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Divergence in the size and composition of the race gap in mental health: Evidence from South Africa

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ABSTRACT

Quantitative studies of mental health in South Africa typically find that Black African adults report significantly more depressive symptoms than other adults on average. However, insufficient attention has been paid to differences among Black African adults, and to how the distribution of depressive symptoms compares between these adults and other adults. We augment existing research by investigating how the size and composition of the race gap in depression scores varies at different percentiles of the mental health distribution. We analyze national self-reported data on the frequency of depressive symptoms, and estimate recentred influence function decompositions of the unconditional race gap at each quantile of the distribution. The analysis identifies a race gap in depression scores that is twice as large at the lower tail of the mental health distribution than at the upper tail, signalling that Black African adults are particularly less likely than other adults to report no, or only a few, symptoms. At the lower tail, the race gap derives mostly from differences in the relationship between characteristics and mental health, while at higher percentiles, differences in the level of endowments, or stressors, are more important. At the upper tail, where depression scores are likely to correspond to major depressive episodes, the race gap narrows to zero. The size and composition of the average race gap in depression scores therefore masks considerable variation about the mean, which should be considered when policy is targeted to redress inequalities in mental health treatment.

1. Introduction

The prevalence of mental health disorders has been identified as one of the "four colliding epidemics" that South Africa has confronted since the transition to democracy in the 1990s (Mayosi et al., 2012).[1] However, the burden of disease continues to be unevenly borne in the country (Schneider et al., 2016), and the social construct of race remains a significant marker of vulnerability. Despite a growing Black African middle class, the legacy of apartheid and racial exclusion remains persistent, and the majority population continues to face considerably more exposure to social stressors. Overall, Black African (henceforth "African") adults are far more likely to be economically disadvantaged, to experience traumatic events, and to have lesser access to basic services and healthcare (Harriman et al., 2022; Mbewu et al., 2024; Visagie & Posel, 2013; Williams et al., 2007; World Bank, 2022; Zizzamia et al., 2022).

Numerous studies of mental health in South Africa have found that African adults report significantly more depressive symptoms or more psychological distress than other adults (e.g. Ardington & Case, 2010; Burger et al., 2017; Burns et al., 2017; Eyal & Burns 2019; Harriman et al., 2022; Jackson et al., 2010; Mungai & Bayat, 2019; Tomita & Burns, 2013; Williams et al., 2007; Williams et al., 2008). However, as a recent study by Harriman et al. (2022) notes, insufficient attention has been paid to differences among African adults, and to the distribution of depressive symptoms or distress among African adults compared to the distribution among other groups. Rather, studies both in South Africa and more broadly, typically investigate average differences in the symptomology of depression or distress. Ordinary least squares regressions, for example, assume that the association between race and mental health outcomes is constant at different levels of the mental health scale.

In this paper, we further explore the relationship between race and mental health in South Africa. The research makes two key contributions to the literature. First, in contrast to earlier research, we interrogate non-

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[1] The other three epidemics are identified as "HIV and tuberculosis", "deaths related to injury and violence", and "a silent epidemic of maternal, neonatal and child mortality" (Mayosi et al., 2012).

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linearity in the race gap in mental health. We use nationally representative data on depressive symptoms, derived from the ten questions that make up the Center for Epidemiologic Studies Short Depression Scale (CES-D 10), and demonstrate that there is significant variation in the size of the race gap about the mean. Unconditional quantile regressions show that race differences in depressive symptoms are largest at the lower tail of the CES-D 10 distribution, where adults report only a few symptoms over a week, and they are smallest at higher quantiles of depression scores, which correspond to the typical depression threshold applied to the CES-D 10.

Findings of significant heterogeneity in the race gap may contribute to explaining a "paradox" that has been identified particularly in the US literature (George & Lynch, 2003; Barnes & Bates, 2017; Moazen-Zadeh & Assari, 2016), but that also appears in South African research. In the US, studies have found that African Americans consistently report lower rates of major depression disorders than non-Hispanic whites (Breslau, Kendler, Su, Gaxiola-Aguilar, & Kessler, 2009; Shim et al., 2012; Barnes et al., 2013; Barnes & Bates, 2017; Moazen-Zadeh & Assari, 2016; Chen et al., 2019), although several studies have also found that African Americans report a greater occurrence of depressive symptoms on average (Ettman et al., 2020; George & Lynch, 2003; Kessler & Neighbors, 1986). In South Africa, where a significant race gap in average depressive symptoms is consistently identified, some studies have similarly found that race differences are not evident in cases of major depression over 12 months or a lifetime (Herman et al., 2009; Tomlinson et al., 2009). The distribution of depression scores is relevant to this paradox if race differences among adults with comparable characteristics attenuate at higher depression scores, scores which are more likely to signal major depression disorders.

The second main contribution of the study is that we investigate the distributional implications of different stressors or covariates by race. To do this, we estimate recentred influence function (RIF) decompositions (Firpo et al. 2009, 2018), to identify how much of the unconditional race gap can be attributed to African adults facing more stressors than other adults, and how much derives from differences in the relationship between stressors and symptoms. In contrast to earlier decomposition approaches (such as the traditional Oaxaca-Blinder and DiNardo-Fortin-Lemieux methods), RIF decompositions detail the contribution of each stressor (or covariate) to the race gap at each unconditional quantile of the distribution in depression scores.

As the decompositions distinguish between the contribution of characteristics and the 'influence' of characteristics, they can be used to test two key hypotheses that have been put forward to explain race differences in depressive symptomology (George & Lynch, 2003). The first is the "differential stress" or the "stress exposure" hypothesis, viz. That race gaps in depressive symptoms arise because African adults are confronted with greater levels of stress or adversity than other adults (i.e. because of differences in characteristics or stressors). The second is the "differential vulnerability" hypothesis, viz. That for any given level of stress, African adults exhibit stronger responses in mental health (i.e. differences in the coefficients).

Previous research on depression in South Africa has not identified consistent support for the differential vulnerability hypothesis among African adults. In their analysis of national data collected during the COVID-19 pandemic, for example, and in contrast to studies of depressive symptoms before the pandemic, Posel et al. (2021) found that African adults reported significantly fewer depressive symptoms than other adults during the initial lockdown periods. A possible explanation, they suggest, is that African adults were better able to adapt to the stresses associated with the lockdown, compared to other adults who confronted socio-economic shocks less frequently. i.e. Rather than being sensitized because of their previous exposure to economic adversity, Africans may have been more resilient to the hardships associated with the COVID-lockdown.[2]

The RIF decompositions allow us to probe not only whether African adults display different sensitivities to stressors, but further, which characteristics appear as significant along the distribution, and whether associations vary at different quantiles of the mental health distribution. Given persistent overall race differences in socio-economic status and spatial geography, key potential stressors we consider concern access to resources, location, and indicators of adverse events. Union and household formation also differ substantially by race in South Africa, and we test whether far lower marriage rates among African adults, which co-exist with higher rates of child co-residence (Posel & Casale, 2013; Posel & Hall, 2021), contribute to race gaps in depression scores.

2. Methods

2.1. Data and sample

The data for the study come from the fifth and final wave of the National Income Dynamics Study (NIDS), a national household survey which was conducted in 2017 by the Southern African Labour and Development Research Unit at the University of Cape Town (UCT). The dataset is publicly available and can be accessed at http://www.nids.uct.ac.za.

Although designed to be nationally representative, approximately 27 percent of the original sample interviewed in the first wave in 2008 was lost through attrition by 2017, with attrition rates highest among "White, Indian/Asian and high-income individuals" (Brophy et al., 2018, p. 10). In the wave analyzed in this study, a top-up sample (of 2775 individuals from these groups) was added to make the data more nationally representative (Brophy et al., 2018). The sample for the study includes all adults (aged 18 years and older[3]) with non-missing information for all the variables considered in the analysis, amounting to 20,707 individuals. In all the analysis that follows, population totals are estimated using post-stratified weights that adjust for systematic differences in response rates across the different socio-economic groups (see Brophy et al., 2018 for further discussion).

2.2. Depressive symptoms

An important advantage of the NIDS survey is that, in addition to detailed information on socio-economic status and household composition, information on depressive symptoms is also collected from all adults (aged 15 years and older) through the 10-item Center for Epidemiologic Studies Short Depression Scale (CES-D 10). Most of the questions capture information on negative effects, but the two positive mood indicators were reverse coded, so that the scale is increasing in the occurrence of negative symptoms. Original responses ranged from 1 (a symptom occurred very rarely or not at all in a week) to 4 (all the time), which were then re-scored from 0 to 3, to create a total score from 0 (no symptoms experienced in the previous week) to 30 (all symptoms experienced all the time). Only adults who answered all 10 questions in the module were included in the sample (comprising 99.1 percent of the sample of adults with non-missing information on individual and household characteristics).

The CES-D 10 scale is a psychometric scale that is among "the most widely used instruments for measuring depressive symptoms" (James et al., 2020, p. 2). It has been validated as a reliable screening tool to

[2] Whereas the study by Posel et al. (2021) had to rely on data collected in the 2-question version of the Patient Health Questionnaire, this study explores race differences using the more extensive information collected in the CES-D 10.

[3] We use 18 as the age threshold as this is the legal age of consent in South Africa.

identify adults at risk of depression in South Africa (Baron et al., 2017). In the 2017 NIDS data analyzed in this study, Cronbach's alpha for the CES-D 10 was 0.73 for the pooled sample of adults, signalling internal reliability of the depression scale.

Many studies analyze the scale as a continuous measure rather than imposing a threshold to identify a binary variable for depression (e.g. Ardington & Case, 2010; Burger et al., 2017; Posel, 2021; Tomita & Burns, 2013). This is because the appropriate cutoff for depressive symptoms in South Africa has also been found to vary (from 10, the typical threshold, to 13) across the different language groups (Baron et al., 2017). As we are also interested in the size of the race gap, we follow the same approach in this study.

2.3. Methods of analysis

To interrogate the race gap in depressive symptoms at the mean and along the distribution of CES-D 10 scores, we use the Oaxaca-blinder decomposition of the unconditional race gaps. For the mean gap, we consider the difference between average CES-D 10 scores written as

$$\overline{A}_A - \overline{A}_{NA} = \overline{X}_A\widehat{\beta}_A - \overline{X}_{NA}\widehat{\beta}_{NA} \ldots\ldots\ldots\ldots\ldots \quad (1)$$

where $\overline{A}_A$ is the average CES-D 10 score for African adults and $\overline{A}_{NA}$ is the corresponding average score for non-African adults. Equation (1) allows for group-specific returns $\{\widehat{\beta}_A, \widehat{\beta}_{NA}\}$ to the set of covariates X. Therefore $\overline{X}_A\widehat{\beta}_A$ is the OLS regression estimate of the CES-D10 score amongst African adults and the corresponding estimate amongst other adults is given by $\overline{X}_{NA}\widehat{\beta}_{NA}$. To decompose the mean gap in equation (1) we write

$$\overline{A}_A - \overline{A}_{NA} = \overline{X}_A\widehat{\beta}_A - \overline{X}_{NA}\widehat{\beta}_A + \overline{X}_{NA}\widehat{\beta}_A - \overline{X}_{NA}\widehat{\beta}_{NA} \ldots\ldots\ldots \quad (2)$$

$$\overline{A}_A - \overline{A}_{NA} = (\overline{X}_A - \overline{X}_{NA})\widehat{\beta}_A + (\widehat{\beta}_A - \widehat{\beta}_{NA})\overline{X}_{NA} \ldots\ldots\ldots \quad (3)$$

where the term $\overline{X}_{NA}\widehat{\beta}_A$ is a counterfactual that represents African adults' average depression scores if they had the characteristics of other adults. We use the distribution of characteristics of adults who are not African as the reference category (rather than the pooled group), because of significant differences between African and other adults for many of the characteristics that are modelled in the analysis, and because African individuals comprise the large majority of the adult population.

Equation (3) decomposes the gap in CES-D 10 scores at the mean into a component that is due to differences in the distribution of characteristics between African and other adults $(\overline{X}_A - \overline{X}_{NA})\widehat{\beta}_A$ or the composition effect, and another component that is due to differences in returns to these characteristics $(\widehat{\beta}_A - \widehat{\beta}_{NA})\overline{X}_{NA}$ or the unexplained effect. The detailed decomposition further decomposes the gap into the contribution of individual covariates.

For the decomposition across the distribution of the CES-D 10 scores, we first estimate the RIF of the quantiles $RIF(A; q_\tau)$ of the depression score distribution i.e.

$$RIF(A; q_\tau) = q_\tau + IF(q_\tau) \ldots\ldots\ldots\ldots \quad (4)$$

where the influence function $IF(q_\tau)$ is given by $\frac{[\tau - I(A \le q_\tau)]}{f_A(q_\tau)}$, τ is the quantile of interest, $f_A(q_\tau)$ is the marginal density of A at the point q_τ and $I(A \le q_\tau)$ is an indication function specifying if the value of CES-D 10 is below the τ. Using the estimated RIF for each quantile τ, similar decompositions to equations (1)–(3) can be applied to decompose the gap in CES-D 10 scores at each quantile, and then to derive the contribution of individual covariates to this gap.

2.4. Covariates

Almost all the covariates that we model as potential stressors in the decomposition analysis vary considerably by race and have also been found to be significant correlates of average depression scores in South Africa. They include socio-economic status (SES), where higher SES is widely identified as a significant protector of mental health status (although the direction of causality is difficult to determine) (Lorant et al., 2003; Shim et al., 2012; Mutyambizi et al., 2019). In this study, SES is captured partly through the logarithm of average per capita household income and a living conditions asset index.[4] These measures are not sensitive to differences in household composition and the possibilities of economies of scale in household consumption (Lanjouw & Ravallion, 1995; Posel et al., 2020), which helps to explain why money-metric measures of economic status have been found to be lower than subjective assessments in South Africa (Posel & Rogan, 2016). We therefore also include a subjective measure of where adults think their household ranks on a six-step ladder of the national income distribution. For the asset and subjective measures, we consider specifically whether adults live in households that are placed in the lowest tercile of the asset distribution or on the bottom two rungs of the ladder.

The legacy of apartheid geographies in South Africa means that location also proxies for socio-economic status, where urban areas continue to be far better resourced than rural areas (Zimbalist, 2017). We do not directly model the adult's employment status, which has been found to be endogenous to mental health in South Africa (Nwosu, 2018; Posel et al., 2021); rather, we use a measure of education (completed years of schooling), which is highly correlated with the likelihood of being employed (Branson & Lam, 2021).

Further indicators of potential stress include if the individual experienced any health concerns in the month prior to the survey (such as a fever, persistent cough or cough with blood, chest pain, joint pain or arthritis, diarrhea, and severe weight loss); and negative life events. These events include the death of a household member over the previous two years, where research suggests that the most common trauma experienced in South Africa is the unexpected death of a family member or close other (Williams et al., 2007); and whether there was any theft, fire or destruction of property over the same period. We also model whether burglaries, theft or mugging are common or very common in the adult's neighborhood.

Marital status and household composition vary considerably by race in South Africa (Posel & Hall, 2021), and they may be additional sources of stress, for example by affecting the burden of care provided by adults (and particularly women) in the household (Posel & Oyenubi, 2023). We therefore also investigate whether being single or previously married (rather than in a marital or cohabiting union) and living in a household with younger (0–6 years) or older (7–14 years) children contributes to the race gap in depression scores. As these influences may be moderated by age and gender, which are themselves found to be significant correlates of average depression scores in South Africa (e.g. Ardington & Case, 2010; Burger et al., 2017), we also control for these individual characteristics in the analysis.

In international studies, racial discrimination or self-perceived racial discrimination has been identified as a significant risk factor for mental health (Bailey et al., 2019; Jackson et al., 1996; Paradies, 2006; Paradies et al., 2015; Shim et al., 2012; Williams et al., 2019). Ethnic density has been found to provide some protection from this stress, partly through offering more opportunities for social support and community engagement (Bécares et al., 2018). There is unfortunately no direct measure of discrimination in the data we analyze, but we capture racial diversity in the adult's area of residence (or district council), by calculating a diversity index:

[4] The index is created using principal components analysis of a range of assets, which include ownership of a car, cellphone, computer, sound system, television, refrigerator, stove, cellphone and washing machine), together with a household's access to clean water (Burger et al., 2017; Posel, 2021).

$$1 - \sum_{R} S_{Rc}^2$$

where S_{Rc} represents the proportion of race R in the population of the district council (c). The index lies from 0 to 1 and is increasing in racial diversity (Alesina & La Ferrara, 2002) across each of the 52 district councils in South Africa.

3. Results

3.1. Race and depression scores

The four main racial categories in South Africa, assigned during the Apartheid era and still identified in a wide range of survey instruments since the democratic transition, are African (the majority population), Coloured (of mixed race), Indian (of south Asian descent) and White (of European descent). Of the total unweighted sample of 20,707 adults in the study, the racial shares are: 79.5 percent African; 13.5 percent Coloured; 1.7 percent Indian; and 5.3 percent White.

For the analysis of race differences, we group non-African adults into a single category. The decomposition analysis of the race gap is undertaken by comparing two groups of adults, and the samples of Indian and White adults are too small for meaningful comparison and decomposition across a range of covariates.[5] CES-D 10 scores are significantly higher on average among African adults (7.37; standard error 0.03), compared to Coloured adults (6.31; standard error 0.09), Indian adults (5.73; standard error 0.24), and White adults (5.39; standard error 0.13). Kernel density plots of the CES-D 10 scores (reported in Appendix 1) also describe clear differences in the distribution of CES-D 10 scores between African adults and both Coloured adults and Indian/White adults, in ways that mirror the comparisons drawn below.

Fig. 1 presents kernel density plots for African adults and the combined group of non-African adults. The distribution for African adults clearly lies to the right of that for non-African adults, although differences are larger at lower CES-D 10 scores, and they narrow towards the upper tail. Non-African adults are twice as likely as African adults to report no depressive symptoms during the week (11.2 % of non-African adults in the weighted sample compared to 5.4 % of African adults); but similar shares report scores of 15 or higher (5.7 % of non-African adults compared to 5.4 % of non-African adults).

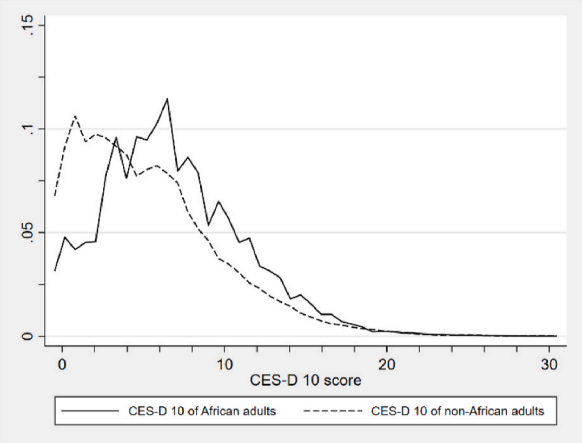


Fig. 1. Kernel density plots of CES-D 10 scores, among African and non-African adults.
Notes: The data are scaled with population weights. The sample is restricted to adults aged 18 years or older.
Source: National Income Dynamics Study (NIDS), 2017

3.2. Descriptive statistics

Table 1, which describes the characteristics of African and non-African adults using data collected in NIDS 2017, shows that African adults not only report significantly more depressive symptoms on average; they are also considerably more likely than other adults to experience stressors that would be expected to undermine mental health. For example, their socio-economic status remains significantly below that of non-African adults: average per capita household income is almost three-fold lower; the share living in households in the bottom tercile of the asset distribution is more than three times larger; and they are almost twice as likely to assess their economic status as corresponding to the bottom two rungs of a national income ladder. Their lower socio-economic status is reflected further in fewer years of completed education, and in the far smaller percentage living in urban areas, which are better resourced overall than rural areas in South Africa. African adults are also substantially less likely to be married or cohabiting with a partner, yet a significantly larger share lives in a household with younger or older children.

Significantly higher proportions of African adults reported the death of a household member over the two years prior to the survey. However, race differences in the share reporting a health concern in the previous month, the theft/fire or destruction of their property, and crime being common in the neighborhood, are small and not statistically significant.

In some respects, Table 1 shows that African adults also exhibit characteristics that may be associated with lower depression scores. They are considerably younger on average (partly because of their lower life expectancy, as well as higher rates of immigration among working-age non-African individuals (Bredenkamp et al., 2021; Lam et al., 2024,

Table 1
Individual and household characteristics of adults by race.

Mean/proportion	African	Non-African
Average CES-D 10 score	6.95[a] (0.051)	5.97 (0.127)
Individual characteristics		
Average age	37.70[a] (0.163)	44.21 (0.434)
Female	0.53 (0.007)	0.56 (0.013)
Never married	0.59[a] (0.006)	0.29 (0.012)
Previously married	0.10[a] (0.004)	0.15 (0.009)
Married or cohabiting	0.31[a] (0.006)	0.56 (0.013)
Years of schooling	9.83[a] (0.040)	10.91 (0.085)
Health concern in the previous month	0.38 (0.006)	0.37 (0.014)
Household characteristics		
At least one young child (<7) in household	0.43[a] (0.006)	0.30 (0.011)
At least one older child (7−14) in household	0.45[a] (0.006)	0.31 (0.012)
Per capita household income (Rands)	3234.39[a] (121.461)	9527.26 (598.002)
Lowest third of asset index	0.37[a] (0.006)	0.11 (0.008)
Lowest third on the income ladder	0.45[a] (0.006)	0.23 (0.011)
Urban location	0.58[a] (0.006)	0.91 (0.005)
Death of a household member in previous 24 months	0.08[a] (0.003)	0.05 (0.006)
Negative event: theft/fire/destruction of property	0.08 (0.004)	0.06 (0.005)
Neighborhood/district characteristics		
Crime is common in the neighborhood	0.53 (0.006)	0.50 (0.013)
Racial diversity score of the district of residence	0.23[a] (0.003)	0.42 (0.005)
Unweighted sample size	16,469	4237

Notes: The data are scaled with population weights. Standard errors are in parentheses. The sample is restricted to adults aged 18 years or older.
[a] Means or proportions are significantly different between African and non-African adults at the 95 percent confidence level.
Source: National Income Dynamics Study (NIDS), 2017

[5] However, our key findings that the race gap in depression scores attenuates at higher depression scores remains robust for a comparison of African adults and Indian/White adults.

pp. 1–26)) and mental health in South Africa typically has been found to improve non-linearly with age (Ardington & Case, 2010; Burger et al., 2017; Posel, 2021). African adults are also more likely to live in districts with less racial diversity, and a systematic review of 41 studies from the US found that ethnic density was positively related to better mental health (Bécares et al., 2018).

3.3. Decomposing average depression scores

The decomposition of the race gap in average depression scores (CES-D 10 scores of African adults minus scores of non-African adults) is reported in Table 2. As shown also in the descriptive statistics, African adults score almost one point higher on the CES-D 10 scale, on average, than non-African adults. Almost half of this gap (48 %) is accounted for by differences in the characteristics of African and non-African adults, described in the previous table. The remainder (52 %) derives from differences in the relationship between characteristics and depressive symptoms.

Stressors that were shown to be significantly larger or more prevalent among African adults in Table 1 contribute most to the explained part of the average race gap: the lower socio-economic status of African adults (particularly income as well as access to assets and lower years of schooling, although not the subjective assessment of economic ranking); and far higher rates of non-marriage. Together, these characteristics more than account for the decomposed difference in the explained portion of the mean gap (0.87 of 0.47), therefore providing support for the differential stress-exposure hypothesis.

There is also evidence to support the differential vulnerability hypothesis for both socio-economic and marital status. Being in the lowest third of the asset distribution is associated with significantly higher depression scores among African adults than non-African adults. In addition, the mental health associations of not marrying appear to be significantly larger among African adults (accounting for 0.21 of the 0.51 unexplained gap in depression scores).

However, as suggested in the previous sub-section, there are also several group characteristics that are protective of the mental health of African adults relative to non-African adults. These characteristics include being younger on average, not living in an urban area, and living in districts with less racial diversity, which all significantly moderate the composition effect or the explained gap in depression scores. African adults are also significantly more likely to live with children, which is associated with lower depression scores (reducing the explained gap). However, the protection afforded by living with a young child is smaller among African than non-African adults, and this different relationship contributes 0.24 to the unexplained gap of 0.51.

Not all the estimated coefficients point to a greater vulnerability to stressors among African adults. For example, there is no difference in the strength of the negative relationship between per capita household income and depression for the two groups of adults; and among those who provide low subjective assessments of economic status, or who live in neighborhoods where crime is common, the association with higher depression scores is significantly larger among non-African compared to African adults. Although average depression scores are higher among women than men, this is also significantly more pronounced among non-African than African women (therefore also reducing the unexplained gap in scores, by −0.33).

Table 2
Oaxaca-Blinder decomposition of the average race gap in depression scores.

	Explained	Unexplained
Total difference (African – non-African scores)	0.98[a]	
Decomposed difference	0.47[a]	0.52[a]
(Share of total difference)	47.96 %	52.04 %
By characteristic		
Age	−0.81[a]	2.63
Age^2	0.67[a]	−0.70
Female	−0.00	−0.33[b]
Never married	0.20[a]	0.21[b]
Previously married	−0.05[a]	−0.02
Years of schooling	0.04*	−0.05
Health concern	0.01	−0.10
At least one young child (<7) in household	−0.04[b]	0.24[a]
At least one older child (7−14) in household	−0.03[b]	0.00
Per capita household income (log, Rands)	0.60[a]	−1.30
Lowest third of asset index	0.07[b]	0.10[b]
Lowest third on the income ladder	0.04	−0.42[a]
Urban location	−0.08[b]	−0.82[a]
Death of a household member in previous 24 months	0.01	−0.01
Negative event: theft/fire/destruction of property	0.00	0.03
Crime is common in the neighborhood	−0.00	−0.48[a]
Racial diversity score of the district of residence	−0.16[b]	0.18
Constant		1.35

Notes: The data are scaled with population weights. The sample is restricted to adults aged 18 years or older.
[a] Significant at the 99 % level.
[b] Significant at the 95 % level.
Source: National Income Dynamics Study (NIDS), 2017

3.4. Decompositions at the unconditional quantiles of the CES-D 10 distribution

The analysis of the average gap in depression scores, however, masks significant variation in the size of the gap at lower and higher depression scores. Table 3 presents the results from the RIF decompositions along the distribution of depression scores, starting from the 20th percentile, for African and non-African adults. The table shows that the unconditional race gap (African minus non-African scores) varies considerably at different percentiles of the distribution by group, also described visually in Fig. 2. Specifically, differences in depression scores are considerably higher at lower percentiles than at the upper segment of the distribution. For example, at the 20th and 30th percentiles, where average CES-D 10 scores are far below the threshold (of 10) typically used to identify depression as a binary variable, race differences in CES-D 10 scores are 1.69 and 1.73 respectively. Beyond the 70th percentile, where CES-D 10 scores approach and then exceed 10, the gap falls significantly. At the 80th percentile, it drops by more than 50 % to 0.72 and at the 90th percentile, it is no longer significantly different from zero. A comparison of the race gap at the median of the distribution (1.27) and the average race gap (0.98) described in Table 2, further indicates that the distribution of race gaps in depression scores is left-skewed.

The RIF decomposition analysis shows that along the distribution, the race gap derives from differences both in characteristics (the composition effect), and in the relationship between characteristics and depressive symptoms (unexplained factors). Whilst the contributions are relatively similar for the average race gap, there is considerable variation at higher or lower depression scores. At lower percentiles, most of the race gap in the CES-D 10 derives from differences in the coefficients (accounting for over two-thirds of the total unconditional gap). At the 80th and 90th percentiles, not only is the race gap far smaller or insignificant, but unexplained factors are far less important (contributing only 12 percent at the 80th percentile, and they are not relevant at the 90th percentile).

Characteristics which are important in accounting for the explained portion of the race gap include those identified for the mean gap in Table 2. Lower average per capita household income and high rates of never marriage are significant contributors to the explained gap along the length of the distribution. Other indicators of socio-economic status are not consistently significant: having lower access to assets and lower subjective rankings of economic status are both important when accounting for the higher depression scores of African adults, but only at the tails of the distribution.

As highlighted earlier, compared to other adults, African adults also have endowments that are protective of mental health. These include that they are a younger population of adults who are less likely to be

Table 3
RIF decompositions at unconditional quantiles of the CES-D 10 distribution for African and non-African adults.

	20	30	40	50	60	70	80	90
Non-African depression score (standard error)	2.10 (0.14)	3.23 (0.14)	4.60 (0.14)	5.84 (0.13)	6.86 (0.13)	8.14 (0.16)	10.19 (0.20)	13.01 (0.29)
African depression score (standard error)	3.79 (0.05)	4.96 (0.06)	6.12 (0.07)	7.11 (0.06)	8.06 (0.07)	9.30 (0.08)	10.91 (0.10)	13.15 (0.13)
Total difference (African – non-African scores)	**1.69**[a]	**1.73**[a]	**1.53**[a]	**1.27**[a]	**1.20**[a]	**1.16**[a]	**0.72**[a]	**0.14**
Explained (Share of total difference)	0.46[a] (27 %)	0.53[a] (31 %)	0.47[a] (31 %)	0.34[a] (27 %)	0.39[a] (33 %)	0.52[a] (45 %)	0.63[a] (88 %)	0.66[a] (471 %)
Unexplained (Share of total difference)	1.23[a] (73 %)	1.20[a] (69 %)	1.06[a] (69 %)	0.93[a] (73 %)	0.81[a] (67 %)	0.64[a] (55 %)	0.09 (12 %)	−0.52 (−371 %)
Explained								
Age	−0.40[a]	−0.53[a]	−0.63[a]	−0.70[a]	−0.96[a]	−1.20[a]	−1.36[a]	−1.15[a]
Age^2	0.33[a]	0.48[a]	0.55[a]	0.58[a]	0.79[a]	1.00[a]	1.03[a]	0.91[a]
Female	0.00	−0.00	0.00	0.00	−0.00	−0.00	−0.00	−0.00
Never married	0.10[b]	0.13[a]	0.14[a]	0.15[a]	0.20[a]	0.26[a]	0.35[a]	0.42[a]
Previously married	−0.03[a]	−0.04[a]	−0.04[a]	−0.05[a]	−0.04[a]	−0.06[a]	−0.06[b]	−0.07[b]
Years of schooling	0.02	0.07[a]	0.07[a]	0.05[b]	0.05[b]	0.06[c]	−0.02	0.05
Health concern	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
At least one young child (<7) in household	−0.03[c]	−0.03[c]	−0.05[a]	−0.04[b]	−0.03	−0.03	−0.03	−0.02
At least one older child (7−14) in household	−0.01	−0.03	−0.03	−0.02	−0.03	−0.03	−0.05	−0.04
Per capita household income (log, Rands)	0.52[a]	0.62[a]	0.70[a]	0.67[a]	0.68[a]	0.66[a]	0.77[a]	0.53[a]
Lowest third of asset index	0.02	0.03	0.03	0.04	0.07[c]	0.12[b]	0.18[a]	0.11
Lowest third on the income ladder	−0.07[a]	−0.00	−0.02	−0.00	0.04	0.10[b]	0.11[b]	0.16[b]
Urban location	0.05	−0.00	−0.04	−0.08	−0.09	−0.10	−0.22[a]	−0.21[c]
Death of a household member (last 24 months)	−0.00	0.00	0.00	−0.00	0.01	0.01	0.01	0.02
Theft/fire/destruction of property	−0.00	−0.00	−0.00	0.00	0.00	0.00	0.00	0.00
Crime is common in the neighborhood	−0.01	−0.00	0.00	0.00	−0.00	0.00	−0.00	0.00
Racial diversity score of the district of residence	−0.04	−0.17[b]	−0.20[b]	−0.29[a]	−0.31[a]	−0.28[a]	−0.10	−0.06
Unexplained								
Age	1.92	2.00	0.73	1.36	3.61	5.64[b]	4.73	2.06
Age^2	−0.59	−0.59	0.19	−0.18	−1.29	−2.30[c]	−1.19	0.22
Female	−0.29[c]	−0.22	−0.33[c]	−0.21	−0.11	−0.22	−0.30	−0.77[b]
Never married	0.17	0.21[c]	0.17	0.07	0.10	0.07	0.25	0.61[b]
Previously married	0.04	0.08	0.05	0.01	−0.05	−0.09	−0.25[b]	−0.02
Years of schooling	0.66	0.64	0.22	0.05	−0.35	−0.38	0.37	−0.59
Health concern	−0.20[c]	−0.15	−0.15	−0.16	−0.06	0.14	0.04	0.14
At least one young child (<7) in household	0.16	0.22[b]	0.20[c]	0.18[c]	0.25[b]	0.31[a]	0.29[c]	0.55[b]
At least one older child (7−14) in household	−0.05	−0.11	−0.04	−0.00	0.07	0.08	0.03	−0.04
Per capita household income (log, Rands)	−1.10	−0.91	−1.33	−0.75	0.06	−0.49	−2.14	−1.30
Lowest third of asset index	0.09[c]	0.08[c]	0.05	0.07	0.05	0.05	0.14[c]	0.33[b]
Lowest third on the income ladder	−0.32[a]	−0.27[a]	−0.37[a]	−0.30[a]	−0.32[a]	−0.38[a]	−0.57[a]	−0.95[a]
Urban location	−0.77[b]	−0.79[c]	−0.86[b]	−0.61	−1.04[a]	−1.15[a]	−1.16[b]	−0.88
Death of a household member (last 24 months)	−0.04[c]	−0.05[c]	−0.03	0.01	0.03	0.03	0.01	0.00
Theft/fire/destruction of property	0.04	0.00	0.01	0.02	0.01	−0.01	−0.01	0.08
Crime is common in the neighborhood	−0.67[a]	−0.47[a]	−0.39[b]	−0.41[a]	−0.45[a]	−0.33[c]	−0.45[b]	−0.72[b]
Racial diversity score of the district of residence	−0.18	−0.07	0.10	0.24	−0.00	−0.10	0.19	0.88
Constant	2.37	1.62	2.84	1.54	0.31	−0.25	0.12	−0.14

Notes: The data are scaled with population weights. The sample is restricted to adults aged 18 years or older.
[a] Significant at the 99 % level.
[b] Significant at the 95 % level.
[c] Significant at the 90 % level.
Source: National Income Dynamics Study (NIDS), 2017

widowed, characteristics which are significant in reducing the race gap along the length of the CES-D 10 distribution. Being less likely to live in an urban area is protective at the upper tail of the distribution, while being more likely to live in areas with less racial diversity reduces the race gap in the middle of the distribution but it is not significant at the upper and lower tails.

Although the relationships between characteristics and depression scores contribute more to the race gap than the levels of characteristics, many of the relationships that would account for higher depression scores among African adults are not individually significant. African adults exhibit stronger responses to living in the lowest third of the asset distribution assets, but only at the lower and upper percentiles of the distribution. Living with young children also affords more protection of mental health among non-African adults compared to Africans adults at all the percentiles from 30 percent. The unexplained gap derives also from group differences in characteristics that are not adequately modelled in the specification. This is captured by the constant term, the coefficient for which is large in the lower half of the CES-D distribution, but nowhere significant.

The contribution of unexplained factors to the race gap in depression scores would be consistent with the hypothesis that African adults respond more to stressors than non-African adults. But investigating the individual decompositions further suggests that African adults are "more resilient" than non-African adults for most of the stressors that are statistically significant. For example, along the CES-D distribution, African adults appear less affected by subjective assessments of low economic rank than non-African adults, by living in an urban area and in neighbourhoods where crime is more common. Being in poor health predicts higher depression scores for both Africans and non-African adults, but again, the relationship for the African population is mostly weaker than for the non-African population (and only significantly different at the 20th percentile). The association between being a woman and higher

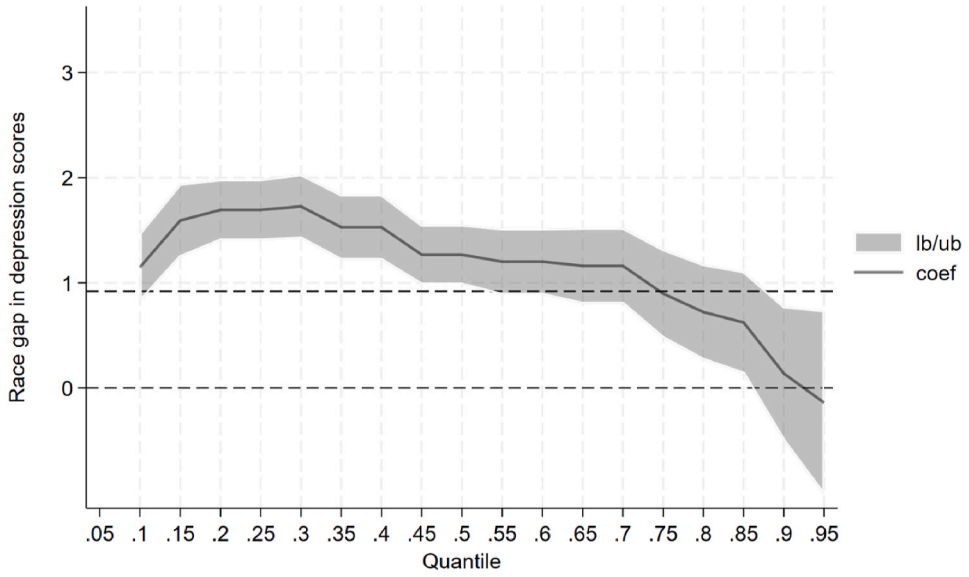


Fig. 2. Differences in CES-D 10 scores (African adults – non-African adults).
Notes: The data are scaled with population weights. The sample is restricted to adults aged 18 years or older.
lb (lower bound), ub (upper bound), coeff (unconditional race gap).
Source: National Income Dynamics Study (NIDS), 2017

depression scores is also larger among non-African than African adults, although the difference is significant only at the tails of the distribution. There is also no evidence that African adults are more affected by the death of a household member over the two years prior to the survey, and where the difference in coefficients is significant (only at the 20th and 30th percentiles), this reduces, rather than contributes to, the unexplained part of the race gap.

4. Discussion and conclusion

Numerous studies for South Africa have documented that on average, African adults report significantly more depressive symptoms than non-African adults (e.g. Ardington & Case, 2010; Burger et al., 2017; Harriman et al., 2022; Mungai & Bayat, 2019; Tomita & Burns, 2013; Williams et al., 2007, 2008). Race differences are typically identified by including a race dummy variable or variables in OLS or probit regressions, and the source of the estimated gap is then uncovered by adding covariates to the regressions and observing how race coefficients change. Ardington and Case (2010), for example, include socio-economic characteristics in their regression analysis of CES-D 10 scores, and by measuring the change in the race coefficient, they conclude that sixty percent of the average gap between African and white adults is explained by differences in socio-economic status.

In this study, we extended the understanding of race differences in depressive symptoms by estimating RIF decompositions at different percentiles of the CES-D 10 distributions for African and non-African adults (18 years and older). This makes it possible both to measure the full distribution of the unconditional race gap, rather than simply the average gap, and to probe the source of race differences, by considering the marginal impacts of different race distributions of explanatory variables on depression scores.

We found that in South Africa, both the size and composition of the race gap vary considerably along the distribution of CES-D 10 scores. The unconditional gap in depression scores is significantly higher at lower percentiles of the distribution, where only a few depressive symptoms are reported during the week. The gap falls substantially at the upper percentiles, where depression scores approach or exceed the threshold of 10, typically signalling depression onset. For non-African and African adults at the 80th percentile of their CES-D 10 distribution, the unconditional race gap in depressive symptoms is more than 50 percent smaller than at the lower percentiles; and at the 90th percentile, race differences are not evident.

Findings that the race gap attenuates (to zero) at higher depression scores may contribute to explaining the paradox documented in the literature on race differences in depression, particularly in the US, but also in South Africa, viz. That race differences are far more likely to be observed in depression scores than in major depression episodes (George & Lynch, 2003; Barnes & Bates, 2017; Moazen-Zadeh & Assari, 2016).

The RIF decompositions further disentangle the contribution of different characteristics to the race gap (the explained component), capturing the different-stress exposure hypothesis, and different relationships between characteristics and depression scores (the unexplained component), representing the differential vulnerability hypothesis. The decompositions provide support for both hypotheses in the South African context, albeit with qualifications.

First, African adults face far more exposure to economic adversity than non-African adults: they are at least three-fold more likely than other adults to live in households where average per capita household income or household assets are in the bottom third of the income or asset distribution. Marital rates among African adults are also substantially lower: in the data we analyze, only 31 percent were married or cohabiting, compared to 56 percent of non-African adults. The higher incidence of these characteristics is relevant for the race gap, particularly at the upper tail of the distribution which signals depression onset.

However, compared to other adults, African adults are also younger, more likely to live in households with children and in districts with lower racial diversity, all factors that are negatively related to the vulnerability to depression. The race gap in depression scores would therefore have been substantially higher in the absence of these differences in characteristics.

Second, the unexplained component is relatively more important in accounting for the race gap at lower depression scores. However, evidence of a higher vulnerability among African adults is not consistent across all stressors. Rather, African adults appear more resilient to the negative associations between mental health and living in neighborhoods with more crime, poor physical health, the death of a household member and being female. These findings would be consistent with other research which suggests that frequent exposure to adversity has

had a 'steeling' rather than 'sensitizing' effect (Assari and Lankarani, 2016; Ettman et al., 2020; Posel et al., 2021; Posel & Oyenubi, 2023), with the result that African adults are often better able to deal with stressors than other adults.

South Africa has taken important steps to improve the provision of mental healthcare infrastructure and resources in the post-apartheid period, but a "large treatment gap … for mental health conditions" remains (Sorsdahl et al., 2023, p. 1; see also Schneider et al., 2016). Contributing to this gap is the location of psychiatrists, most of whom work in the private health sector, although approximately 80 percent of South Africans rely on the provision of care through the public healthcare system. This is compounded by the overall "shortage of trained mental healthcare providers" (Sorsdahl et al., 2023, p. 2), and the limited availability of community-based care services. Where resources are limited, a case can be made for redress to focus particularly on African adults who exhibit the largest difference in depressive symptoms relative to comparable adults of different races or ethnic groups. However, by interrogating heterogeneity in race differences, this study estimates that the largest race gaps in mental health occur among adults for whom the risk of depression is small.

CRediT authorship contribution statement

Dorrit Posel: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Adeola Oyenubi:** Writing – original draft, Methodology, Formal analysis.

Ethical statement

Generative AI was not used in any part of the paper.

The household survey analyzed was conducted by the Southern Africa Labour and Development Research Unit at the University of Cape Town (UCT), with ethical clearance for the study given by the Commerce Faculty Ethics Committee at UCT. The data are in the public domain and can be accessed at: http://www.nids.uct.ac.za.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1

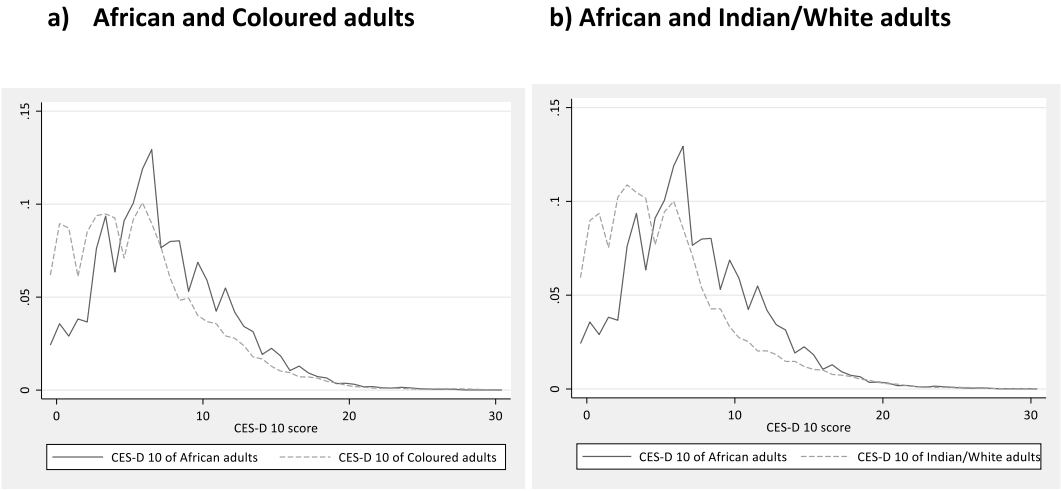


Fig. A1. Kernel density plots of CES-D 10 scores
Source: National Income Dynamics Study (NIDS), 2017
Notes: The data are scaled with population weights. The sample is restricted to adults aged 18 years or older.

Data availability

The data are in the public domain and the URL to access the data has been provided in the paper.

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