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Health indicators and poor health dynamics during COVID-19 pandemic

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Abstract
It is expected that the coronavirus pandemic will exacerbate inequality in wellbeing compared to the pre-pandemic situation. However, there are theories (e.g., the Conservation of Resource (COR) theory) that acknowledge situation-specific lower wellbeing for individuals who typically have more resources. The argument is that perception of loss might occur differently across the socioeconomic spectrum such that individuals with higher socioeconomic status perceive that they experience more loss. Therefore, given the pandemic situation, it is possible that indicators of poor wellbeing (e.g., depression) becoming less concentrated among the poor, contrary to expectation. Given the above, we examine income-related inequality in self-assessed health and depressive symptoms in South Africa. This is done using both pre-pandemic data (i.e. National Income Dynamic Study) and data collected during the pandemic (National Income Dynamic Study-Coronavirus Rapid Mobile Survey). Consistent with expectation, we find that poor self-assessed health is not only disproportionately concentrated amongst the poor, but this concentration has increased compared to the pre-pandemic period. However, contrary to expectation, depressive symptoms have become less concentrated amongst the poor compared to the pre-pandemic period. We note that while there may be an alternative explanation for this change in trend, it may also be due to situation-specific lower wellbeing for individuals who typically have more resources. We argue that this has implication for tracking population health in a crisis.

Keywords Wellbeing indicators · Depressive symptoms · COVID-19 · Inequality · South Africa

Introduction

It is important from a policy point of view to track changes in the wellbeing of the population over time. This is especially true in the context of a public health crisis like the coronavirus (COVID-19) pandemic. However, to track changes in wellbeing over time researchers and policymakers often rely on arguably imperfect wellbeing indicators like self-assessed health and depression scores (specifically since these measures are self-reported they may be influenced by individual perception). A priori, one would expect the COVID-19 crisis to exacerbate existing inequality in wellbeing through its effect on health and the economy. This is especially important in a developing country like South Africa where inequality in various facets of life is rife. For example, it has been shown that the COVID-19 pandemic and the associated lockdown led to massive job loss (Jain et al., 2020; Ranchhod & Daniels, 2021; Spaull et al., 2020) and that the economic shock disproportionately affected vulnerable workers like women, informal sector workers and workers in precarious employment in general (Benhura & Magejo, 2020; Casale & Posel, 2020; Casale & Shepherd, 2020; Ranchhod & Daniels, 2021; Rogan & Skinner, 2020; Strauss et al., 2020). The COVID-19 crisis has also been shown to have implications for wellbeing as measured by depressive symptoms (Oyenubi et al., 2021; Oyenubi & Kollamparambil, 2020; Posel et al., 2021) and self-assessed health (Nwosu & Oyenubi, 2021). This is important for the prevalence of depressive symptoms across socioeconomic status during the pandemic since individuals with pre-existing mental health issues have been shown to be at higher risk of hospitalization and death due to COVID-19 (Ceban et al., 2021; De Hert et al., 2021).

Prior to the COVID-19 pandemic point prevalence of depression has been shown to vary by Human Development

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index (HDI) - a composite measure based on life expectancy, education and income per capita. Specifically, it has been found that depression is highest in countries with medium HDI (Lim et al., 2018). Another pre-pandemic paper found that HDI does not have a simple linear relationship with Major depressive episode (Cifuentes et al., 2008). This is perhaps counterintuitive since one will expect a negative relationship between HDI and depression. However, it has been noted that medium HDI countries may be exposed to higher stressors because of higher expectations, cost of living and the cost of managing depression (Ho et al., 2013). Further a recent study on the impact of the pandemic on physical and mental health in low and middle income countries show that factors like age, single or separated status and higher education are correlated with depression during COVID (Wang et al., 2021). Again, the finding that higher education increases risk of depression may be regarded as counterintuitive since this factor is expected to have the opposite effect (since income and employment are expected to reduce the risk of depression). These results suggests that within and between countries socioeconomic status can vary with depressive symptoms in unexpected ways.

In South Africa, existing studies suggest that the pre-pandemic socioeconomic inequality in self-assessed health and depressive symptoms disadvantage the poor (Mukong et al., 2017; Omotoso & Koch, 2018). Therefore, it is expected that COVID-19 would have exacerbated the socioeconomic inequality in depressive symptoms and self-assessed health. However, other strands of the literature suggest that this conclusion may not be accurate. An example is the Conservation of Resource theory (COR) (Hobfoll, 1989, 2010; Hobfoll et al., 2003, 2016). Although counterintuitive, COR acknowledges situation-specific lower wellbeing for individuals who typically have more resources. According to the theory, individuals acquire and store up resources to protect themselves and ease challenges in life. These resources include valued conditions or situations, personal resources such as self-efficacy, and material and energy resources such as money (Wanberg et al., 2020). When individuals lose or fear losing valued resource, wellbeing is negatively impacted (Hobfoll, 1989). Therefore reduced wellbeing in a specific context depends on how one's resource is perceived to have contracted (Hobfoll, 2010; Hobfoll et al., 2003).

In the context of high socioeconomic inequality (in South Africa) and the crisis precipitated by COVID-19, a key question is whether wellbeing might have differentially changed for individuals of lower and higher socioeconomic status (SES). Note that the argument here is that while everyone's wellbeing will be negatively impacted because of the universal nature of the crisis, the degree of perceived loss of wellbeing might depend on SES. The COR theory suggests that the loss of wellbeing depends on the perception of how one's resource contracts so that it is possible for perceived decrease in wellbeing to disproportionately affect the poor or the non-poor. The implication of this is that income-related inequality in wellbeing might differ from expectation, and the departure from expectation might be sensitive to the measure of wellbeing (since they are self-reported and therefore depend on perception). In the case of the poor, individuals with lower level of resource may be more likely to lose additional resource (for example the case of lockdown where vulnerable workers are locked out of employment because they are less likely to be able to work from home (Nwosu et al., 2022; Rogan & Skinner, 2020) while individuals of high SES may have stored up resources to buffer the shock (Hobfoll, 2010). While there is a scarcity of studies examining the relationship between SES and wellbeing in the context of a crisis (especially in developing countries), few studies from the developed world support the premise that individuals with lower SES experience a greater reduction in wellbeing (Ginexi et al., 2000; Phifer, 1990). In contrast to this finding (and in the case of the non-poor), some evidence suggests that in the context of the COVID-19 pandemic, decrease in perceived wellbeing may be higher for individuals of higher SES. For example, an Axios-Ipsos poll conducted in the United States shows that a higher proportion of higher SES individuals report a decline in their emotional wellbeing due to the pandemic compared to those of lower SES (Talev, 2020)[1]. Further descriptive analysis based on South African data during the pandemic suggests that the income-health gradient (in depressive symptoms) seems to have weakened during the pandemic (Oyenubi & Kollamparambil, 2020).

It is, therefore, possible for individuals of higher SES to perceive a greater decrease in wellbeing if perception of loss of resource occurs differentially for individuals with different SES. We note that South Africa is an interesting context to study this relationship because it is one of the most unequal countries in the world[2]. For example, being a higher SES individual could be associated with greater loss of interpersonal resources because of isolation (Wanberg et al., 2020). This is plausible in the South African context because spatial inequality (and security concerns) is such that while the built environment in richer (and urban) areas is suitable for isolation, isolation might not be a practical aspiration in poorer and more crowded areas even if it is desirable. Further, a recent paper argues that due to labour migration and decline in rates of marital union, there has been a rise in solo living in South Africa and this has adverse mental health implications (Posel, 2021). The other side of

1 Also see https://www.brookings.edu/research/well-being-and-mental-health-amid-covid-19-differences-in-resilience-across-minorities-and-whites/.

2 See https://www.worldbank.org/en/country/southafrica/overview.

this argument is that individuals with lower SES are more likely to have lower perceived control even before the pandemic. Therefore they may experience a lower drop in wellbeing due to COVID-related uncertainties (Wanberg et al., 2020). Lastly, an increase in social assistance pay-outs in the earlier stages of the pandemic (Bhorat & Köhler, 2020) may also have assisted individuals of lower SES to cope financially under lockdown conditions. This will further reduce the sense of loss for low SES individuals since such programmes are targeted at them.

A related argument that supports the notion that (perceived) wellbeing loss may be greater for high SES individuals is proposed under the "steeling effect" perspective (Holtge et al., 2018). The "steeling effect" suggests that past experiences of adversity may increase resistance to later adversities. The idea is that under certain conditions, past adversity may have the potential for positive outcomes, such as increased resilience and thriving (Carver, 1998; Rutter, 1987).

The implication of the arguments above is that if the COR theory is a valid explanation in the context of COVID-19, the relationship between self-assessed wellbeing measures and SES may have changed compared to the pre-pandemic pattern. In other words, if wellbeing is measured by health[3], one may expect a weakening of the income-health gradient in the context of a public event crisis like COVID-19. As noted earlier this will have implications for policies that are designed to address the devastation caused by the pandemic. This also raises the possibility that *when it comes to the relationship between wellbeing and SES, this relationship may vary by different indicators used to capture wellbeing*. The central point is that how different indicators used to capture wellbeing behave in a special context like COVID-19 might vary (based on perception of loss) and this will have implications for inferences that rely on different measures (at least as it relates to their relationship with SES). Specifically, this paper compares the pre-and-during pandemic dynamics in depressive symptoms and self-assessed health to ascertain if socioeconomic inequalities in these indicators are similar over the two periods or whether there is a divergence. A divergence will suggest that COR/steeling effect is applicable in the context of the indicator that diverges from the pre-pandemic pattern of inequality. This is important because it can help put the interpretation of research based on various measures in proper context.

[3] Note that the WHO definition links health explicitly with wellbeing, see https://www.healthknowledge.org.uk/public-health-textbook/medical-sociology-policy-economics/4a-concepts-health-illness/Sect.2/activity3 for some discussion on this issue.

Brief review of literature and motivation

We note that while self-assessed health and depressive symptoms are correlated to the extent that the latter has been shown to be a predictor of the former (Ishida et al., 2020; Rantanen et al., 2019), they measure different aspects of wellbeing. Specifically, self-rated health is a more general concept when compared with self-rated depressive symptoms. This is because the former provides an assessment of subjective health that includes physical and psychological aspects of health (Ambresin et al., 2014; Mavaddat et al., 2011). Despite this positive relationship, research that is based on the National Income Dynamic Study-Coronavirus Rapid Mobile (NIDS-CRAM)[4] suggests that there is a divergence in the pattern of socio-economic inequality in these variables. Analysis based on wave 1 of NIDS-CRAM shows that socioeconomic inequality in self-assessed health is not only concentrated amongst the poor (as it was before the pandemic), the concentration has increased (Nwosu & Oyenubi, 2021). In contrast, analysis based on waves 2 and 3 data suggests that while poor mental health as measured by depressive symptoms is still concentrated amongst the poor (as it was before the pandemic) this inequality has weakened with the concentration index being statistically insignificant in wave 3 (Oyenubi et al., 2021; Oyenubi & Kollamparambil, 2020)[5].

It is important to note that there are three plausible explanations for this. First, compared to the pre-pandemic data (i.e., National Income Dynamic Study (NIDS) data on which NIDS-CRAM was based) the instrument used to measure depressive symptoms has changed. The pandemic situation meant that the NIDS-CRAM survey is a shorter telephonic survey which necessitated the switch from the longer 10-item Centre for Epidemiological Studies Depression Scale (CESD-10) (Radloff, 1997) to the shorter 2-question version of the Patient Health Questionnaire (PHQ-2).[6] Even though both measures have been validated as reliable screening measures of depression in South Africa (Baron et al., 2017; Bhana et al., 2015), it is still possible that differences in the measuring instrument may explain the difference observed. For example, Bhana et al. (2015) noted that the PHQ-2 has lower sensitivity than specificity; however, it remains a valid option for use specifically in

[4] A broadly nationally representative survey based on the adult South African population during the COVID-19 pandemic.

[5] Note that in the NIDS-CRAM surveys (waves 1 to 4) only one of these measures is included in the survey. Self-assessed health question is asked in waves 1 and 4, while questions on depressive symptoms are asked in waves 2 and 3. It is only in the current wave (wave 5) that the two health-based wellbeing questions feature together.

[6] PHQ-2 is the abbreviated version of the widely used PHQ-9 (Kroenke et al., 2003).

time-constrained settings (Bhana et al., 2015). The implication is that differences in patterns of socio-economic inequality in health may be explained by differences in measures of depressive symptoms especially since the pattern of socio-economic inequality in self-assessed health remains comparable with the pre-pandemic pattern.

The second plausible explanation is that the COR theory and the steeling effect perspective is applicable for the COVID era data. It may very well be that the perceived sense of loss due to the pandemic may have occurred differentially across the SES spectrum such that the observed weakening of the income-health gradient in depressive symptoms is due to the explanations offered by the COR theory. This is a possibility because to the extent that both the PHQ-2 and the CESD-10 measure the same construct (depressive symptoms), differences in socioeconomic inequality in these measures may not be purely due to differences in the instruments.

A third option is that the change observed is due in part to differences in measures and the explanation offered by the COR theory and the steeling effect. While we could not disentangle these effects, the second and third reasons have implication for the relationship between SES and wellbeing. The fact that one measure of wellbeing (PHQ-2) signals a reversal in the direction of inequality while another measure (self-assessed health) suggests that inequality in wellbeing has been exacerbated by the pandemic implies that the indicator used to measure wellbeing matters in the context of a public event crisis like the COVID-19 pandemic.

Wave 5 of the NIDS-CRAM data provides a unique opportunity to compare inequality and factors that explain inequality in both measures for the same individuals. Earlier waves of NIDS-CRAM include only one of these measures per wave (wave 1 & 4 – self-assessed health, waves 2 & 3 – depressive symptoms) while wave 5 contain both measures. Using wave 5 data rules out the possibility that decomposition results are influenced by time difference or the fact that the surveys are based on slightly different samples. For example, about 13% of the NIDS-CRAM wave 3 sample are NIDS survey participants that were not selected to be interviewed in waves 1 & 2 of NIDS-CRAM but were added in wave 3 to replenish the sample because of attrition (Ingle et al., 2021). This coincides with the concentration index of PHQ-2 in wave 3 being statistically insignificant. Further, to better establish the pattern of inequality in these measures before and during the pandemic, we estimate concentration indices for the measures of interest in all waves of NIDS and NIDS-CRAM data.

Our result shows that while socioeconomic inequality in poor self-assessed health is concentrated amongst the poor both before and during the pandemic, socioeconomic inequality in depressive symptoms has at least weakened during the pandemic i.e., is less concentrated amongst the poor. Furthermore, decomposition of the wave 5 concentration index in the two measures shows that the difference in socioeconomic inequality has implication for inferences. Specifically, while eliminating the contribution of the white racial group to the socioeconomic inequalities in health will make self-assessed health less concentrated amongst the poor, the same action will make depressive symptoms more concentrated amongst the poor. This is problematic if one assumes that the measures are correlated as observed before the pandemic. The important point is that in the context of a public event crisis like COVID-19, some measures of wellbeing may be sensitive to SES (because of the influence of perception on self-reported measures). Therefore, inferences that are based on different measures of wellbeing may not agree with what is expected in more normal times. Lastly, we discuss plausible mechanisms that may explain this divergence in our concluding remarks.

Data and methods

Our data is sourced from the five waves of the NIDS and NIDS-CRAM survey. NIDS is a nationally representative panel survey conducted by the South African Labour and Development Research Unit. The survey studies the well-being of South Africans, their households and how these change over time. The first and fifth waves were conducted in 2008 and 2017, respectively. NIDS-CRAM is a special follow up of the NIDS 2017 adult sample. In comparison to the core NIDS panel study, NIDS-CRAM uses a much shorter questionnaire, with a focus on the coronavirus pandemic and the national lockdown (Ingle et al., 2021). Further, unlike NIDS where face-to-face interviews were conducted, NIDS-CRAM is a computer-assisted telephone interview repeated five times between May 2020 and May 2021.

The NIDS-CRAM sample was selected using a stratified design but with 'batch sampling'. This approach offered flexibility in adjusting the sampling rate as the survey progressed, and as information about stratum response became available (Kerr et al., 2020). Our measure of self-assessed health is based on the question that asks respondents to describe their current health status. The responses were captured on a Likert scale comprising *excellent, very good, good, fair and poor* with higher values indicative of worse health outcomes. As noted earlier, depressive symptoms are measured by a 2-question version of the Patient Health Questionnaire (PHQ-2).[7] The two questions administered to derive the PHQ-2 measure are: "*Over the last 2 weeks,*

[7] PHQ-2 is the abbreviated version of the widely used PHQ-9 (Kroenke et al., 2003). It has been validated as a reliable screening method for depressive symptoms in South Africa (Baron et al., 2017).

Table 1 Prevalence of poor health by quintiles of per capita household income (%)

Waves	1	2	3	4	5	1	2	3	4	5
Income quintiles	Self-assessed poor health					Screen positive for depressive symptoms				
1	17.47	8.58	9.43	10	9.19	36.11	20.7	28.12	24.11	31.09
2	19.97	12.16	11.76	10.8	11.22	31.59	21.21	27.25	25.2	29.45
3	18.74	10.59	11.74	12.1	10.6	29.64	22.9	24.82	24.84	24.17
4	16.18	11.32	13.09	11.53	11.9	25.85	20.19	24.08	25.21	22.65
5	7.96	6.57	8.24	9.26	6.87	15.8	9.54	13.53	21.11	17.31
population	15.97	9.47	10.63	10.59	9.3	28.48	18.39	22.42	23.59	21.78

NIDS waves 1 to 5 prevalence estimates weighted by post-stratification weights

have you had little interest or pleasure in doing things?" and "*Over the last 2 weeks, have you been feeling down, depressed or hopeless*". Both questions could be responded to as "*not at all*", "*several days*", "*more than half the days*" or "*nearly every day*". The responses are coded from 0 to 3, creating the outcome variable of the PHQ-2 scale with a range of 0 to 6, with increasing values indicating higher levels of depressive symptoms.

For the calculation of concentration indices (using all 5 waves of NIDS and NIDS-CRAM), we used both the original and dichotomized versions of the outcome variables to show that our inference does not depend on the way the variables are constructed. For the decomposition analysis (using wave 5 of data collected during the pandemic) we used the dichotomized versions of the outcome variables. Specifically, we follow the literature and create a dummy for poor self-assessed health that is equal to 1 if the respondent reports their health as fair or poor and zero otherwise (Nwosu & Oyenubi, 2021). The dummy for poor mental health is 1 if the PHQ-2 depression score is 3 or above and zero otherwise. Household income per capita was used as an indicator of socioeconomic status against which health inequality was measured. Note that household income was not available in wave 3 of NIDS-CRAM. Therefore, for the NIDS-CRAM computation, we used years of education as an alternative socioeconomic ranking variable.

The concentration index was computed as follows (O'donnell et al., 2007):

$$C_S = \frac{2}{\mu_S} cov(S, r) \tag{1}$$

where S is the health variable of interest, C_S refers to the concentration index of the health variable, μ_S refers to its mean, and r is the fractional rank of the individual/household in the income distribution. Thus, the concentration index is hereby defined as twice the covariance of the health outcome and the fractional rank of the individual in the income distribution, divided by the mean of the health outcome. $C_S$ranges from -1 to $+1$ with a negative (positive) index indicating the poor health is concentrated amongst the poor (rich). An index value of zero indicates that there is no inequality in health.

We decomposed the income-related inequalities in health-based wellbeing measures using the Wagstaff et al. approach (Wagstaff et al., 2001). Thus, we specified a logit model of poor health/wellbeing as follows:

$$S_i = \alpha + \sum\nolimits_k \beta_k z_{ki} + \varepsilon_i \tag{2}$$

where α and β are parameters, ε is the error term and z represent the covariates. Equation (2) was appropriately weighted to the population while correcting for heteroscedasticity. We decomposed the concentration index in Eq. (1) as follows:

$$C_S = \sum\nolimits_{k=1}^{K} \left(\frac{\beta_k \bar{z}_k}{\mu_S} \right) C_k + \left(\frac{GC_\varepsilon}{\mu_S} \right) \tag{3}$$

where $\left(\frac{\beta_k \bar{z}_k}{\mu_S} = \eta_k \right)$ denotes the elasticity of poor health to marginal changes in the kth explanatory variable, while C_k denotes the concentration index of the kth explanatory variable. GC_ϵ refers to the generalised concentration index of the error term, and $\left(\frac{GC_\epsilon}{\mu_S} \right)$ represents the unexplained component. Our analysis accounts for the survey design by using survey weights, and to obtain valid standard errors, we bootstrapped the estimates 1000 times.

Results

Table 1 displays the prevalence of poor health as measured by self-assessed health and depressive symptoms based on waves 1 to 5 of NIDS data (the outcomes are dummy variables as described in Section 3). The results show that the higher quantiles generally have lower prevalence compared to the lower quantiles (especially for depressive symptoms). Table 2 displays the corresponding concentration indices. The indices are all negative and mostly statistically significant showing that they are consistent with the expected

Table 2 Concentration indices for waves 1 to 5 of NIDS (before the pandemic)

	Obs	Total	Female	Male
	Self-assessed health (ranking variable: income)			
Wave 1	15,536	-0.064***	-0.050***	-0.054***
Wave 2	17,426	-0.024**	-0.019	-0.014
Wave 3	18,677	-0.036***	-0.022*	-0.034**
Wave 4	22,732	-0.022**	-0.014	-0.016
Wave 5	23,864	-0.038***	-0.028***	-0.035***
	CESD-10 Depression scores (ranking variable: income)			
Wave 1	15,342	-0.081***	-0.076***	-0.076***
Wave 2	16,196	-0.043***	-0.037***	-0.045***
Wave 3	18,485	-0.062***	-0.064***	-0.057***
Wave 4	22,615	-0.019***	-0.019**	-0.017**
Wave 5	23,628	-0.051***	-0.048***	-0.053***

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3 Concentration indices for waves 1 to 5 of NIDS -CRAM (during the pandemic)

	Obs	Total	Female	Male
Panel A				
	Self-assessed health (ranking variable: income)			
Wave 1	4364	-0.093***	-0.092***	-0.084***
Wave 4	5244	-0.117***	-0.107***	-0.118***
Wave 5	5452	-0.108***	-0.098***	-0.113***
	PHQ-2 Depression scores(ranking variable: income)			
Wave 2	4682	0.011	0.034*	-0.015
Wave 5	5463	-0.024	-0.019	-0.022
Panel B				
	Self-assessed health (ranking variable: schooling)			
Wave 1	6981	-0.113***	-0.117***	-0.109***
Wave 4	5553	-0.132***	-0.128***	-0.134***
Wave 5	5810	-0.109***	-0.115***	-0.100***
	PHQ-2 Depression scores (ranking variable: schooling)			
Wave 2	5553	0.044**	0.060***	0.027
Wave 3	5965	-0.012	0.001	-0.026
Wave 5	5828	-0.026*	-0.024	-0.028

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

negative relationship between income and health, irrespective of how health is measured.

The results use the original scale of the variables (i.e., not based on the dichotomized version of the variables) using the Erreygers (Erreygers, 2009) normalization. Similar results using the dichotomized version of the variables show that the results are consistent irrespective of how the wellbeing measures are used (see the Appendix for these results).

The results use the original scale of the variables (i.e., not based on the dichotomized version of the variables) using the Erreygers (Erreygers, 2009) normalization. Similar results using the dichotomized version of the variables show that the results are consistent irrespective of how the wellbeing measures are used (see the Appendix for these results).

Table 3 shows a similar result for the COVID era data (i.e., NIDS-CRAM). Because household income is not available for wave 3, we calculate the concentration indices using both household income (where available) and the number of years of schooling as an alternative measure of SES. Panel A of Table 3 shows the result when household income per capita is used as the ranking variable. The result shows that while income-related health inequality in self-assessed health still conforms to the pre-pandemic pattern in waves 1, 4 and 5 (in fact the concentration index has increased in the COVID-era data), the income-related inequality in depressive symptoms is not statistically significant (in waves 2 &5) and positive in wave 2. Further the size of the indices has decreased in the COVID-era data. The disaggregated analysis (by gender) follows the same patter with the concentration index for females being positive and statistically significant. These results suggest that income-related inequality in depressive symptoms is less concentrated on the poor for the pandemic data.

Panel B of Table 3 show similar results when education is used as the ranking variable (this allows us to add analysis on wave 3 that excludes income information). Income related inequality in self-assessed health remain concentrated amongst the poor even for the disaggregated analysis. For depressive symptoms, income related inequality is only negative and statistically significant in wave 5 (at 10%) while in the other two waves (waves 2 & 3) it is either not statistically significant or positive and statistically significant. Consistent with the result when income is used as the ranking variable income related inequality in depressive symptoms appear to have weakened for the pandemic era data contrary to expectation.

As noted earlier there are at least 3 plausible explanations (possibly more). We note that while it may not be possible to disentangle which explanation is at play, it remains valid to say that the relationship between SES and depressive symptoms as measured by PHQ-2 departs from what is expected in normal times. This has implication for inferences that are based on wellbeing indicators. Even though self-assessed health is a general measure of health that includes physical and psychological aspects of health (Ambresin et al., 2014; Mavaddat et al., 2011), our result suggests that this does not necessarily translate into similar relationship in the data. The existence of theories like the COR theory and the steeling effect perspective create a possibility that the relationship between income and some measures of wellbeing might not conform to what we would expect in normal times.

Table 4 Decomposition Result (depressive symptoms)

	Concentration index	Elasticity	Contribution
COVID risk	0.115**	0.128**	0.015**
	(0.018)	(0.025)	(0.004)
Able to avoid COVID	-0.006	-0.076	0.000
	(0.005)	(0.098)	(0.001)
Household hunger	-0.396**	0.060**	-0.024**
	(0.026)	(0.012)	(0.005)
No of Child Support Grants	-0.395**	0.015	-0.006
	(0.017)	(0.029)	(0.011)
No of Old Age pensions	-0.113**	-0.000	0.000
	(0.024)	(0.026)	(0.003)
Respondent receives any Govt grant	-0.264**	-0.035	0.009
	(0.019)	(0.033)	(0.009)
HH income decreased	-0.072**	0.020	-0.001
	(0.030)	(0.020)	(0.001)
Household income unchanged	0.049**	-0.017	-0.001
	(0.009)	(0.089)	(0.004)
Informal settlement	-0.002	-0.003	0.000
	(0.065)	(0.010)	(0.000)
Township	-0.042**	-0.038	0.002
	(0.020)	(0.040)	(0.002)
Formal residence	0.296**	-0.006	-0.002
	(0.024)	(0.032)	(0.010)
Farm	-0.214**	-0.005	0.001
	(0.038)	(0.010)	(0.002)
Small holding	-0.153**	-0.016**	0.002
	(0.075)	(0.008)	(0.002)
Age (years)	0.021**	0.054	0.001
	(0.005)	(0.654)	(0.014)
Age squared	0.041**	-0.020	-0.001
	(0.011)	(0.340)	(0.014)
Male = = 1	0.125**	-0.015	-0.002
	(0.015)	(0.043)	(0.005)
Coloured	0.055	0.038**	0.002
	(0.062)	(0.009)	(0.002)
Asian	0.360**	-0.008	-0.003
	(0.080)	(0.011)	(0.004)
White	0.715**	0.031*	0.022*
	(0.025)	(0.016)	(0.012)
HH income per capita	0.702**	0.006	0.004
	(0.012)	(0.024)	(0.017)
Has a partner	0.120**	0.002	0.000
	(0.019)	(0.030)	(0.004)
Traditional/Mud	-0.363**	-0.019*	0.007*
	(0.037)	(0.010)	(0.004)
Informal/shack	-0.128**	0.022*	-0.003
	(0.044)	(0.012)	(0.002)
Other	-0.115	0.003	-0.000
	(0.075)	(0.004)	(0.000)
Unemployment discouraged	-0.248**	-0.022	0.005
	(0.042)	(0.017)	(0.004)
Unemployment strict	-0.380**	0.020	-0.008

Table 4 (continued)

	Concentration index	Elasticity	Contribution
	(0.028)	(0.017)	(0.007)
Employed	0.204**	-0.074	-0.015
	(0.012)	(0.056)	(0.011)
Years of schooling	0.067**	0.771**	0.052*
	(0.004)	(0.387)	(0.027)
Years of schooling squared	0.115**	-0.585**	-0.067**
	(0.007)	(0.256)	(0.030)
No of preventative measures	0.015**	-0.068	-0.001
	(0.005)	(0.090)	(0.001)
Residual			-0.006
			(0.014)
Total			-0.017
			(0.024)
N	4948		

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Decomposition results and implication for inference

In this section, we decompose the concentration indices based on NIDS-CRAM wave 5 data. Our result illustrates the implication of the variation in the relationship between health and SES.

Tables 4 and 5 show the decomposition results for PHQ-2 and self-assessed health (note that the number of observations has dropped compared to Table 3 due to missing observation in some covariates). Consistent with our earlier results, the concentration index is negative for both outcomes but only statistically significant for self-assessed health. We controlled for other covariates, i.e. COVID risk perception, perception of ability to avoid COVID, household hunger, number and type of grant received by the respondent and their household, an indication as to whether household income has changed over the last 4 weeks, area description (e.g. informal settlement), demographic characteristics (i.e. age, gender and race), relationship status, dwelling type (e.g. informal/shack), employment status, years of schooling and number of preventative measures adopted. See Table 8 in the Appendix for the summary statistics table.

The variables that significantly contribute to inequality in depressive symptoms include risk perception, race (i.e. white dummy), traditional/mud dwelling type, years of schooling and hunger. Of these variables only hunger and the square of years of schooling have negative contributions. A positive contribution means that eliminating inequality in the covariate and/or the relationship between the covariate and depressive symptoms (i.e. elasticity) will increase the extent to which depressive symptoms disfavour the poor. For example, eliminating inequality in risk perception or years of schooling (and/or the relationship between these covariates and depressive symptoms (elasticity)) will increase inequality to the detriment of individuals with lower SES. Therefore, such variables contribute to mitigating the extent to which depressive symptoms disfavour the poor. Conversely, variables with a negative contribution worsen the extent to which depressive symptoms disfavour the poor. On the other hand, the variables that contribute significantly to inequality in self-assessed health include risk perception, hunger, white dummy, and employment status. Here hunger, white dummy and employment status have negative contributions. The same interpretation applies. For example, eliminating inequality in employment status (and/or the relationship between employment and depressive symptoms (i.e. elasticity)) will mitigate the extent to which self-assessed health is concentrated amongst the poor.

The important results in relation to the sensitivity of these indicators to inequality in SES are highlighted in the white dummy variable. The elasticity of this variable in Table 4 is positive (0.031) and significant at the 10% level while it is negative (-0.124) and significant at the 5% level in Table 5. The implication is that while being white increases the probability of reporting depressive symptoms, it reduces the probability of reporting poor self-assessed health. This translates into the dummy having a positive and significant contribution for depressive symptoms (Table 4) but a negative and significant contribution for self-assessed health (Table 5). Interpreting the contribution of this variable will then mean that eliminating inequality in the white dummy (and/or its relationship with depressive symptoms (elasticity)) will make depressive symptoms more concentrated amongst the poor while the same action will make poor self-assessed health less concentrated

Table 5 Decomposition Result (self-assessed health)

	Concentration index	Elasticity	Contribution
COVID risk	0.115**	0.141**	0.016**
	(0.018)	(0.030)	(0.004)
Able to avoid COVID	-0.006	-0.195**	0.001
	(0.005)	(0.098)	(0.001)
Household hunger	-0.396**	0.055**	-0.022**
	(0.026)	(0.011)	(0.004)
No of Child Support Grants	-0.395**	-0.021	0.008
	(0.017)	(0.035)	(0.014)
No of Old Age pensions	-0.113**	0.025	-0.003
	(0.024)	(0.025)	(0.003)
Respondent receives any Govt grant	-0.264**	-0.032	0.008
	(0.019)	(0.032)	(0.008)
HH income decreased	-0.072**	0.027	-0.002
	(0.030)	(0.019)	(0.002)
Household income unchanged	0.049**	0.013	0.001
	(0.009)	(0.086)	(0.004)
Informal settlement	-0.002	-0.003	0.000
	(0.065)	(0.011)	(0.000)
Township	-0.042**	0.047	-0.002
	(0.020)	(0.038)	(0.002)
Formal residence	0.296**	-0.021	-0.006
	(0.024)	(0.040)	(0.012)
Farm	-0.214**	0.014	-0.003
	(0.038)	(0.010)	(0.002)
Small holding	-0.153**	-0.007	0.001
	(0.075)	(0.007)	(0.001)
Age (years)	0.021**	0.840	0.018
	(0.005)	(0.619)	(0.014)
Age squared	0.041**	-0.293	-0.012
	(0.011)	(0.317)	(0.013)
Male	0.125**	-0.036	-0.004
	(0.015)	(0.044)	(0.005)
Coloured	0.055	-0.092**	-0.005
	(0.062)	(0.039)	(0.005)
Asian	0.360**	-0.033*	-0.012
	(0.080)	(0.018)	(0.008)
White	0.715**	-0.124**	-0.088**
	(0.025)	(0.035)	(0.025)
HH income per capita	0.702**	0.023	0.016
	(0.012)	(0.030)	(0.021)
Has a partner	0.120**	-0.008	-0.001
	(0.019)	(0.032)	(0.004)
Traditional/Mud	-0.363**	0.010	-0.004
	(0.037)	(0.010)	(0.004)
Informal/shack	-0.128**	-0.023	0.003
	(0.044)	(0.016)	(0.002)
Other	-0.115	0.007*	-0.001
	(0.075)	(0.004)	(0.001)
Unemployment discouraged	-0.248**	-0.026	0.006
	(0.042)	(0.019)	(0.005)
Unemployment strict	-0.380**	-0.002	0.001

Table 5 (continued)

	Concentration index	Elasticity	Contribution
	(0.028)	(0.025)	(0.009)
Employed	0.204**	-0.172**	-0.035**
	(0.012)	(0.078)	(0.016)
Years of schooling	0.067**	-0.345	-0.023
	(0.004)	(0.472)	(0.032)
Years of schooling squared	0.115**	0.038	0.004
	(0.007)	(0.295)	(0.034)
No of preventative measures	0.015**	-0.137	-0.002
	(0.005)	(0.116)	(0.002)
Residual			0.013
			(0.019)
Total			-0.128**
			(0.023)
N	4948		

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

amongst the poor. This is confusing from a policy point of view because it says the elimination of racial inequality in SES can help and harm the poor based on the difference in wellbeing measure. This is better expressed by saying eliminating inequality in the white dummy (which is concentrated amongst the affluent) will make the income-health gradient in depressive symptoms steeper while it will make the income-health gradient in self-assessed health less steep.

This result suggests that while there has been a decrease in wellbeing in the population in general, the self-assessed health indicator suggests that a decrease in wellbeing affects the poor more than the non-poor. However, in the case of the indicator of depressive symptoms, it appears that the decrease in wellbeing disproportionately affects the non-poor (relative to the pre-pandemic period). As noted earlier, the COR theory and the steeling effect perspective acknowledge this possibility. What our result shows is that if these theories explain the pattern of socioeconomic inequality in PHQ-2 but not self-assessed health, then the choice of wellbeing measure matters specifically in a special period like the COVID-19 period. This is contrary to what one will expect in normal times when one can perhaps safely assume that the relationship between these measures and SES as shown in Tables 1 and 2 largely agree with the existence of an income-health gradient that favours the non-poor.

One plausible explanation for what is being observed in the case of PHQ-2 is the result on risk perception. Note that COVID risk perception is only applicable in the COVID era. This variable is correlated with the increase in the report of depressive symptoms and poor self-assessed health (Oyenubi & Kollamparambil, 2020). However, consistent with other results based on similar data, risk perception is concentrated amongst individuals of higher SES (Burger et al., 2020; Kollamparambil & Oyenubi, 2020, 2021). One could therefore argue that inequality in risk perception is one of the many plausible reasons why the income-health gradient in depressive symptoms has become less steep.

Concluding remarks and implications for policy

This paper examines the hypothesis that the relationship between perceived wellbeing and SES might be situation-specific in the context of the COVID-19 pandemic in South Africa. Further, we hypothesize that the relationship between wellbeing and SES might depend on the measure of wellbeing under consideration. Using self-assessed health and depressive symptoms, we examine if income-related health inequality supports the expected positive relationship that exists between income and health before the pandemic. The premise is that the COR theory and the steeling effect perspective suggest that situation-specific perceived lower wellbeing for individuals who typically have more resources is plausible during a public crisis event. This will imply that the income-health gradient is weaker or that the income-health gradient for some measure of health is weaker than otherwise expected.

We exploit the fact that the COVID-19 pandemic is a global phenomenon that negatively impacts the wellbeing of individuals irrespective of SES to examine if the decrease in wellbeing in this period is mediated by SES. This is important to the question of tracking population health and wellbeing especially during a crisis period like the COVID-19. Our results show that while income-related health inequality in self-assessed health is consistently negative and significant both before and during the pandemic, this is not the case for self-assessed depressive symptoms. Inequality in depressive symptoms as measured by PHQ-2 appear to be less concentrated amongst the poor compared to the pre-pandemic period. In some cases, the concentration index is positive and significant suggesting that depressive symptoms are concentrated amongst the rich during the pandemic. While we are unable to disentangle whether this is as a result of the change in instrument used to measure depressive symptoms across the two periods or that the COR is in operation in this specific variable or both, we argue that this result implies that indicators used to capture health/wellbeing matter specifically in the context of a crisis like COVID-19. Further, we show that this has implication for the interpretation of results based on different measures. Specifically, our result suggests that the same policy action can help and harm the poor depending on the measure of wellbeing under consideration.

This result is important since it is suggested that there is a change in income-related inequality in ill-health, where it is found to have weakened in a measure of wellbeing while becoming stronger in another. The implication is that income-related inequality in a period like the COVID-19 period might be sensitive to the indicator used to capture wellbeing. While the change in measure is a disadvantage in this study, there is at least one other study that shows that a larger increase in depressive symptoms amongst the rich is consistent with data even when the same measure of depression is used to capture depressive symptoms before and during the COVID-19 pandemic. Specifically, using data from the USA, Wanberg et al. (2020) found that individuals of higher SES report a larger increase in depressive symptoms and life satisfaction from before to during the COVID-19 pandemic. This reduces the possibility that the weakening of the income-depressive health gradient in this study is purely due to the change in measure.

Since there are a number of scales used to measure depressive symptoms (see https://www.apa.org/depression-guideline/assessment for example), it is important for future studies to examine how these measures behave in the context of a public health crisis like COVID-19. This will enable a better interpretation of these measures and enable more accurate tracking of public health based on these measures.

In terms of policy implication, we note that it clear that the COVID-19 pandemic increases the incidence of depressive symptoms in the population. However, irrespective of the section of the population that is disproportionately affected, timely intervention by the government in terms of social distancing restrictions (Bauer et al., 2021) and social transfers (Lee et al., 2021) has been shown to be effective in reducing the risk of depression. Evidence also suggests the adoption of internet cognitive behavioral therapy (I-CBT) interventions can assist to mitigate the upsurge in reports on depressive symptoms. First the approach can be deployed even under social distancing restrictions (subject to availability of necessary infrastructure). Second, this approach is not only cost effective, it is associated with large effect size reductions in anxiety, symptom severity for depression and psychological distress (Mahoney et al., 2021; Zhang & Ho, 2017).

Appendix

Tables 6, 7, and 8

Table 6 Concentration indices for Waves 1 to 5 of NIDS (before the pandemic)

	Obs	Total	Female	Male
Dummy (poor health if SAH is fair or poor, screen positive for depressive symptoms if CSD-10≥10)				
	Self-assessed health (income)			
Wave 5	5452	-0.117***	-0.095***	-0.135***
Wave 4	5244	-0.110***	-0.120***	-0.099***
Wave 1	4364	-0.117***	-0.132***	-0.093**
	PHQ-2 Depression scores(income)			
Wave 5	5463	-0.012	-0.008	-0.007
Wave 2	4682	0.035	0.047	0.022
	Self-assessed health (schooling)			
Wave 5	5810	-0.106***	-0.122***	-0.082**
Wave 4	5553	-0.126***	-0.112***	-0.139***
Wave 1	6981	-0.099***	-0.144***	-0.047
	PHQ-2 Depression scores(schooling)			
Wave 5	5828	-0.031	-0.035	-0.026
Wave 3	5965	-0.035*	0.023	-0.049*
Wave 2	5553	0.065*	0.094***	0.034

Table 7 Concentration indices for Waves 1 to 5 of NIDS -CRAM (during the pandemic)

	Obs	Total	Female	Male
Dummy (poor health if SAH is fair or poor, screen positive for depressive symptoms if CSD-10≥10)				
	Self-assessed health (income)			
Wave 5	23,864	-0.094***	-0.052**	-0.123***
Wave 4	22,732	-0.048**	-0.011	-0.068**
Wave 3	18,677	-0.045**	-0.013	-0.054*
Wave 2	17,426	-0.048*	-0.032	-0.023
Wave 1	15,536	-0.101***	-0.065***	-0.119***
	CESD-10 Depression scores(income)			
Wave 5	23,628	-0.112***	-0.099***	-0.119***
Wave 4	22,615	-0.051***	-0.054**	-0.042*
Wave 3	18,485	-0.145***	-0.136***	-0.145***
Wave 2	16,196	-0.124***	-0.097***	-0.150***
Wave 1	15,342	-0.144***	-0.127***	-0.144***

Table 8 Summary Statistics (wave 5 data)

Variables	(1) Mean (Standard deviation)
sick	0.280
	(0.449)
depressed	0.286
	(0.452)
COVID risk	0.391
	(0.488)
Able to avoid COVID	0.883
	(0.321)
Household hunger	0.192
	(0.394)
No of Child Support Grants	1.494
	(1.681)
No of Old Age pensions	0.390
	(0.628)
Respondent receives any Govt grant	0.451
	(0.498)
HH income increased	0.184
	(0.387)
Household income decreased	0.151
	(0.358)
Household income unchanged	0.665
	(0.472)
Informal settlement	0.273
	(0.446)
Township	0.035
	(0.185)
Formal residence	0.346
	(0.476)
Farm	0.216
	(0.412)
Small holding	0.097
	(0.295)
Not Categorized	0.033
	(0.177)
Age (years)	41.288
	(15.459)
Age squared	1,943.645
	(1,473.323)
male	0.366
	(0.482)
African	0.863
	(0.344)
Coloured	0.085
	(0.278)
Asian	0.009
	(0.095)
White	0.043
	(0.203)
Household income per capita	1,730.643
	(3,913.775)
Has a partner	0.317
	(0.465)
House/flat	0.770
	(0.421)
Traditional/Mud	0.116
	(0.320)
Informal/shack	0.091
	(0.287)
Other	0.024
	(0.153)
Not economically active	0.235
	(0.424)
Unemployment discouraged	0.119
	(0.324)
Unemployment strict	0.159
	(0.365)
Employed	0.487
	(0.500)
Years of schooling	10.711
	(4.093)
Years of schooling squared	1.315
	(0.795)
No of preventative measures	2.760
	(1.021)
Observations	4,948

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Data availability The data is available from http://www.nids.uct.ac.za/nids-cram/data-access.

Declarations

Ethics approval and consent to participate Ethics approval for the NIDS-CRAM Survey was granted by the Commerce Faculty Ethics Committee of the University of Cape Town and the Research Ethics Committee: Social, Behavioral and Education Research, of the University of Stellenbosch.

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