033 - 0.057). It is worth noting that the coefficients for living in any region other than the North region are all positive and statistically significant. It is also worth noting that the coefficient associated with being female was significantly larger in magnitude in 2019 than in 2013. Factors with the largest negative association in 2019 were having support from family members and/or friends – -0.056 (95%CI: -084 - -0.028)– being between 55 and 65 years old – -0.047 (95%CI: -0.065 - -0.029)–, being 65 or older – -0.075 (95%CI: -0.095 -

-0.055)– and exercising once or twice – -0.027 (95%CI: -0.039 - -0.015)– or more – -0.031 (95%CI: -0.04 - -0.021)– per week.

Figure 2 – Linear probability model: depression and treatment gap for depression, 2013 and 2019



Note: the figure plots the coefficients from four independent linear probability models linking covariates with the probability of being depressed and of falling in the treatment gap –conditional on being depressed– in 2013 and in 2019. Full results are available in Table A1 in the Appendix.

Looking at the probability of falling in the treatment gap, region of residence is the most relevant factor: living in any region other than the North region is negatively associated with the probability of being untreated if depressed, being stronger for the South – -0.204 (95%CI: -0.259 - -0.149)– and South-

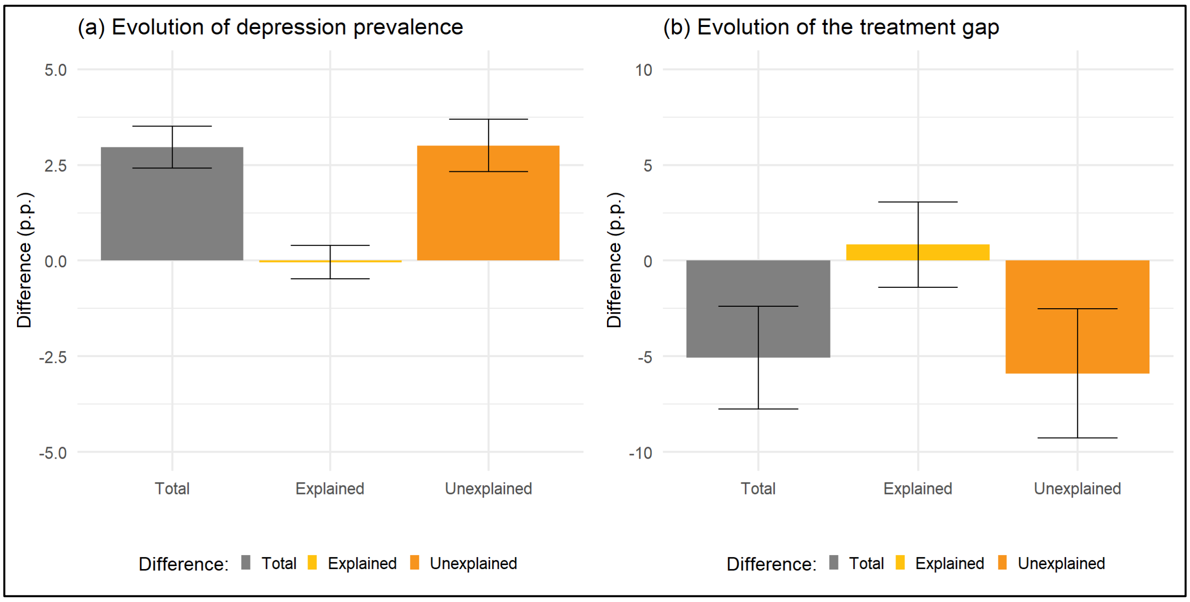
East – -0.148 (95%CI: -0.194 - -0.102)– regions. It is worth noting that the coefficients for any frequency of alcohol consumption are all positive and statistically significant for both years.

3.2. Decomposition analysis

3.2.1. Decomposition of evolution

Figure 3 shows the result of the Oaxaca Blinder decompositions of the evolution of the prevalence of depression and of the evolution of the treatment gap between 2013 and 2019. Results from the decomposition of the evolution of the prevalence of depression are depicted in panel a. They show that the large increase in the prevalence of depression between the two years was entirely driven by the unexplained part of the decomposition –i.e., changes in observable socio-demographical and socio-economic characteristics, social support, relationship with healthcare services and risk factors were not the drivers of the increase in the share of the population showing symptoms compatible with depression. Changes in the mean values of covariates between the two years also fail to account for the decrease in the treatment gap. Detailed results from the decomposition exercise are shown in Table A2 in the Appendix.

Figure 3 – Oaxaca-Blinder decomposition for the evolution of the prevalence of depression and the treatment gap for depression (2013 – 2019)

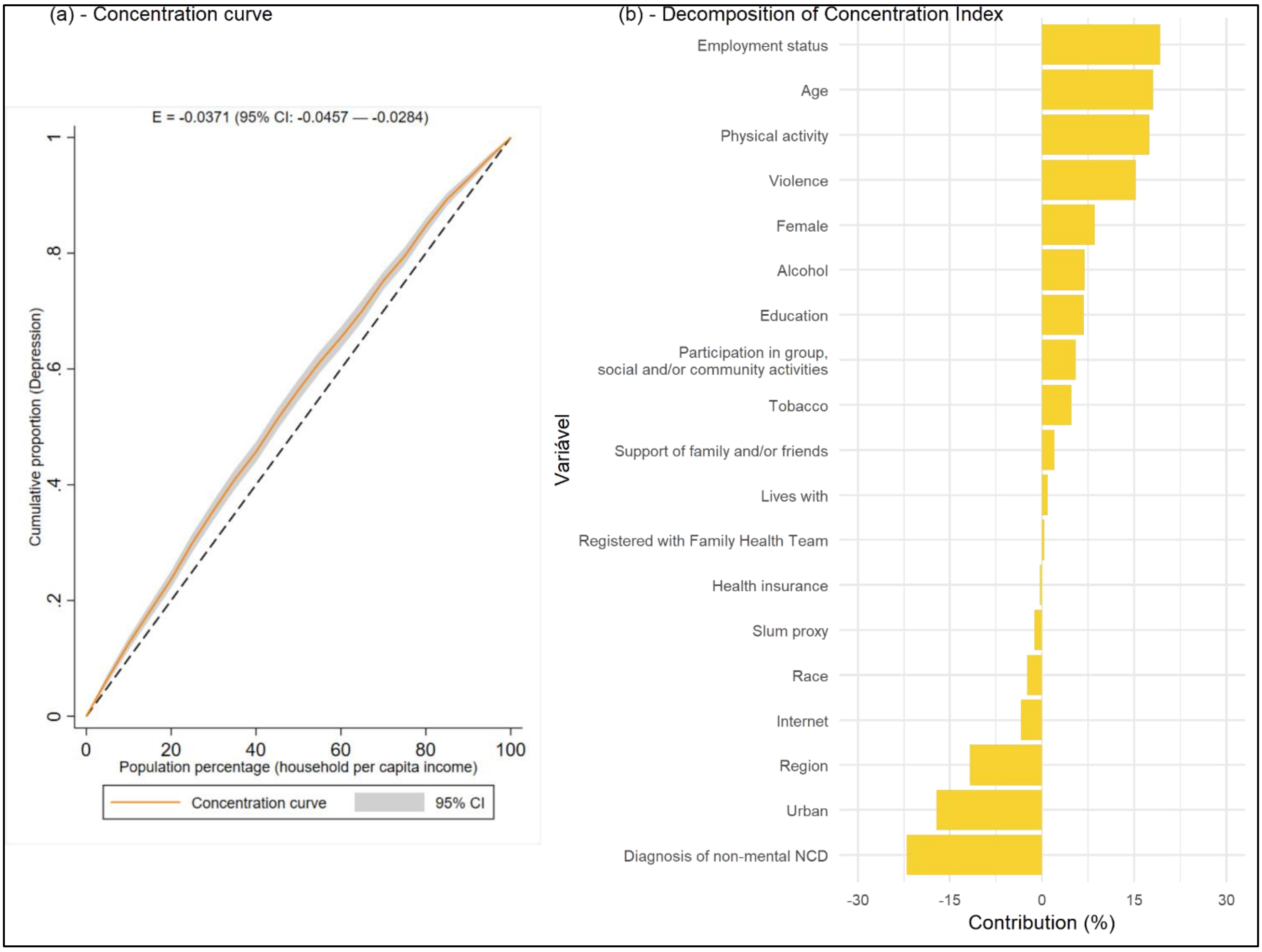


Note: the figure shows results from Oaxaca-Blinder decompositions of the evolution of the prevalence of depression (panel a) and of the treatment gap for depression (panel b) between 2013 and 2019. Error bars display de 95% confidence interval. Full results from the decomposition are shown in Table A2 in the Appendix. For the analysis of the treatment gap, sampling strata without depressed individuals were dropped from regressions and therefore the mean is slightly different from the mean for the whole sample presented in Figure 1.

3.2.2. Decomposition of socioeconomic inequalities in depression prevalence

While socio-economic gradient in the prevalence of depression was already shown in panel c of Figure 1, it is also relevant to assess socio-economic inequalities across the full distribution of household income per capita. Figure 4 (panel a) shows the concentration curve for depression prevalence in 2019 and the associated Erreygers-corrected concentration index (E). The curve lies completely above the 45º line and the concentration index is negative – -0.0371 (95%CI: 0.0457 - -0.0284)–, pointing to depression being more prevalent among the poorer.

Figure 4 – Concentration Curve and decomposition of the Erreygers-corrected concentration index for Depression



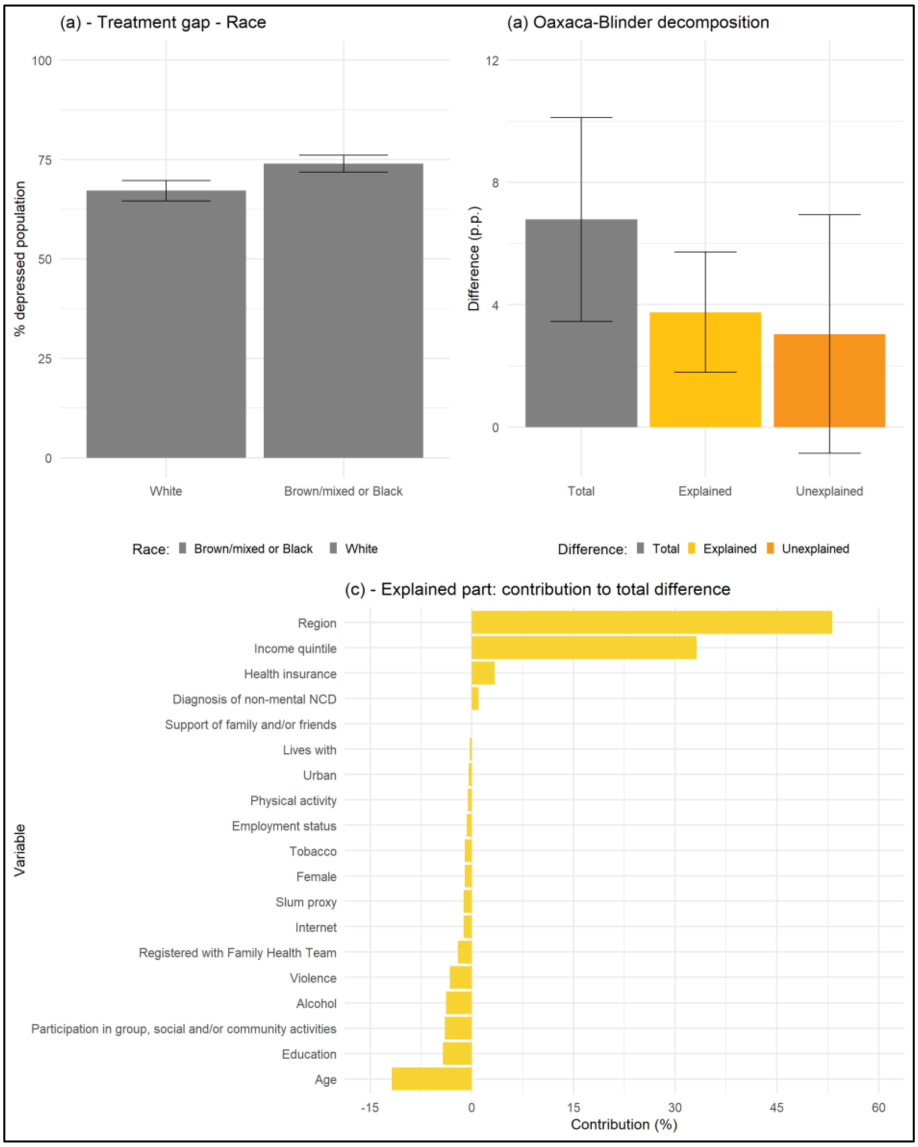
Note: the figure shows the concentration curve and the Erreygers-corrected concentration index for the prevalence of depression in 2019 (panel a) and results from the decomposition of the concentration index (panel b). A variable indicating income quintile according to per capita household income was included in the analysis but results were excluded from the plot in panel b. Full results are available in Table A3 in the Appendix.

Panel b of figure 4 shows the results of the decomposition of the concentration index. Main contributors to socio-economic inequalities in the prevalence of depression are employment status (differences in employment status account for 19.2% of socioeconomic inequalities in depression), age (18.1%), exposure to violent episodes (15.3%) and physical activity (17.5%). These are factors that are either negatively associated with the probabilities of being depressed and more concentrated among the richer –like doing physical activity or being older– or positively associated with the probabilities of being depressed and more concentrated among the poor –like exposure to violence. It is also worth noting that there are factors whose contribution goes in the opposite direction. Living in an urban area (-17.2%) and having been diagnosed with any non-mental NCD (-22%) are factors that are positively associated with the probabilities of being depressed and have a pro-rich distribution and, therefore, diminish socio-economic inequalities in the prevalence of depression.

3.2.3. Decomposition of racial inequalities in the treatment gap for depression

Figure 5 shows the results of the Oaxaca-Blinder decomposition of differences in the treatment gap between white individuals and brown/mixed or black individuals. Detailed results are in Table A4 in the Appendix. Differences in observable characteristics between the two groups account for 55.4% of the total difference in the treatment gap. The most relevant driver of racial differences in the treatment gap are differences in the region of residence, which explain 53.2% of observed differences between the two groups, and income quintile, which explains 33.1% of the total differences.

Figure 5 – Oaxaca-Blinder decomposition for differences in the treatment gap for depression according to race



Note: the figure shows the treatment gap for depression according to racial self-identification for White and Brown/mixed or Black individuals (panel a). Additionally, it shows results from an Oaxaca-Blinder decomposition of the differences in the treatment gap for depression between the two groups (panel b). Error bars display 95% confidence intervals. The percentual contribution of the explained part of each contributing factor to the total difference are displayed in panel c –for covariates with more than one category, the bars display the sum of the percentual contribution of all categories. Detailed results are shown in Table A4 in the Appendix.

4. Discussion

This study found that between 2013 and 2019, there was a large increase in the prevalence of depression in Brazil and a more modest decrease in the treatment gap, which remains large. Prevalence of depression increased over 36%, reaching over 10% of the adult population in 2019. At the same time, the treatment gap fell 6.9% and still affected over seven out of ten depressed individuals in 2019. These results are in line with past results showing that providing care for mental disorders in Brazil have been a long-lasting challenge. A study with data from the city of São Paulo between 1994 and 1996, estimated that 49.4% of individuals with major depression did not receive any kind of treatment (Kohn et al., 2004). Another study, also using data from São Paulo but between 2005 and 2007, estimated that 78.1% of individuals with any mental disorder did not receive any kind of treatment. That same study, which also included data from Argentina, Canada, Chile, Colombia, Guatemala, Mexico, Peru, and the United States, showed that the mean treatment gap for any mental disorder was above 71%, and no smaller than 58% in any country (Kohn et al., 2018).

Results showed that being female, having previous diagnosis of other NCDs and living in urban areas are positively associated with depression, as had been previously shown in other studies from Brazil (Lopes et al., 2016; Stopa et al., 2015). They also show that region of residence is a key determinant for the probabilities of falling in the treatment gap, which is also in line with previous results (Lopes et al., 2016). Decomposition analysis showed that changes in observable characteristics could not account for the increase in the prevalence of depression and the decline in the treatment gap.

Our results also show that there are socioeconomic inequalities in depression prevalence and the treatment gap, but they are more pronounced for the former. In 2019, the prevalence of depression was 56% higher among individuals in the lowest income quintile than among individuals in the highest income quintile. Those inequalities also exist when looking at the whole income distribution and manifest themselves in a negative concentration index –i.e., depression is more prevalent among the poorer. Results from decomposition analysis showed that employment status, age, exposure to violent episodes and frequency of physical activity are the main contributing factors to socio-economic inequalities in the prevalence of depression.

Results showed that neither depression prevalence nor the probabilities of being depressed conditional on a large set of covariates changed with racial self-identification. However, differences in the size of the treatment gap between white and brown/mixed or black individuals were significant. These results contradict previous results showing higher prevalence or increased odds of depression among non-whites than among white individuals (Smolen & Araújo, 2017) and are in line with previous results showing higher probabilities of treatment for depressed white individuals than for depressed non-white individuals (Faisal-Cury et al., 2021; Lopes et al., 2016). Results from decomposition analysis show that the largest contributing factor to racial differences in the treatment gap is the region of residence, and that income quintile is also a relevant contributor.

Overall, results show the growing relevance of depression as a population health issue in Brazil and the persistent necessity of increasing access to mental health care services to bridge the treatment gap. The fact that changes in observable factors between 2013 and 2019 do not account for the large increase in the prevalence of depression is somewhat surprising, considering the large number of covariates included in our analysis. It is probable that aggregate shocks that affected the whole population are behind this trend, but further studies are needed to identify what are the driving factors.

Some of the factors driving socioeconomic differences in the prevalence of depression, like exposure to violence and physical activity, show that economic inequalities and higher exposure to risk factors can be intertwined. Policies aimed at improving the levels of exposure of lower-income individuals to risk factors –for example, promoting physical activity and diminishing exposure to different kinds of violent episodes– might have a positive impact on mental health and mental health inequalities.

The relevance of region of residence as a determinant of the treatment gap and observed racial inequalities related to it points to the necessity of further looking at the distribution of mental health care services and professionals across Brazilian regions. For example, in the South region –where 72.4% of individuals in our sample self-identified as white– there were 48 psychologists and psychiatrists per 100,000 residents in 2019. In the South-East region –where 50.6% of individuals in our sample self-identified as white– there were 55.3 psychologists and psychiatrists per 100,000 residents in 2019. In the North and North-East regions –where only 18.5% and 24.6% of individuals self-identified as white, respectively– there were only 17.6 and 24.8 psychologists and psychiatrists per 100,000 residents in 2019, respectively (Ministry of Health, 2021). Increasing the supply of mental health services and professionals in those regions could possibly reduce the treatment gap and related inequalities. In the short term, a feasible alternative which has been proven to provide positive results in other contexts (Baranov et al., 2020; Patel et al., 2018) could be to train community health workers, which are largely available and geographically more evenly distributed in Brazil than other professionals, to deliver psychosocial interventions.

This study used a large, recent, and nationally representative survey to assess the evolution of depression prevalence and the treatment gap for depression, as well as socioeconomic and racial inequalities related to them. A major strength of the study was the use of the PHQ-9 as a screening tool, which made it feasible to compute the true prevalence of depression, independent of medical diagnosis (Kroenke et al., 2001; Levis et al., 2019; Santos et al., 2013). However, there are limitations to the study. First, the nature of the study does not make it possible to make causal statements about the relationship between contributing factors and the evolution of depression prevalence and the treatment gap. It is also not possible to make causal statements about the relationship between contributing factors and socioeconomic and racial inequalities in depression and the treatment gap. Second, while the PHQ-9 is a widely used instrument and it has shown to have high sensitivity and specificity in Brazil (Santos et al., 2013), it does not provide a clinical diagnosis of depression. Finally, changes in the definition of variables and of response categories made it impossible to include exposure to violence as a covariate in the decomposition analysis of the evolution of the prevalence of depression. As it is a factor strongly correlated with the probabilities of being depressed, the large unexplained component in the analysis of the evolution might be related to its omission.

In spite of those limitations, this study provides a comprehensive picture of the challenges related to the growing prevalence of depression, the large size of the treatment gap and related socioeconomic and racial inequalities. Results point to the necessity of further studies to understand the drivers behind large increases in the prevalence of depression. In relation to inequalities, the study points to the necessity of investing in policies that diminish the exposure of the poorer to risk factors like physical inactivity and violence and of increasing the supply of mental health care in underserved regions.

5. References

Athié, K., Menezes, A. L. do A., da Silva, A. M., Campos, M., Delgado, P. G., Fortes, S., & Dowrick, C. (2016). Perceptions of health managers and professionals about mental health and primary care integration in Rio de Janeiro: A mixed methods study. *BMC Health Services Research*, *16*(1), 532. https://doi.org/10.1186/s12913-016-1740-8

Baranov, V., Bhalotra, S., Biroli, P., & Maselko, J. (2020). Maternal Depression, Women's Empowerment, and Parental Investment: Evidence from a Randomized Controlled Trial. *American Economic Review*, *110*(3), 824–859. https://doi.org/10.1257/aer.20180511

Barbosa, E. C., & Cookson, R. (2019). Multiple inequity in health care: An example from Brazil. *Social Science & Medicine*, *228*, 1–8. https://doi.org/10.1016/j.socscimed.2019.02.034

Bastos, M. L., Menzies, D., Hone, T., Dehghani, K., & Trajman, A. (2017). The impact of the Brazilian family health on selected primary care sensitive conditions: A systematic review. *PLOS ONE*, *12*(8), e0182336. https://doi.org/10.1371/journal.pone.0182336

Bhalotra, S., Rocha, R., & Soares, R. R. (2020). Does Universalization of Health Work? Evidencefrom Health Systems Restructuring and Maternal and Child Health in Brazil. *IEPS Working Paper Series*.

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, *8*(4), 436. https://doi.org/10.2307/144855

Boing, A. C., Bertoldi, A. D., Barros, A. J. D. de, Posenato, L. G., & Peres, K. G. (2014). Socioeconomic inequality in catastrophic health expenditure in Brazil. *Revista de Saúde Pública*, *48*(4), 632–641. https://doi.org/10.1590/S0034-8910.2014048005111

Brydsten, A., Hammarström, A., & San Sebastian, M. (2018). Health inequalities between employed and unemployed in northern Sweden: A decomposition analysis of social determinants for mental health. *International Journal for Equity in Health*, *17*(1), 59. https://doi.org/10.1186/s12939-018-0773-5

Brzezinski, M. (2019). What accounts for the rise of low self-rated health during the recent economic crisis in Europe? *International Journal for Equity in Health*, *18*(1), 21. https://doi.org/10.1186/s12939-019-0926-1

Castro, M. C., Massuda, A., Almeida, G., Menezes-Filho, N. A., Andrade, M. V., de Souza Noronha, K. V. M., Rocha, R., Macinko, J., Hone, T., Tasca, R., Giovanella, L., Malik, A. M., Werneck, H., Fachini, L. A., & Atun, R. (2019). Brazil's unified health system: The first 30 years and prospects for the future. *The Lancet*, *394*(10195), 345–356. https://doi.org/10.1016/S0140-6736(19)31243-7

Erreygers, G. (2009). Correcting the concentration index. *Journal of Health Economics*, *28*(2), 504–515. https://doi.org/10.1016/j.jhealeco.2008.02.003

Esponda, G. M., Hartman, S., Qureshi, O., Sadler, E., Cohen, A., & Kakuma, R. (2020). Barriers and facilitators of mental health programmes in primary care in low-income and middle-income countries. *The Lancet Psychiatry*, *7*(1), 78–92. https://doi.org/10.1016/S2215-0366(19)30125-7

Evans-Lacko, S., Aguilar-Gaxiola, S., Al-Hamzawi, A., Alonso, J., Benjet, C., Bruffaerts, R., Chiu, W. T., Florescu, S., de Girolamo, G., Gureje, O., Haro, J. M., He, Y., Hu, C., Karam, E. G., Kawakami, N., Lee, S., Lund, C., Kovess-Masfety, V., Levinson, D., … Thornicroft, G. (2018). Socio-economic variations in the mental health treatment gap for people with anxiety, mood, and substance use disorders: Results from the WHO World Mental Health (WMH) surveys. *Psychological Medicine*, *48*(9), 1560–1571. https://doi.org/10.1017/S0033291717003336

Faisal-Cury, A., Rodrigues, D. M. O., & Matijasevich, A. (2021). Are pregnant women at higher risk of depression underdiagnosis? *Journal of Affective Disorders*, *283*, 192–197. https://doi.org/10.1016/j.jad.2021.01.057

Fortin, N., Firpo, S., & Lemieux, T. (2011). Decomposition Methods in Economics. In O. Ashenfelter & D. E. Card (Orgs.), *Handbook of labor economics. Vol. 4A: ...* (1. ed). North-Holland.

França, G. V. A., Restrepo-Méndez, M. C., Maia, M. F. S., Victora, C. G., & Barros, A. J. D. (2016). Coverage and equity in reproductive and maternal health interventions in Brazil: Impressive progress following the implementation of the Unified Health System. *International Journal for Equity in Health*, *15*(1), 149. https://doi.org/10.1186/s12939-016-0445-2

Garcia, L. P., & Santana, L. R. (2011). Evolução das desigualdades socioeconômicas na mortalidade infantil no Brasil, 1993-2008. *Ciência & Saúde Coletiva*, *16*(9), 3717–3728.

Hone, T., Mirelman, A. J., Rasella, D., Paes-Sousa, R., Barreto, M. L., Rocha, R., & Millett, C. (2019). Effect of economic recession and impact of health and social protection expenditures on adult mortality: A longitudinal analysis of 5565 Brazilian municipalities. *The Lancet Global Health*, *7*(11), e1575–e1583. https://doi.org/10.1016/S2214-109X(19)30409-7

Hone, T., Rasella, D., Barreto, M. L., Majeed, A., & Millett, C. (2017). Association between expansion of primary healthcare and racial inequalities in mortality amenable to primary care in Brazil: A national longitudinal analysis. *PLOS Medicine*, *14*(5), e1002306. https://doi.org/10.1371/journal.pmed.1002306

Hone, T., Saraceni, V., Medina Coeli, C., Trajman, A., Rasella, D., Millett, C., & Durovni, B. (2020). Primary healthcare expansion and mortality in Brazil's urban poor: A cohort analysis of 1.2 million adults. *PLOS Medicine*, *17*(10), e1003357. https://doi.org/10.1371/journal.pmed.1003357

Hone, T., Stokes, J., Trajman, A., Saraceni, V., Coeli, C. M., Rasella, D., Durovni, B., & Millett, C. (2021). Racial and socioeconomic disparities in multimorbidity and associated healthcare utilisation and outcomes in Brazil: A cross-sectional analysis of three million individuals. *BMC Public Health*, *21*(1), 1287. https://doi.org/10.1186/s12889-021-11328-0

IBGE, I. B. de G. e E. (2014). *Pesquisa nacional de saúde, 2013: Percepção do estado de saúde, estilos de vida e doenças crônicas: Brasil, grandes regiões e unidades da Federação*. Instituto Brasileiro de Geografia e Estatística - IBGE.

IBGE, I. B. de G. e E. (2019). *Desigualdades Sociais por Cor ou Raça no Brasil* (Nº 41; Estudos e Pesquisas - Informação Demográfi e Socioeconômica). https://biblioteca.ibge.gov.br/visualizacao/livros/liv101681_informativo.pdf

IBGE, I. B. de G. e E. (2020). *Pesquisa nacional de saúde, 2019: Percepção do estado de saúde, estilos de vida, doenças crônicas e saúde bucal*. Instituto Brasileiro de Geografia e Estatística - IBGE.

IHME, I. for H. M. and E. (2021). *Global Burden of Disease Results Tool*. http://ghdx.healthdata.org/gbd-results-tool

Kjellsson, G., & Gerdtham, U.-G. (2013). On correcting the concentration index for binary variables. *Journal of Health Economics*, *32*(3), 659–670. https://doi.org/10.1016/j.jhealeco.2012.10.012

Kohn, R., Ali, A. A., Puac-Polanco, V., Figueroa, C., López-Soto, V., Morgan, K., Saldivia, S., & Vicente, B. (2018). Mental health in the Americas: An overview of the treatment gap. *Revista Panamericana De Salud Publica = Pan American Journal of Public Health*, *42*, e165. https://doi.org/10.26633/RPSP.2018.165

Kohn, R., Saxena, S., Levav, I., & Saraceno, B. (2004). The treatment gap in mental health care. *Bulletin of the World Health Organization*, *82*(11), 858–866. https://doi.org//S0042-96862004001100011

Kroenke, K., Spitzer, R. L., & Williams, J. B. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Levis, B., Benedetti, A., & Thombs, B. D. (2019). Accuracy of Patient Health Questionnaire-9 (PHQ-9) for screening to detect major depression: Individual participant data meta-analysis. *BMJ*, l1476. https://doi.org/10.1136/bmj.l1476

Lopes, C. S., Hellwig, N., e Silva, G. de A., & Menezes, P. R. (2016). Inequities in access to depression treatment: Results of the Brazilian National Health Survey – PNS. *International Journal for Equity in Health*, *15*(1), 154. https://doi.org/10.1186/s12939-016-0446-1

Ministry of Health. (2021). *TABNET - DATASUS*. https://datasus.saude.gov.br/informacoes-de-saude-tabnet/

Mullachery, P., Silver, D., & Macinko, J. (2016). Changes in health care inequity in Brazil between 2008 and 2013. *International Journal for Equity in Health*, *15*(1), 140. https://doi.org/10.1186/s12939-016-0431-8

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, *14*(3), 693. https://doi.org/10.2307/2525981

O'Donnell, O., van Doorslaer, E., Wagstaff, A., & Lindelow, M. (2007). *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and their Implementation*. The World Bank. https://doi.org/10.1596/978-0-8213-6933-3

Paim, J., Travassos, C., Almeida, C., Bahia, L., & Macinko, J. (2011). The Brazilian health system: History, advances, and challenges. *The Lancet*, *377*(9779), 1778–1797. https://doi.org/10.1016/S0140-6736(11)60054-8

Patel, V., Saxena, S., Lund, C., Thornicroft, G., Baingana, F., Bolton, P., Chisholm, D., Collins, P. Y., Cooper, J. L., Eaton, J., Herrman, H., Herzallah, M. M., Huang, Y., Jordans, M. J. D., Kleinman, A., Medina-Mora, M. E., Morgan, E., Niaz, U., Omigbodun, O., … UnÜtzer, Jü. (2018). The Lancet Commission on global mental health and sustainable development. *The Lancet*, *392*(10157), 1553–1598. https://doi.org/10.1016/S0140-6736(18)31612-X

Patel, V., Xiao, S., Chen, H., Hanna, F., Jotheeswaran, A. T., Luo, D., Parikh, R., Sharma, E., Usmani, S., Yu, Y., Druss, B. G., & Saxena, S. (2016). The magnitude of and health system responses to the mental health treatment gap in adults in India and China. *The Lancet*, *388*(10063), 3074–3084. https://doi.org/10.1016/S0140-6736(16)00160-4

Ridley, M., Rao, G., Schilbach, F., & Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, *370*(6522), eaay0214. https://doi.org/10.1126/science.aay0214

Rocha, R., & Soares, R. R. (2010). Evaluating the impact of community-based health interventions: Evidence from Brazil's Family Health Program. *Health Economics*, *19*(S1), 126–158. https://doi.org/10.1002/hec.1607

Santos, I. S., Tavares, B. F., Munhoz, T. N., Almeida, L. S. P. de, Silva, N. T. B. da, Tams, B. D., Patella, A. M., & Matijasevich, A. (2013). Sensibilidade e especificidade do Patient Health Questionnaire-9 (PHQ-9) entre adultos da população geral. *Cadernos de Saúde Pública*, *29*(8), 1533–1543. https://doi.org/10.1590/S0102-311X2013001200006

Smolen, J. R., & Araújo, E. M. de. (2017). Raça/cor da pele e transtornos mentais no Brasil: Uma revisão sistemática. *Ciência & Saúde Coletiva*, *22*(12), 4021–4030. https://doi.org/10.1590/1413-812320172212.19782016

Soares, S., & de Oliveira, W. F. (2016). The matrix approach to mental health care: Experiences in Florianopolis, Brazil. *Journal of Health Psychology*, *21*(3), 336–345. https://doi.org/10.1177/1359105316628752

Srivastava, S., Purkayastha, N., Chaurasia, H., & Muhammad, T. (2021). Socioeconomic inequality in psychological distress among older adults in India: A decomposition analysis. *BMC Psychiatry*, *21*(1), 179. https://doi.org/10.1186/s12888-021-03192-4

Stopa, S. R., Malta, D. C., Oliveira, M. M. de, Lopes, C. de S., Menezes, P. R., & Kinoshita, R. T. (2015). Prevalência do autorrelato de depressão no Brasil: Resultados da Pesquisa Nacional de Saúde, 2013. *Revista Brasileira de Epidemiologia*, *18*(suppl 2), 170–180. https://doi.org/10.1590/1980-5497201500060015

Triaca, L. M., dos Santos, A. M. A., & Tejada, C. A. O. (2020). Socioeconomic inequalities in obesity in Brazil. *Economics & Human Biology*, *39*, 100906. https://doi.org/10.1016/j.ehb.2020.100906

UN-Habitat. (2016). *Slum Almanac 2015/2016: Tracking Improvement in the Lives of Slum Dwellers*. https://unhabitat.org/slum-almanac-2015-2016-0

Van Doorslaer, E., & Van Ourti, T. (2011). Measuring Inequality and Inequity in Health and Health Care. In S. Glied & P. C. Smith (Orgs.), *The Oxford handbook of health economics*. Oxford University Press.

Werlen, L., Puhan, M. A., Landolt, M. A., & Mohler-Kuo, M. (2020). Mind the treatment gap: The prevalence of common mental disorder symptoms, risky substance use and service utilization among young Swiss adults. *BMC Public Health*, *20*(1), 1470. https://doi.org/10.1186/s12889-020-09577-6

WHO, W. H. O. (2019). *The WHO special initiative for mental health (2019-2023): Universal health coverage for mental health*. https://apps.who.int/iris/handle/10665/310981

World Bank. (2021). *World Bank Open Data*. https://data.worldbank.org/

Appendix

Table A1 – Linear probability model: depression and treatment gap for depression, 2013 and 2019

	Depression				**Treatment gap**			
	2013		**2019**		**2013**		**2019**	
	Coef.	**p.val**	**Coef.**	**p.val**	**Coef.**	**p.val**	**Coef.**	**p.val**
Female	0.044***	0.000	0.071***	0.000	-0.020	0.424	-0.062***	0.001
Age				*omitted: 18-24*				
25-34	0.002	0.702	-0.009	0.257	-0.019	0.568	-0.041	0.164
35-44	0.003	0.622	-0.013*	0.090	-0.064*	0.080	-0.089***	0.003
45-54	0.007	0.309	-0.020**	0.015	-0.057	0.122	-0.113***	0.000
55-64	-0.024***	0.001	-0.047***	0.000	-0.069	0.108	-0.113***	0.003
65 or older	-0.035***	0.000	-0.075***	0.000	0.069	0.132	0.029	0.492
Race				*omitted: White*				
Black	0.004	0.558	0.004	0.500	0.003	0.925	0.052**	0.039
Asian	0.008	0.643	-0.019	0.486	0.051	0.469	0.102	0.294
Browns/Mixed	0.004	0.403	-0.001	0.839	0.012	0.597	0.020	0.293
Indigenous	-0.009	0.664	0.017	0.416	-0.061	0.676	0.050	0.533
Education				*omitted: None*				
Basic incomplete	-0.010	0.106	-0.009	0.244	-0.089***	0.001	-0.030	0.332
Basic complete	-0.016*	0.055	-0.018*	0.066	-0.077**	0.048	-0.047	0.267
Secondary incomplete	-0.023***	0.006	-0.006	0.615	-0.082*	0.082	-0.094**	0.041
Secondary complete	-0.028***	0.000	-0.028***	0.001	-0.071**	0.041	-0.044	0.244
Higher incomplete	-0.031***	0.000	0.008	0.543	-0.124**	0.038	-0.040	0.441
Higher complete	-0.023***	0.006	-0.019**	0.046	-0.098**	0.038	-0.059	0.170
Urban	0.035***	0.000	0.039***	0.000	-0.027	0.331	0.031	0.189
Region				*omitted: North*				
North-East	0.014***	0.004	0.017***	0.000	-0.056***	0.009	-0.061***	0.001
South-East	0.016***	0.005	0.025***	0.000	-0.108***	0.000	-0.148***	0.000
South	0.033***	0.000	0.020***	0.002	-0.215***	0.000	-0.204***	0.000
Center-West	0.025***	0.000	0.030***	0.000	-0.059**	0.028	-0.106***	0.000
Slum proxy	-0.007	0.169	-0.004	0.453	0.003	0.896	-0.013	0.502
Internet	-0.010**	0.033	0.011**	0.034	-0.052**	0.047	0.018	0.423
Employment status				*omitted: Inactive*				
Unemployed	-0.007	0.523	0.009	0.382	0.035	0.495	0.029	0.423
Employed	-0.022***	0.000	-0.025***	0.000	0.089***	0.000	0.069***	0.001
Log family income per capita (R$ 2019)	-0.006***	0.001	-0.008***	0.000	-0.023***	0.000	-0.022***	0.008
Support of family and/or friends	-0.047***	0.000	-0.056***	0.000	-0.035	0.285	-0.002	0.969
Lives with				*omitted: Alone*				
Partner	-0.007	0.182	-0.019***	0.000	0.048	0.102	0.023	0.297
Other person	0.001	0.815	0.003	0.568	0.044	0.149	-0.011	0.644
Participation in group, social and/or community activities				*omitted: Never*				
Less than monthly	-0.002	0.762	-0.001	0.847	-0.029	0.340	0.001	0.979
At least once per month	-0.002	0.721	-0.015***	0.008	-0.015	0.523	-0.056**	0.012
Health insurance	-0.006	0.230	-0.002	0.698	0.004	0.884	-0.051**	0.027
Registered with Family Health Team				*omitted: No / Does not know*				
Yes, and no home visits in last 12 months	0.008	0.170	0.017***	0.002	-0.026	0.477	0.015	0.522
Yes, and at least one home visit in last 12 months	-0.001	0.903	-0.001	0.887	-0.016	0.465	-0.015	0.427
Diagnosis of non-mental NCD	0.079***	0.000	0.096***	0.000	-0.075***	0.001	-0.104***	0.000
Tobacco	0.033***	0.000	0.045***	0.000	-0.017	0.527	-0.044*	0.052
Physical activity				*omitted: No*				
Yes, less than weekly	0.006	0.765	0.009	0.597	0.104	0.131	-0.003	0.957
Yes, once or twice a week	-0.013***	0.006	-0.027***	0.000	0.049	0.176	-0.025	0.446
Yes, three or more times per week	-0.021***	0.000	-0.031***	0.000	0.023	0.459	-0.007	0.744
Alcohol				*omitted: Never*				
Yes, less than weekly	-0.015***	0.001	-0.009*	0.074	0.071**	0.012	0.065***	0.006
Yes, once a week	-0.013**	0.016	-0.013**	0.026	0.123***	0.000	0.108***	0.000
Yes, twice or more per week	-0.010*	0.075	-0.009	0.105	0.104***	0.003	0.104***	0.000
Constant	0.107***	0.000	0.151***	0.000	1.160***	0.000	1.132***	0.000
Observations	60,188		88,500		5,049		9,251	
R-squared	0.049		0.058		0.091		0.079	

Note: the table shows detailed results from four independent linear probability models linking covariates with the probability of being depressed and of falling in the treatment gap —conditional on being depressed— in 2013 and in 2019.

Table A2 – Oaxaca-Blinder decomposition for the evolution of the prevalence of depression and the treatment gap for depression (2013 – 2019)

	Depression		Treatment gap	
2019	0.1083***		0.7117***	
2013	0.0787***		0.7623***	
Aggregate decomposition	**Estimate**	**%**	**Estimate**	%
Difference	0.0296***		-0.0506***	
Explained	-0.0004	-1.35%	0.0084	-16.60%
Unexplained	0.0301***	101.69%	-0.0590***	116.60%

Detailed decomposition	Explained			
	Estimate	**%**	**Estimate**	%
Female	0.0002***	0.68%	-0.0010	1.98%
Age	-0.0026***	-8.78%	0.0023	-4.55%
Race	0.0001	0.34%	0.0012	-2.37%
Education	-0.0010	-3.38%	-0.0070	13.83%
Urban	0.0000	0.00%	0.0005	-0.99%
Region	-0.0001***	-0.34%	0.0008	-1.58%
Slum proxy	0.0001	0.34%	0.0006	-1.19%
Internet	0.0038**	12.84%	0.0078	-15.42%
Employment status	0.0002	0.68%	0.0027	-5.34%
Log family income per capita (R$ 2019)	0.0002	0.68%	-0.0007	1.38%
Support of family and/or friends	-0.0026***	-8.78%	-0.0001	0.20%
Lives with	-0.0001	-0.34%	-0.0019*	3.75%
Participation in group, social and/or community activities	-0.0010***	-3.38%	-0.0021*	4.15%
Health insurance	0.0000	0.00%	-0.0011	2.17%
Registered with Family Health Team	0.0008**	2.70%	0.0012	-2.37%
Diagnosis of non-mental NCD	0.0055***	18.58%	0.0004	-0.79%
Tobacco	-0.0009***	-3.04%	0.0013	-2.57%
Physical activity	-0.0029***	-9.80%	-0.0013	2.57%
Alcohol	-0.0002*	-0.68%	0.0049***	-9.68%

Note: the table shows full results from Oaxaca-Blinder decompositions of the evolution of the prevalence of depression and the treatment gap for depression between 2013 and 2019. Results for categorical variables are the sum of the results of each category. For the analysis of the treatment gap, sampling strata without depressed individuals were dropped from regressions and therefore the mean is slightly different from the mean for the whole sample presented in Figure 1.

Table A3 – Decomposition of the Concentration Index for economic inequalities in depression prevalence, 2019

Variable	Regression coefficient	Mean	C	Contribution	Contribution %
Female	0.0660***	0.5316	-0.0228	-0.0032	8.62%
Age					
25-34	0.0021	0.1810	-0.0800	-0.0001	0.33%
35-44	0.0012	0.2024	-0.0652	-0.0001	0.17%
45-54	0.0018	0.1785	0.0348	0.0000	-0.12%
55-64	-0.0208**	0.1505	0.1139	-0.0014	3.84%
65 or older	-0.0448***	0.1490	0.1929	-0.0052	13.88%
Race					
Black	0.0002	0.1147	-0.1461	0.0000	0.04%
Asian	-0.0180	0.0092	0.1877	-0.0001	0.34%
Browns/Mixed	-0.0039	0.4380	-0.1603	0.0011	-2.95%
Indigenous	0.0079	0.0054	-0.2179	0.0000	0.10%
Education					
Basic incomplete	-0.0090	0.2866	-0.1956	0.0020	-5.44%
Basic complete	-0.0159*	0.0776	-0.1150	0.0006	-1.53%
Secondary incomplete	-0.0082	0.0672	-0.2292	0.0005	-1.36%
Secondary complete	-0.0256***	0.2981	-0.0100	0.0003	-0.82%
Higher incomplete	0.0063	0.0512	0.2495	0.0003	-0.87%
Higher complete	-0.0180*	0.1583	0.5473	-0.0062	16.81%
Urban	0.0325***	0.8618	0.0568	0.0064	-17.15%
Region					
North-East	0.0149***	0.2645	-0.2841	-0.0045	12.07%
South-East	0.0241***	0.4344	0.1341	0.0056	-15.14%
South	0.0198***	0.1468	0.1978	0.0023	-6.20%
Center-West	0.0305***	0.0757	0.1002	0.0009	-2.49%
Slum proxy	-0.0038	0.1514	-0.1982	0.0005	-1.23%
Internet	0.0080	0.8459	0.0476	0.0013	-3.47%
Employment status					
Unemployed	0.0057	0.0527	-0.4217	-0.0005	1.37%
Employed	-0.0312***	0.6125	0.0866	-0.0066	17.84%
Income quintile					
Q2	-0.0033	0.2032	-0.3956	0.0011	-2.86%
Q3	-0.0132**	0.1963	0.0039	0.0000	0.11%
Q4	-0.0088	0.2108	0.4109	-0.0030	8.22%
Q5	-0.0242***	0.1891	0.8109	-0.0148	40.01%
Support of family and/or friends	-0.0455***	0.9815	0.0043	-0.0008	2.07%
Lives with					
Partner	-0.0142***	0.6139	0.0011	0.0000	0.10%
Other person	0.0033	0.3112	-0.0752	-0.0003	0.83%
Participation in group, social and/or community activities					
Less than monthly	-0.0074	0.1886	-0.0588	0.0003	-0.88%
At least once per month	-0.0223***	0.6442	0.0436	-0.0025	6.75%
Health insurance	0.0003	0.2964	0.4177	0.0001	-0.40%
Registered with Family Health Team					
Yes, and no home visits in last 12 months	0.0153***	0.1442	0.0198	0.0002	-0.47%
Yes, and at least one home visit in last 12 months	0.0012	0.4711	-0.1486	-0.0003	0.91%
Violence	0.1479***	0.1827	-0.0524	-0.0057	15.27%
Diagnosis of non-mental NCD	0.0833***	0.5442	0.0451	0.0082	-22.04%
Tobacco	0.0374***	0.1259	-0.0952	-0.0018	4.83%
Physical activity					
Yes, less than weekly	0.0004	0.0155	0.1336	0.0000	-0.01%
Yes, once or twice a week	-0.0274***	0.1467	0.0795	-0.0013	3.45%
Yes, three or more times per week	-0.0297***	0.2582	0.1700	-0.0052	14.06%
Alcohol					
Yes, less than weekly	-0.0113**	0.1578	0.0157	-0.0001	0.30%
Yes, once a week	-0.0154***	0.1179	0.1161	-0.0008	2.27%
Yes, twice or more per week	-0.0157***	0.1460	0.1766	-0.0016	4.36%
Explained				-0.0347	93.51%
Residual				-0.0024	6.49%
E			-0.0371		

Note: the table shows the detailed decomposition of the Erreygers-corrected concentration index in 2019. The first three columns show: the coefficients of the association between all covariates and the probabilities of being depressed obtained from a linear probability model, the mean, and the concentration index of each covariate. The contribution of each factor is equal to four times the product of the regression coefficient, the mean and the concentration index.

Table A4 – Oaxaca-Blinder decomposition for differences in the treatment gap for depression according to race

	Treatment gap	
Brown/Mixed + Black	0.7397***	
White	0.6717***	
Aggregate decomposition	**Estimate**	**%**
Difference	0.0679***	
Explained	0.0376***	55.38%
Unexplained	0.0304	44.77%

Detailed decomposition	**Explained**	
	Estimate	**%**
Female	-0.0007	-1.03%
Age	-0.0080**	-11.78%
Education	-0.0029	-4.27%
Urban	-0.0003	-0.44%
Region	0.0361***	53.17%
Slum proxy	-0.0008	-1.18%
Internet	-0.0008	-1.18%
Employment status	-0.0005	-0.74%
Income quintile	0.0225**	33.14%
Support of family and/or friends	0.0000	0.00%
Lives with	-0.0002	-0.29%
Participation in group, social and/or community activities	-0.0027*	-3.98%
Health insurance	0.0023	3.39%
Registered with Family Health Team	-0.0014	-2.06%
Violence	-0.0022*	-3.24%
Diagnosis of non-mental NCD	0.0007	1.03%
Tobacco	-0.0007	-1.03%
Physical activity	-0.0004	-0.59%
Alcohol	-0.0026	-3.83%

Note: the table shows full results from Oaxaca-Blinder decompositions of differences in the treatment gap for depression between individual self-identified as white and self-identified as brown/mixed or black. Results for categorical variables are the sum of the results of each category. For the analysis of the treatment gap, sampling strata without depressed individuals were dropped from regressions and therefore the mean is slightly different from the mean for the whole sample presented in Figure 1.