

Does Socioeconomic status mediate the relationship between income loss and depression scores? Evidence from South Africa

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Abstract

This paper examines the role of socioeconomic status (SES) in mediating the effect of job and household income loss on mental health during the COVID-19 pandemic. We note that even though job loss will invariably reduce household income, the relationship between these factors and mental health may be mediated by SES. Specifically, in the context of COVID-19 induced shock, job loss may not be a threat to survival for an individual with relatively high SES, while this is not the case for individuals with low SES. Our empirical analysis uses threshold regression under the assumption that the relationship between depressive symptoms and pandemic induced job/ income loss has a threshold effect. We find that job loss (but not the decline in household income) is a stronger predictor of poor mental health for individuals that live in households above a certain SES threshold. This suggests that the psychological trauma of job loss due to loss of identity and purpose outweighs the financial loss for individuals with higher SES. On the other hand, a decrease in household income (as against the loss of individual income) is a stronger predictor of poor mental health for individuals with lower SES. We argue that these findings are related to high-income inequality in South Africa. The results highlight the different implications of job loss and income loss for depressive symptoms in the context of high socioeconomic inequality.

Keywords Mental Health · Depression · South Africa · COVID-19 · Social Assistance · Labour Economics

Introduction

Concerns about the mental health consequences of the COVID-19 pandemic, as well as the associated social and economic lockdown, are now widely acknowledged (Oyenubi & Kollamparambil, 2020; Posel et al., 2021). Apart from the anxiety and stress likely to result from health concerns, the response to the pandemic in terms of restriction of movement and economic activities will likely increase the incidence of depression, anxiety, substance use and loneliness (Galea et al., 2020; Vindegaard & Benros, 2020).

Given the aforementioned and consistent with available evidence from elsewhere, mental health problems are likely to have increased relative to the pre-COVID period in South Africa (Oyenubi & Kollamparambil, 2020). Furthermore, because South Africa is one of the most unequal countries in the world (Leibbrandt & Díaz Pabón, 2021; Leibbrandt

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² Such families are also likely to have lower level of saving thus making the financial pressure worse under lockdown restrictions.



et al., 2012), there will be significant differences in how South African residents experience the lockdown (i.e. the experience of the poor might be different from to those who are wealthy). The restriction of movement and the need to change behaviour (e.g., social distancing) may introduce additional stressors for a minority of relatively affluent families living in the suburbs. However, for low-income families living in informal settlements (or "townships") who rely on the informal economy (i.e. economic activities that are not regulated or protected by the state¹; International Labour Organization, 2010) for a living, earnings loss as a result of forced disengagement from the labour market may cause severe economic strain.² While for the wealthy, loneliness may contribute to depression (Erzen & Çikrikci, 2018), poverty and mental illness are widely considered to operate in a vicious cycle for the poor. This is because povertyrelated stress can predispose individuals to mental illness

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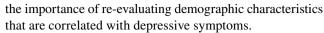
¹ Examples include informal trading like street hawking of various products, adhoc jobs in the hospitality industry like waiting tables, private cleaning services etc.

(including depression), and psychological problems, in turn, can increase the risk of falling into or remaining in poverty (Lund et al., 2011).³

Available literature suggests that the pandemic's impact on job and income loss varies by gender, race, and nature of employment (Spaull et al., 2020). It has also been shown that the poor, women and informal workers are disproportionately affected (Casale & Shepherd, 2020; Oyenubi, 2021; Rogan & Skinner, 2020). In terms of the impact of the pandemic on health, those who live in poorer households are more likely to report poor health in 2020 compared to 2017 (i.e. before and after the pandemic) (Nwosu & Oyenubi, 2021). This higher level of disparity in (self-reported) poor health is driven by hunger, and loss of employment. Given the impact of the pandemic on the economy, it is expected that the additional burden associated with the pandemic in terms of depressive symptoms will exacerbate existing inequality in health.

On the other hand, the government's efforts to mitigate the effects of the pandemic may aid in addressing financial concerns for the poor. For example, the government increased the amount of social assistance paid out⁴ to help beneficiaries cope during the pandemic. In addition to increasing pay-out for existing grants, a special COVID relief of distress grant was established to assist those who do not qualify for existing social grants but are unemployed (Köhler & Bhorat, 2020).

Apart from the negative impact of the pandemic on mental health through financial stressors, individuals' risk perception constitutes another channel. Risk perception of COVID-19 may exacerbate the negative psychological impact of the pandemic irrespective of socioeconomic status (SES). Therefore, those who believe they are at a greater risk of contracting or transmitting the virus may experience more psychological distress. It has been shown that affluent South Africans have higher (subjective) infection risk perception than poor South Africans (Burger et al., 2020; Kollamparambil & Oyenubi, 2020; Oyenubi & Kollamparambil, 2020; Oyenubi et al., 2021). Therefore, while financial pressure is expected to affect the poor disproportionately, risk perception may disproportionately affect the affluent. This highlights the significance of re-evaluating the prevalence of depressive symptoms in South Africa. It also underscores



The main question examined in this study is how SES mediates the relationship between job/income loss and depressive symptoms. There is a sizeable pre-pandemic literature exploring the relationship between mental health and employment status (Burgard et al., 2007; Graetz, 1993; Murphy & Athanasou, 1999; Paul & Moser, 2009). Literature from the pandemic context is still emerging. However, in South Africa, research has shown that those who retained paid employment during the early stages of the lockdown had substantially lower depression scores than those who lost employment (Posel et al., 2021).

This paper argues that the channel through which the pandemic induced labour market shock influences depressive symptoms is correlated with SES. Our result supports the hypothesis that SES mediates the relationship between depression scores and job/income loss. We find that job loss and decrease in household income are significantly correlated with deteriorating mental health (as measured by depressive symptoms). However, the effect depends on SES; while loss of individual income (as against decrease in household income) is more correlated with depressive symptoms for individuals of higher SES, a decrease in household income (as against the loss of individual income) is more correlated with depression scores for individuals of low SES.

Review and motivation for the study

A priori, the pandemic and associated lockdown would be expected to exacerbate existing inequalities in well-being, similar to the pandemic's negative effect on self-reported health (Nwosu & Oyenubi, 2021). However, some evidence has suggested that individuals with higher SES are more likely to experience worse impact in terms of wellbeing in the initial phases of a crisis. For example, Wanberg et al. (2020) argue that individuals who are better off in terms of SES experience a greater loss in well-being as measured by depressive symptoms and life satisfaction during the COVID-19 pandemic compared to those who are worse- off. This finding is consistent with the Axios-Ipsos poll conducted in the United States, which found similar results when comparing decline in emotional well-being due to the pandemic across SES (Taley, 2020). Although this result appears counterintuitive, it is supported by the Conservation of Resources (COR) Theory (Wanberg et al., 2020). The COR theory acknowledges the possibility that in the context of a public event crisis like COVID-19, lower well-being among individuals of higher SES is possible. The COR theory (Hobfoll et al., 2016) is a psychological theory that seeks to explain stress and trauma. The theory posits that humans want and conserve resources to protect their



³ Also see "http://www.hsrc.ac.za/en/news/general/mental-health-covid-19".

⁴ Existing grants like child support grant, old age pension etc. were topped up temporarily from May to October 2020. Further, a special social redressal of distress grant was initiated for those with no other means of income. As South Africa does not have an unemployment grant, this is seen as a major new initiative to provide relief to the unemployed.

well-being and ease challenges in life. These resources range from valued conditions and situations to personal resources such as self-efficacy and material resources (Hobfoll, 1989). The theory suggests that when individuals sense that they are losing or in danger of losing valued resources, well-being is impacted negatively (Hobfoll, 1989, 2010). However, reduction in well-being depends on one's perception of how his/her resource contracts in a specific context (Hobfoll, 2010; Hobfoll et al., 2003). Therefore, loss of well-being is a function of individual perception of the loss. It is, therefore, possible that loss or fear of loss of resources due to COVID-19 may have occurred differentially for individuals of higher and lower SES (Wanberg et al., 2020).

Another explanation for this phenomenon is provided by the 'steeling effect' (Holtge et al., 2018). Unlike the COR explanation (based on loss or fear of loss of valued resource), the steeling effect suggests that past experiences of adversity may increase resilience to latter adversities by facilitating adaptive functioning. Under both explanations (steeling effect and COR theory), observing worse outcome for individuals with higher SES is plausible. This phenomenon has also been observed in South Africa data, where variables that point to higher SES (non-black race and education) are positively correlated with depressive symptoms (Oyenubi & Kollamparambil, 2020) for data collected during the pandemic, while the pre-pandemic relationship suggests that poor mental health is concentrated amongst the poor (Mukong et al., 2017; Oyenubi et al., 2021).

These findings imply that given the high-income inequality in South Africa, the relationship between psychological distress and job or income loss during the pandemic will be mediated by SES (our central hypothesis). Given the COR theory, it is not apparent that the pandemic will exacerbate existing inequality in psychological distress (which was concentrated among less affluent groups before the pandemic (Mukong et al., 2017)). Therefore, our main research objective is to empirically examine how SES mediates the relationship between depressive symptoms and job loss/household income loss. The central assumption is that the relationship between depressive symptoms and job/income loss is non-linear in SES to accommodate the alternative mechanisms discussed by the COR theory.

It is well established that South Africa experienced massive job losses in the early stages of the COVID-19 pandemic. About a third of the working population in February 2020 have lost their income by April 2020 (Spaull et al., 2020). Job and income losses disproportionately affect vulnerable workers and those in the bottom half of the prepandemic income distribution (Jain et al., 2020; Köhler & Bhorat, 2020; Ranchhod & Daniels, 2020). One can think of the income shock as having two effects on affected workers and their households. For the worker, job loss can give rise to psychological trauma due to loss of identity, purpose

and structure of time (Jahoda, 1981). Further, for the workers and the household that depend on them for livelihood, income loss (or decrease in household income) threatens economic security (Posel et al., 2021; Ting & Kollamparambil, 2015). Given the high level of inequality in South Africa, the implication of the pandemic induced income shock for households may depend on SES. Households with higher SES will be able to rely on their savings if there is a reduction in household income, suggesting that the negative effect of income loss may be milder than the loss related to identity and structure. On the contrary, the threat to survival (through shock to household income) may be more important than loss of identity and structure for households with lower SES.

This provides a plausible explanation for the COR and steeling effect. For example, in terms of the steeling effect, the South African labour market is known to exhibit significant churning and labour market churning (even before the pandemic) is higher for earners at the bottom of the earnings distribution (Andrew Kerr, 2018). This suggests that the adverse condition of losing employment may not be new for individual workers at the bottom end of the earnings distribution. However, the COVID labour market shock meant that many of these workers are affected simultaneously which may have severe implications for household income in poorer households. Such shock might push poorer households further into poverty. Therefore, change in activity status may not be as stressful as the net shock to household income for poorer households. For households at the upper end of the earnings distribution, a change in activity status may be more critical since the negative change in household income due to job loss may not translate into an immediate threat to livelihood.

In terms of the COR theory, even though individuals of higher SES are less likely to be affected by job loss, when this happens, the disutility that emanates from such loss may depend on the worth of valued resources the loss represents. Since the COR theory suggests that loss is correlated with reduced perceived control over one's well-being, the reduction in well-being associated with such loss may be higher for someone with a higher SES. For individuals of lower SES, the amount of income loss may not have the same effect because both the income and the loss of well-being it represents have always been relatively smaller. Therefore, perceived loss of control may not be comparable across SES. In addition, a substantial part of household income for people of low SES may be coming from transfers

⁵ Specifically, this disrupts the ability to insure one another. For example, poor households with multiple adults involve in the labour market may be able to handle employment loss for one of the workers. Under the pandemic there was an abrupt stop to economic activities such that job loss may affect more individuals at the same time.



like social grants rather than wages. Since the grants were increased substantially at the inception of the lockdown, loss of income from employment may not have the same effect for individuals from low SES backgrounds.

Our main hypothesis is that while job loss and decrease in household income are related because the former will invariably lead to the latter, the relationship between these variables and well-being will be mediated by SES. This is because the financial position of households at opposite ends of the SES spectrum is different before the pandemic, which implies that their ability to cope with the income shock will be different. Therefore, loss of identity, purpose and structure of time may be a stronger predictor of psychological distress for higher SES individuals, while a shock to household income might be a better predictor of distress for lower SES individuals. It is expected that job loss and household income loss will have a region-specific relationship with depression scores.

Specifically, loss of personal income may not translate into hunger or a threat to survival for an individual with a high SES. This is because such individuals are more likely to have savings to draw on or live in more affluent households where the shock will not be severe enough to constitute a threat to survival. This is not the case for individuals with low SES whose households are more likely to be living from hand to mouth before the pandemic. Therefore, being locked out of employment because of the pandemic induced lockdown will constitute a threat to survival for individuals of lower SES.

We examine this proposition in South African data using Threshold regression (Gonzalo & Pitarakis, 2002). South Africa is an interesting case for this proposition because of the high level of inequality in the country.

Data

We use waves 1 and 2 of the National Income Dynamic Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM) for our analysis. NIDS-CRAM was developed by academics working in South African universities. NIDS-CRAM is created to assist in tracking the socioeconomic and health effects of the COVID-19 pandemic (including how the lockdown that was introduced to curb the spread of the virus affects the well-being of the population). The NIDS-CRAM sample is sourced from an existing national household survey, namely the National Income Dynamics Study (NIDS). Participants for NIDS-CRAM were drawn from the NIDS Wave 5 adult sample (conducted in 2017). A stratified design

 $^{^{\}rm 6}$ Note that wave 1 of NIDS-CRAM does not ask about depressive symptoms.



with 'batch sampling' was used to select adults from the NIDS wave 5 sample into the NIDS-CRAM sample. Sampling in batches was used to allow flexibility in adjusting the sample rate as information about stratum response became available (Kerr et al., 2020a, 2020b).

In the first wave of NIDS-CRAM, approximately 7000 successful interviews were conducted between May and June 2020. Wave 2 of NIDS-CRAM was conducted between 13 July and 13 August 2020 (Brophy et al., 2018; Ingle et al., 2020; Kerr et al., 2020a, 2020b) and includes 5676 completed interviews. It has been shown that attrition appears to be random between the two waves (Daniels et al., 2020). The Wave 1 questionnaire was translated into 10 of the 11 official languages in South Africa, while the Wave 2 questionnaire was conducted in all 11 languages. The analysis in this study uses wave 2 because the question about depressive symptoms is not part of the wave 1 questionnaire of NIDS-CRAM.

The outcome variable is depressive symptoms, measured by a 2-question version of the Patient Health Questionnaire (PHQ-2). The two questions administered to derive the PHQ-2 measure are: "Over the last 2 weeks, 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 (i.e. "not at all" 0, "several days" 1, "more than half the days" 2 and "nearly every day" 3). The sum of these responses creates the outcome variable of PHQ-2 scale with a range of 0 to 6, with increasing values indicating higher levels of depressive symptoms.

Note that NIDS wave 5 (conducted in 2017) contain depression scores, but the instrument used in the wave 5 dataset is the 10-item Centre for Epidemiological Studies Depression Scale (CESD-10) (Radloff, 1997). Since these instruments are not directly comparable, we refrain from performing a before and after analysis.⁸ However, in our threshold regression, we control differences in the way individuals assess their depressive symptoms (anchoring effects) using the CESD-10 score in wave 5 of NIDS. The CESD-10 and the PHQ-2 scales are employed as a continuum of distress (Burger et al., 2017; Posel et al., 2021; Tomita & Burns, 2013) rather than imposing a threshold to identify depression because the appropriate cut-off has been found

After cleaning the data we were left with 3, 799 observations.

⁸ Note that the analysis in Oyenubi & Kollamparambil (2020) compared the prevalence of depressive symptoms by using recommended cut-offs for CESD-10 and PHQ-2. Their result suggests that the percentage of individuals that screen positive for depression has increased significantly.

to vary across different language groups in South Africa (Baron et al., 2017).

CESD-10 score from wave 5 of NIDS data (2017) offers some control for variation in the individual propensity to exhibit depressive symptoms (Burger et al., 2017) and possible anchoring effects on respondents assessment of their depressive symptoms (Posel et al., 2021; Winkelmann & Winkelmann, 1998). Other covariates include demographic characteristics, i.e. age (in years), race (i.e. African, white, coloured or mixed race and Asian, this is turned into a dummy that is 1 if the respondent is African), gender (male dummy), partner status (i.e. whether respondent is married or living with a partner) and years of schooling. Household characteristics i.e. dwelling type (House/Flat, Traditional or mud house or informal dwelling), geo-location (Traditional or tribal areas, urban area, Farms and others) household hunger (yes or no answer to the question "In the last 7 days has anyone in the household gone hungry because there wasn't enough food"), household income (in waves 1 & 2), a dummy variable indicating whether household lost income within the last four weeks⁹ (for waves 1 & 2). Personal and household receipt of grants i.e. number of Child Support Grants (CSG), number of Old Age Pensions (OAP) and personal receipt of a grant by the respondent. Risk perception and self-efficacy concerning COVID-19¹⁰ and a measure of physical health, i.e. dummy indicating whether the respondent has a chronic illness.

The mean values of the depression scores are both low relative to the recommended cut-off (for screening positive for possible depression, i.e. below 3 for PHQ-2 and below 10 for CESD-10 (Manea et al., 2016)) under the two scales. Almost half (43%) of the respondents believe they are at risk of contracting the virus (this is important because of the relationship between risk perception and depressive symptoms in the context of the pandemic (Kim et al., 2020)) while 83% believe that they can avoid contracting the virus. Average household income reduced slightly between waves 1 & 2 (this suggests that apart from the initial shock, household income continued to reduce as the lockdown progressed).

Methods

We consider the threshold model (Gonzalo & Pitarakis, 2002) defined by a threshold parameter λ . The equation can be written as.

$$y = X_i \beta + Z_i \delta_1 + \varepsilon \text{ if } -\infty < hh_{inc} \leq \lambda.$$

$$y = X_i \beta + Z_i \delta_2 + \varepsilon \text{ if } \lambda < h h_{inc} < \infty$$

where y is the outcome (depression score in this case), we assume that the threshold model has two regions defined by household income per capita and λ is the value of household income per capita that defines the two regions (i.e. the threshold). Household income per capita is denoted by hh_{inc} therefore $hh_{inc} \leq \lambda$ defines the lower region. X represent a vector of covariates (including the lagged depression score). β is a vector of region invariant parameters, while Z_i is a vector of covariates with region-specific coefficient vectors δ_1 and δ_2 . Based on the reported household income, these regions can be thought of as those containing higher and lower SES individuals. We assume that there is one threshold based on our argument in the introduction (i.e. the relationship between depression and SES at least in the initial phases of the pandemic is non-linear), and a data-driven algorithm is used to estimate the threshold parameter (Gonzalo & Pitarakis, 2002). Specifically, the algorithm selects the threshold value (λ) based on the Bayesian information criterion (BIC).

Threshold Regression results

This section presents our threshold regression results. We control for various factors related to this outcome (as listed in Table 1). Note that the threshold regression analysis is not weighted since the threshold command (in Stata) does not allow for weights. Therefore, the result cannot be considered to be nationally representative. However, it provides a way to see if the effect of these factors varies along with the household (per capita) income distribution. For all analyses, we use robust standard errors.

We note that the end of wave 1 survey (27 June 2020) and the start of wave 2 survey (13 July 2020) are less than a month apart. In the analysis that follows, we use 3 model specifications to check the robustness of our results. The results are presented in Tables 2 and 3. For ease of exposition Table 2 presents the region-invariant coefficients while Table 3 presents region-specific coefficients.

Model 1

For model 1, we use household income per capita in wave 2 as the threshold variable, a decrease in household income in



⁹ The wording of the question is "In the last 4 weeks, has the household's main income source increased, decreased or stayed the same?" Note that for our analysis this is coded as a dummy variable that is 1 is household income decreased and zero otherwise. This is because the proportion of individuals that report increase in household income is relatively small.

¹⁰ Risk perception and Self-efficacy are known to be correlated with adoption of preventative measures which could have a feedback effect on mental health i.e. adoption of preventative measures may reduce psychological distress.

Table 1 Summary Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Depression Scores PHQ (2020)	3799	1.29	1.63	0	6
Depression dummy CESD-10 (2017)	3799	6.49	4.29	0	27
age (years)	3799	41.56	15.62	17	102
age squared	3799	1971.73	1503.40	289	10,404
Male (=1)	3799	0.35	0.48	0	1
Has partner	3799	0.48	0.49	0	1
Household experience Hunger	3799	0.19	0.39	0	1
Dwelling type					
Dwelling type (House/flat)	3799	0.28	0.45	0	1
Dwelling type (Trad/mud)	3799	0.69	0.46	0	1
Dwelling type (Informal/shack)	3799	0.03	0.17	0	1
Geolocation					
Traditional	3799	0.75	0.43	0	1
Urban	3799	0.13	0.34	0	1
Farms	3799	0.09	0.29	0	1
Other	3799	0.03	0.17	0	1
Years of Schooling	3799	10.51	4.06	0	16
Years of Schooling (squared/100)	3799	1.27	0.77	0	2.56
COVID Risk Perception	3799	0.43	0.49	0	1
COVID Self-Efficacy	3799	0.83	0.38	0	1
No of Child Support Grants	3799	1.49	1.64	0	11
No of Old Age Pensions	3799	0.45	0.66	0	4
Personal receipt of Grant	3799	0.41	0.49	0	1
African	3799	0.84	0.37	0	1
Chronic illness	3799	0.23	0.42	0	1
Household Income (Wave 2)	3799	1482.29	3778.92	0	115,000
Household Income (Wave 1)	2629	1589.84	3736.31	0	57,500
Unemployed (Wave 1)	3799	0.61	0.49	0	1
Unemployed (Wave 2)	3799	0.59	0.49	0	1
HH lost income (wave2)	3799	0.15	0.35	0	1
HH lost income (wave1)	3746	0.42	0.49	0	1

NIDS-CRAM, Wave 2 (2020) Notes: Data are unweighted

wave 1 is included as a region invariant predictor of depression (recall that PHQ-2 score is not available for wave 1). The region-specific regressors are loss of household income in wave 2 and interaction between employment status in waves 1 & 2. Interacting employment status is essential for 2 reasons. First, employment status in wave 1 refers to employment in April 2020, while employment status in wave 2 refers to employment in June 2020. Given the volatility of labour conditions during this period, activity status change between the two waves may still be relevant for depressive symptoms. Second, it has been shown that the benefits of employment (in terms of depressive symptoms) cumulate over time (Posel et al., 2021).

Column 1 of Table 2 shows the result for the threshold region invariant controls for model 1, While the first two columns of Table 3 present the results for the separate SES regions based on the value of household income per capita.

The threshold is selected by optimizing the Bayesian information criterion (BIC), and the selected threshold for model 1 is 170/person/month (around the 20th percentile of the household per capita income distribution). This translates to about \$11¹¹ (at R15 to a dollar, the average exchange rate in 2019). It is also important to note that the Food Poverty Line in South Africa is R585/person/month as of April 2020, ¹² which means that households at or below the threshold of R170 are very poor.

The threshold region invariant controls result broadly aligns with expectations with age, hunger, risk perception, chronic illness, and decrease in household income (in wave



¹¹ Median income per capita is R500 (\$33) in the sample.

¹² See https://www.farmersweekly.co.za/agri-news/south-africa/stats-sa-adjusts-food-poverty-line-to-r585-per-month/

Table 2 Model 1, 2 & 3 Threshold Regression Results for region invariant covariates

	(1)	(2)	(3)	
VARIABLES	Region invariant covariates $(threshold = R170)$	Region invariant covariates $(threshold = R508)$	Region invariant covariates $(threshold = R508)$	
Depression dummy 2017	<0.01	<0.01	<0.01	
	(0.01)	(0.01)	(0.01)	
age (years)	0.02**	0.02*	0.02**	
	(0.01)	(0.01)	(0.01)	
age squared	<-0.01**	<-0.01**	<-0.01**	
	(0.00)	(0.00)	(0.00)	
Male (= 1)	0.02	0.04	0.06	
` '	(0.06)	(0.06)	(0.05)	
Has partner (yes)	-0.11**	-0.09*	-0.08	
	(0.05)	(0.05)	(0.05)	
Household Hunger	0.66***	0.65***	0.67***	
	(0.08)	(0.07)	(0.07)	
Dwelling type (Trad/mud) ^B	0.12**	0.15***	0.14**	
	(0.06)	(0.06)	(0.06)	
Dwelling type (Informal/shack)	0.09	0.11	0.11	
	(0.15)	(0.14)	(0.15)	
Urban (Geo location) ^C	-0.05	-0.03	-0.06	
	(0.08)	(0.08)	(0.08)	
Farms (Geo location)	-0.16*	-0.15	-0.15*	
	(0.10)	(0.09)	(0.09)	
Others (Geo location)	-0.25*	-0.20	-0.17	
	(0.15)	(0.15)	(0.15)	
Years of Schooling	0.01	< 0.01	<-0.01	
	(0.02)	(0.02)	(0.02)	
Years of Schooling (Squared)	0.04	0.09	0.13	
	(0.12)	(0.11)	(0.11)	
COVID Risk Perception	0.27***	0.29***	0.28***	
	(0.05)	(0.05)	(0.05)	
COVID Self-Efficacy	-0.03	-0.03	-0.03	
	(0.07)	(0.07)	(0.07)	
No of Child Support Grants	0.01	0.02	0.01	
	(0.02)	(0.02)	(0.02)	
No of Old Age Pensions	-0.06	-0.07*	-0.08**	
C	(0.04)	(0.04)	(0.04)	
Personal receipt of grant	-0.17***	-0.17***	-0.15***	
	(0.06)	(0.06)	(0.06)	
African	-0.55***	-0.55***	-0.53***	
	(0.08)	(0.08)	(0.08)	
Chronic illness	0.14**	0.14**	0.14**	
	(0.06)	(0.06)	(0.06)	
Household income loss (wave 1)	0.20***	•		
· · · · · · · · · · · · · · · · · · ·	(0.05)			
Observations	3746	3974	4031	

Base categories $^{\rm A}$ w2_employed#w1_employed; $^{\rm B}$ House/Flat; $^{\rm C}$ Traditional area Robust standard errors in parentheses



^{***} p < 0.01, ** p < 0.05, * p < 0.1

Table 3 Models 1, 2 & 3 Threshold Regression Results for region specific covariates

VARIABLES	(1)		(2)		(3)	
	Region specific covariates $hh_{inc} \leq R170$	Region specific covariates $hh_{inc} > R170$	Region specific covariates $hh_{inc} \le R508$	Region specific covariates $hh_{inc} > R508$	Region specific covariates $hh_{inc} \le R781$	Region specific covariates $hh_{inc} > R781$
Household income loss (wave 1 & 2)					0.34***	0.05
					(0.12)	(0.14)
Household income loss (wave 2)	0.59**	0.06	0.30**	-0.04		
	(0.24)	(0.08)	(0.12)	(0.09)		
Employed(wave 2)#Unemployed (wave 1) ^A	0.40*	0.12	0.20	0.05	0.11	0.15
	(0.24)	(0.10)	(0.14)	(0.12)	(0.12)	(0.15)
Unemployed (wave 2)#Employed(wave 1)	0.05	0.06	-0.10	0.20	-0.07	0.16
	(0.22)	(0.10)	(0.13)	(0.14)	(0.12)	(0.18)
Unemployed (wave 2)#Unemployed(wave 1)	0.26	0.22***	0.08	0.33***	0.03	0.43***
	(0.17)	(0.07)	(0.11)	(0.09)	(0.09)	(0.10)
Constant	0.60**	0.93***	0.92***	0.88***	1.05***	0.86***
	(0.30)	(0.27)	(0.27)	(0.26)	(0.28)	(0.27)
Observations	3746	3746	3974	3974	4031	4031

Base categories ^A w2_employed#w1_employed; ^B House/Flat; ^C Traditional area

Robust standard errors in parentheses

1) being significant and positively correlated with depressive symptoms. Having a partner and personal receipt of grant is significant and negatively correlated with depressive symptoms. There is, however, one notable exception in the result, where a negative and significant association is found between being black African and depressive symptoms. Prepandemic literature predicts a positive relationship between these variables (Burger et al., 2017).

The region-specific covariates (first two columns of Table 2) are mainly in line with the earlier argument. While a decrease in household income (in wave 2) is positively correlated with depressive symptoms for those below the threshold, this relationship is not significant for those above the threshold. Even though reporting unemployment in wave 1 and then employed in wave 2 is positively correlated with depressive symptoms (below the threshold), this relationship is weak as it is only significant at 10%. However, above the threshold, persistent unemployment (i.e. unemployment in both waves) is positively correlated with depressive symptoms (note that below the threshold, this relationship is not significant). These results imply that a decrease in household income is a more important predictor of depressive symptoms for the poor (i.e. those below the threshold), while unemployment over the two waves is a better predictor of depressive symptoms for those above the threshold.



For model 2, we consolidate the household income variables to better measure the household's SES by averaging household income over the two waves. Average income across the two waves will give a better picture of where households are in terms of SES because income for poorer households may be volatile such that income in a particular month is biased. The result for region invariant covariates in model 2 is shown in the second column of Table 2.

The results for the region invariant variables are similar to what is reported for model 1. Hence we will not rehash them. The threshold under model 2 is estimated to be R508 (approximately \$33), much closer to the food poverty line. However, this does not change our substantive result in Table 3. For the region-specific variables (columns 3 & 4 of Table 3), a decrease in household income is significantly positively correlated with depression scores, while none of the employment interactions is significant below the threshold. Above the threshold, only persistent unemployment is significant, and this variable is positively correlated with depression scores. We note that the weak relationship between change in employment status (from unemployed to employed) observed in is model 1 is not applicable under model 2. Perhaps this is due to the better measure of SES.



^{***} p < 0.01, ** p < 0.05, * p < 0.1

Model 3

Model 3 is similar to model 2 in terms of using consolidated household income (for waves 1 & 2), but in addition, model 3 consolidate the dummy variable that indicates a decrease in household income across waves. This is done by creating a dummy variable of 1 when the respondent says there is a decrease in household income in both waves.

The region invariant coefficient for model 3 is shown in column 3 of Table 2. The results remain similar to the results for models 1 & 2. The last two columns of Table 3 show the region-specific relationships. The estimated threshold is now R781 (approximately \$52) which is above the Food Poverty line (also note that the sample size has increased relative to Table 3 because of reconfiguration of the variables). The substantive result remains valid. The employment channel or psychological trauma associated with a loss of identity, purpose and structure of time is a stronger predictor of depressive symptoms for individuals of higher SES (relative to a decrease in household income). The threat to survival through a decrease in household income is a stronger predictor of depressive symptoms (relative to the loss of employment) for those below the threshold.

Discussion

The results show that even though the loss of employment income will invariably translate to loss/reduction in household income, these variables have different implications for depressive symptoms in the context of high socioeconomic inequality. For individuals of higher SES, loss of employment is correlated with a significant increase in depressive symptoms, while a reduction in household income is not. On the other hand, loss of employment is not significant in explaining variation in depressive symptoms for individuals with lower SES, while a decrease in household income is correlated with an increase in depressive symptoms. Consequently, the loss of individual income (as against household income) is more detrimental to mental health for higher SES individuals, while a decrease in household income (as against the loss of individual income) is more detrimental for individuals of lower SES. This is probably because the psychological trauma of job loss, through loss of identity and purpose, overrides the financial consequence of job loss among higher SES individuals. The opposite appears to be the case among lower SES individuals, and hence the protective effect of household income is stronger for individuals that live in poorer households.

Our explanation for the result is that individuals of lower SES who are more likely to be informal workers may be used to job churning (characteristics of a job market where there is frequent change in employment status from employed to unemployed and vice versa) even before the pandemic. Therefore, consistent with what is suggested by steeling effect (and COR), the loss of control experienced due to job loss by these groups of workers may be smaller than their higher SES counterparts. On the other hand, irrespective of individual loss of income, household income has implications for survival in poor SES households. Therefore individuals of low SES respond more to a decrease in household income than the loss of employment. This result implies that the reversal of the relationship between well-being and socioeconomic factors during a crisis like COVID-19 may be context-specific or depend on the economy's structure in question. High inequality may constitute an enabling environment for this kind of a shock to reverse the relationship prevailing before the shock. This suggests that the increase in social grants implemented by the South African government is important in mitigating the effect of the shock on mental health for poorer households.

Consistent with existing literature, other results show that hunger is correlated with well-being in general (Nwosu & Oyenubi, 2021) and depression in particular (Oyenubi & Kollamparambil, 2020). While personal receipt of the social grant and the number of Old Age Pension (OAP) received by the household show a significant negative correlation with depressive symptoms (across the models), receiving multiple Child Support Grant (CSG), however, does not have the same effect. This is perhaps because the payout for CSG is relatively smaller compared to other grants. 13 The result that persistent unemployment is positively correlated with depression scores is consistent with existing research (Posel et al., 2021). However, our result suggests that this relationship is stronger for individuals with higher SES and may have more to do with the loss of identity, purpose and structure of time or loss of control in terms of uncertainty about the future. For individuals of lower SES, who may be familiar with job churning, household income is more important. Lastly, our finding that risk perception is an important correlate of depressive symptoms is consistent with existing literature (Oyenubi & Kollamparambil, 2020; Oyenubi et al., 2021).

Conclusion

This paper examines the role of socioeconomic status in mediating the effect of job/income loss on mental health during the Covid19 pandemic. The implication is that the

¹³ For example, before the top-up CSG payout is R430 /child/month while OAP is R1,860/person/month.



relationship between job loss, decrease in household income and depressive symptoms vary based on SES. The study uses threshold regression to examine the differential relationship between depressive symptoms (measured by PHQ-2) and job/income loss across socioeconomic status in the context of the pandemic.

The result shows a threshold effect in the relationship between depression and a decrease in household income on the one hand and job loss on the other hand. This suggests that the reversal in the relationship between well-being and pandemic induced shock (as articulated under the COR theory) may be aided by the labour market structure. High inequality before the pandemic means that the shock will operate through different channels across socioeconomic status. In our case, high inequality in South Africa is a plausible explanation for the observed reversal. In South Africa, loss of individual income and decrease in household income has different implications for affected individuals depending on their SES. For high SES individuals, changes in activity status may not constitute an immediate threat to survival but may lower well-being through other channels (like loss of identity, purpose and structure of time).

Contrary to this, loss of employment for individuals with low SES may be a familiar situation because of the high level of labour market churning that disproportionately affects individuals with low earnings (Andrew Kerr, 2018). However, when this translates into a significant decrease in household income, it may become a risk factor for psychological distress. Poorer household tends to live in larger groups because this offers considerable economies of scale in the consumption of goods and services (Posel et al., 2020). The pandemic might disrupt such insurance since it is likely that a larger number of working adults in poorer households will lose their income at the same time (because of lockdown), translating into a significant shock to household income.

Further, there is evidence that social transfers during the pandemic have played an important role in reigning in the adverse effect of the forced labour market disengagement, which will typically benefit low SES individuals. Therefore, high-income inequality coupled with a segmented labour market (formal and informal sectors) means that the benefit of these reversals may be dependent on SES.

The main limitation of our analysis is that it is based on the correlation between the factors being studied. Future research should look at the causal relationship between these factors. It is also possible that some respondents may not have answered question on depressive symptoms (especially) truthfully. However we don't expect this to be a widespread problem.



Details for the data used for this analysis is as follows.

Name of Project: National Income Dynamic Study

- Coronavirus Rapid Mobile Survey (NIDS-CRAM).

Data collection Entity: Southern Africa Labour and Development Research Unit (SALDRU), University of Cape Town, South Africa.

Link: https://cramsurvey.org/

References: https://cramsurvey.org/reports/

Authors' contributions All authors contributed equally to this study i.e., both authors contributed equally to the conceptualization, Methodology, design, analysis and interpretation of our findings in this study.

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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.

Consent for publication Not applicable.

Conflict of interest We have no conflict of interest to disclose.

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