Journal of Affective Disorders 308 (2022) 616–622

Contents lists available at ScienceDirect

Journal of Affective Disorders

journal homepage: www.elsevier.com/locate/jad

Research paper

COVID-19 risk perceptions and depressive symptoms in South Africa: Causal evidence in a longitudinal and nationally representative sample

Adeola Oyenubi [a], Andrew Wooyoung Kim [b,c,*], Uma Kollamparambil [a]

[a] *School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa*
[b] *SAMRC/Wits Developmental Pathways for Health Research Unit, Faculty of Health Sciences, University of the Witwatersrand, Johannesburg, South Africa*
[c] *Department of Anthropology, University of California, Berkeley, Berkeley, CA, United States*

ARTICLE INFO

Keywords:
Depression
Risk perceptions
COVID-19
Causal inference
South Africa

ABSTRACT

Background: Studies worldwide have highlighted the acute and long-term depressive impacts of psychosocial stressors due to the 2019 coronavirus disease (COVID-19) pandemic, particularly in low- and middle-income countries. Among the wide range of risk factors for depression that transpired during pandemic, greater perceptions of individual vulnerability to the COVID-19 have emerged as a major predictor of increased depressive risk and severity in adults.

Methods: We estimated the extent to which COVID-19 risk perceptions affected adult depressive symptoms in a longitudinal, nationally representative sample in South Africa. We used covariate balanced propensity scores to minimize the bias from treatment assignment to estimate average causal effects of COVID-19 risk perceptions.

Results: The point prevalence of perceived COVID-19 infection risk increased between the third and fifth months of the pandemic, which corresponded with elevations in national COVID-19 infection rates. Approximately 33% of adults met or surpassed the PHQ-2 cut-off score of 2. An increase in perceived risk of COVID-19 infection predicted worse depressive symptoms in adults four months later.

Conclusions: Our findings highlight the widespread mental health burdens of the COVID-19 pandemic and emphasize the importance of greater psychological resources and structural changes to promote equitable access to COVID-19 risk mitigation policies.

1. Introduction

Depression is the single largest contributor to disability worldwide and accounts for a major portion of the overall global burden of disease (W.H.O, 2017). Low- and middle-income countries (LMICs) face considerable challenges to addressing disease and treatment outcomes related to depression and other mental illnesses due to conditions such as poverty, a high prevalence of comorbidities, and poor access to quality mental healthcare (Rathod et al., 2017; Whiteford et al., 2015). Historical and socioeconomic inequalities in LMICs have continually limited the availability of psychiatric healthcare services and international development assistance for mental health systems in the Global South (Liese et al., 2019). Depressive disorders are predicted to be the second leading cause of disability-adjusted life years in LMICs behind HIV/AIDS by 2030 (Mathers and Loncar, 2006).

Recent research in global mental health has predicted that the ongoing COVID-19 pandemic has exacerbated these pre-existing mental health inequities, particularly in already marginalised groups (Kola et al., 2021). Studies worldwide have increasingly reported the immediate and longer-term psychiatric impacts of COVID-19-related stressors, such as forced isolation, fears of the virus, direct infection, and the added depressive, psychosocial, economic burdens among highly vulnerable communities (Pan et al., 2021; Prati and Mancini, 2021; Robinson et al., 2022), though a smaller portion of studies have not identified negative adult mental health impacts due to the pandemic or report heterogenous findings (Ahrens et al., 2021; Liu et al., 2021; Shevlin et al., 2021). Among the wide range of risk factors for depression that has affected resource-limited settings during the COVID-19 pandemic, greater perceptions of individual vulnerability to the 2019 coronavirus disease (COVID-19) have emerged as an important predictor of increased depressive risk and severity (Ding et al., 2020; Kim et al., 2020; Olagoke et al., 2020).

* Corresponding author at: SAMRC/Wits Developmental Pathways for Health Research Unit, Faculty of Health Sciences, University of the Witwatersrand, 29 Princess of Wales Terrace, Parktown, Johannesburg 2193, South Africa.

E-mail address: andrew.kim@wits.ac.za (A.W. Kim).

https://doi.org/10.1016/j.jad.2022.04.072
Received 21 September 2021; Received in revised form 15 February 2022; Accepted 10 April 2022
Available online 14 April 2022

Past research on perceived disease vulnerability during epidemics (e.g. Ebola, HIV, SARS) has documented strong associations between increased risk perceptions - specifically greater perceived vulnerability to infection - and worse depressive symptoms in adults (Hsieh, 2013; Jalloh et al., 2018; Liu et al., 2012). Researchers have proposed that this relationship operates through a variety of pathways across multiple levels, including personality traits (Nikčević et al., 2021; Sica et al., 2021), emotional responses and regulation (Han et al., 2021), and psychosocial stress and trauma (Ding et al., 2020; Kim et al., 2020). While these pathways have been purported, the extent to which the depressive impacts of perceived COVID-19 infection risk manifest are relatively unknown as many existing studies have examined cross-sectional analyses associations between COVID-19 risk perceptions and adult depressive symptoms.

In this paper, we examine the causal effects of COVID-19 risk perceptions on adult depressive outcomes in a nationally representative sample in South Africa. South Africa is a middle-income country and considered one of the most unequal societies in the world (Statistics South Africa, 2019). The country is also affected by drastic rates of psychiatric morbidity and an overburdened mental healthcare system, where close to a third (30.3%) of South Africans are expected to develop a mental illness and about a quarter (27%) of severe psychiatric cases receive treatment (Docrat et al., 2019). While recent epidemiological estimates of depression in South Africa are lacking, one study calculated that the 4-year incidence of adult depression was 20.8% using nationally representative data between 2008 and 2012 (Cuadros et al., 2019). To our knowledge, this is the first study to estimate the causal effects of COVID-19 risk perceptions on adult depressive symptoms.

2. Methods

2.1. Study sample

Data come from the National Income Dynamic Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM), which aimed to examine the conditions, experiences, and impacts of the 2019 coronavirus pandemic and the national lockdown (Ingle et al., 2020). NIDS-CRAM is a follow up study of a subsample of adults from the fifth wave of the larger National Income Dynamic Study (NIDS) in South Africa, which is the country's first national household panel study. We used data on COVID-19 risk perceptions from two waves of NIDS-CRAM: Wave 1 of NIDS-CRAM took place between 7 May and 27 June 2020, and Wave 2 occurred between 13 July and 13 August 2020. Data on depressive symptoms only collected in Wave 2. To mitigate the impacts of the COVID-19 pandemic, the South African national government instituted a tiered, risk-adjusted lockdown policy that varied across five levels of severity (e.g., Level 5 as most severe, Level 1 as least severe). There were 5676 successful interviews in Wave 2 (i.e., during lockdown level 3). The weighted NIDS-CRAM survey data reflects the outcomes in 2020 for a broadly representative sample of those 15 years and older from NIDS Wave 5 in 2017, who were followed up 3 years later for Wave 2 of NIDS-CRAM (Kerr et al., 2020).

2.2. The COVID-19 pandemic and lockdown in South Africa

On March 5, 2020, the Minister for Health confirmed the first COVID-19 virus infection in South Africa. Following this development, the President declared a State of National Disaster on March 15, and immediately measures like travel restriction and closure of schools were put in place. South Africa went into a nationwide "lockdown" on March 26, which prohibited citizens from leaving a mandated quarantine except for food, medicine, and essential labor. This response to the pandemic, while necessary to slow down the virus transmission, has been argued to exacerbate mental health problems (Kim et al., 2020; Oyenubi and Kollamparambil, 2020). Since March 26, the government has reduced the severity of COVID-19 risk mitigation policies by transitioning into less stringent phases of the national lockdown to permit economic recovery from the extended job and income losses in the country (Casale and Posel, 2020; Jain et al., 2020; Statistics South Africa, 2020). The government declared the transition from the strictest level of lockdown, Level 5, to Level 4 from May 1, to Level 3 from June 1 and, Level 2 from August 18. Studies estimate that between 2.2 and 2.8 million jobs were lost in South Africa between February and April 2020 (Jain et al., 2020; Spaull et al., 2020). This has led to heightened financial concerns that can have detrimental effect on mental health.

Enforcement of the lockdown was not universally successful in South Africa. For example, media reports suggested that life continued as normal in some parts of the country despite the lockdown, particularly in rural areas with lower population densities and access to large outdoor spaces. Furthermore, after just seven days of lockdown, a total of 2289 people were arrested by the South African Police Service (SAPS) for violating lockdown restrictions. Based on the same data we use for this analysis, Kollamparambil & Oyenubi (2021) showed that subjective risk perception of COVID-19 infection increased by 17% between April and June 2020. They also show that risk perception varies by income, education, and age (i.e., there is considerable heterogeneity in the perception of risk of contracting COVID-19).

2.3. Survey data

COVID-19 risk perceptions were assessed during Wave 1 of NIDS-CRAM using the question, "Do you think you are likely to get the coronavirus?", to which respondents answered yes or no. Depressive symptoms were assessed during Wave 2 of NIDS-CRAM using the 2-question version of the Patient Health Questionnaire (PHQ-2). The two questions administered included: "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?" Responses were summed to create a total score with a range of 0 to 6, and increasing values indicated higher levels of depressive symptoms. Sociodemographic questions querying personal characteristics, social experience, and household conditions were included as covariates.

2.4. Empirical strategy

Our empirical strategy exploited changes in risk perception reported in the data at time t (Wave 2) but occurring somewhere between t-1 (Wave 1) and t (Wave 2). We used this change to identify the responses on depressive outcomes at time t by comparing outcomes for the 'treated' individuals (i.e., those who experienced a change in their risk perception) with outcomes of observationally identical (as of t-1) controls who did not report a "positive" change (e.g., from "No" to "Yes") in their risk perception. Fig. 1 shows the weighted proportion of those who report positive risk perception by waves of NIDS-CRAM data. It is obvious that the largest difference in proportion is recorded between Waves 1 and 2 of NIDS-CRAM, where the proportion of individuals that reported a "positive" risk perception (i.e., "Yes") increased by 48%. A plausible explanation for this is that the period prior to and during the Wave 1 survey coincided with the initial phase of the pandemic and the associated lockdown. During this period the country was under stringent lockdown conditions (Levels 5 just prior to the commencement of the interviews and Levels 4 & 3 during the interviews). However by Wave 2, the country has spent a couple of months under lockdown level 3 restrictions and the whole of Wave 2 was conducted under Level 3 restrictions. This was characterized by a gradual return of economic and social activities.

The implication is that Wave 1 survey was conducted under stricter lockdown conditions that reduce the risk of contracting the virus (because of limitation to movement). Further, the initial phases of the pandemic are characterized by conflicting information about the transmission and seriousness of the threat of COVID-19 leaving some in doubt. As the economy reopened (during Wave 2 data collection) with

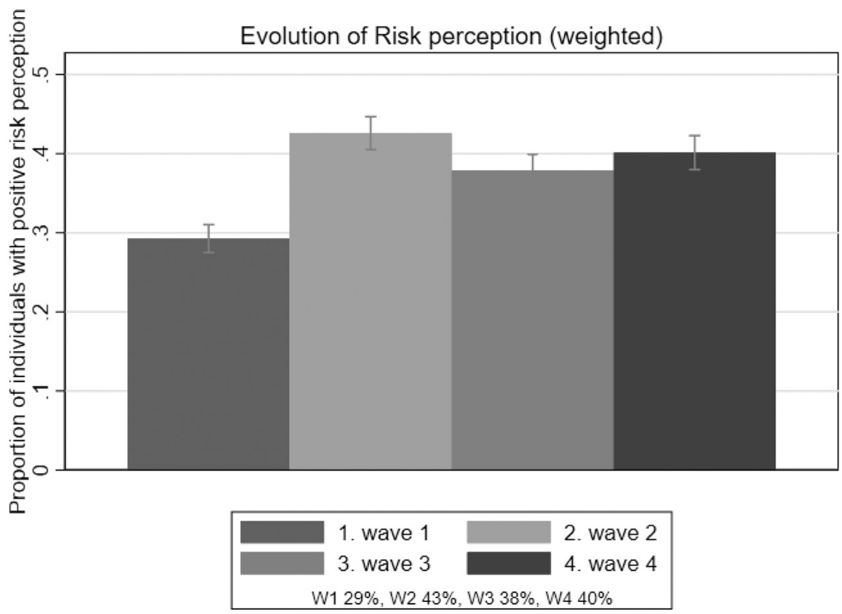

Fig. 1. Risk perception across waves of NIDS-CRAM.

less stringent measures that allowed for movement and inadvertently increased the chances of contracting COVID-19, we found that a large percentage of the population revised their risk perceptions concerning contracting the virus (Fig. 1). One can argue that the reason for the revised perception is very likely to be exogeneous to the individual since it coincides with less stringent conditions (which is an administrative decision taken by the Government) and more knowledge (relative to Wave 1) about the seriousness and the mode of transmission of the virus.

To exploit this plausibly exogeneous variation in reported risk perception, we restricted our sample to those who answer no to the risk perception question in Wave 1 (about 70% of the population). Using the response to the risk perception question in Wave 2, this population was separated into the treated and control group with the treated being those who change their risk assessment to positive in Wave 2. Under the Conditional Independence Assumption (CIA) (Rosenbaum and Rubin, 1983) we created observationally equivalent groups based on Wave 1 characteristics. These variables were expected to be correlated with the outcome and treatment indicator. The set of variables used included (baseline) self-assessed health (SHA). SHA is a more general concept because it provides an assessment of subjective health that includes physical and psychological aspects of health (Ambresin et al., 2014; Mavaddat et al., 2011). Therefore the inclusion of this variable was expected to remove unobserved effects specific to individuals and their health.

Rosenbaum and Rubin (1983) highlighted the central role of propensity scores, or the probability of exposure to treatment conditional on observed covariates, to reduce bias associated with treatment assignment. Since this quantity is not known in observational studies, it is estimated based on data. Using the estimated propensity scores, many statistical methods are proposed to estimate the mean causal effect. One popular method is the inverse probability of weighting (IPTW) approach (Hirano and Imbens, 2001; Robins et al., 1994). But despite the popularity of this method, researchers have found that IPTW is sensitive to the specification of the propensity score model (Kang and Schafer, 2007). To overcome this problem, we used covariate balancing propensity scores (CBPS) (Imai and Ratkovic, 2014) to directly optimize the balance of covariates between the treatment and control groups so that even when the propensity score model is mis-specified, we still obtained a reasonable balance between the two treatment arms (Table 3). We used this technique to adjust the covariate distribution in the control group (i.e. those who did not revise their risk assessment) by reweighting units such that such that it becomes more similar to the covariate distribution in the treatment group. Having obtain the weights we use Weighted Least Square estimator (WLS) to estimate the outcome equation given by

$$h_{wave2} = \alpha + \beta d_{i,\Delta wave1\ 2} + X_{i,wave\ 1} + \varepsilon_{i,wave\ 2}$$

where h_{wave2} is the PHQ-2 score in Wave 2, $d_{i,\ \Delta wave1\ 2}$ is a dummy variable that identifies treated individuals (i.e. individuals that revised their risk perception between Wave 1 and 2), $X_{i,\ wave\ 1}$ is the set of Wave 1 covariates that is used to obtain the CPBS balancing weights. Note that our CIA assumption requires that the variables contained in $X_{i,\ wave\ 1}$ are sufficient to account for systematic differences between the groups being compared. Finally, $\varepsilon_{i,\ wave\ 2}$ is the usual idiosyncratic error term. To make population inferences, we incorporated survey weights in the equation above. The literature suggests that whether or not survey weights are incorporated into the estimation of propensity scores does not influence the performance of estimators (Austin et al., 2018; Lenis et al., 2019).

Even though we argue for plausible exogeneity of $d_{i,\ \Delta wave1\ 2}$ because this measure coincides with the change in lockdown restriction, it is important to control for variables that are correlated with $d_{i,\ \Delta wave1\ 2}$ (treatment) and/or h_{wave2} (outcome) (Caliendo and Kopeinig, 2008; Kang and Schafer, 2007; Oyenubi, 2020). The variables controlled for includes demographic variables (age, age squared, gender, race and partner status), socio-economic/household characteristics (household structure such as flat, traditional and informal dwelling, receipt of government grant, a dummy that indicates whether a household member has gone hungry in the last week because there wasn't enough food, whether the household has access to water and electricity, unemployment, whether respondent has tertiary education, household size, and a dummy that indicates loss of household income between the waves), and variables that describe the response of respondent to the pandemic (dummy variable that indicates self-efficacy[1] and the number of preventative measures the respondent has adopted as a response to the pandemic). We assumed that these set of covariates and the fact that

[1] This is a yes/no answer to the question “Can you avoid getting Coronavirus”.

relaxation of lockdown were likely exogeneous to individuals, which makes the CIA assumption we relied on plausible.[2] We then used multiple linear regression models to estimate the effect of COVID-19 risk perceptions on depressive symptoms using the balancing weights obtained from the CBPS. We note that our approach is similar to the empirical strategy employed by (Jacob et al., 2021).

3. Results

Complete data were available for n = 3773 adults (Table 1). Fig. 1 shows point prevalences of perceived COVID-19 risk over four waves of the NIDS-CRAM panel survey, which displays a sharp increase between Waves 1 and 2, and consistently elevated point prevalences between Waves 2 and 4. Approximately 33% of adults met or surpassed the PHQ-2 cut-off score of 2 (Manea et al., 2016), while 20% of adults met or surpassed the PHQ-2 cut-off score of 3 (Kroenke et al., 2003). We do not treat this cut-off score as a universal criteria for “caseness” in our sample, however, as appropriate cut-offs have been found to vary across different ethnic and linguistic groups in South Africa (Baron et al., 2017). The use of covariate balancing propensity scores succeeded in improving the balance in most covariates. Specifically, the absolute standardized difference in means (SDM) of three variables were above the threshold of 0.10 before matching while all SDMs are below this threshold after weighting. It is recommended that SDM below this threshold is indicative of adequate balance (Stuart et al., 2013).

Table 2 presents results from our regression models. The first column displays results from regression analyses predicting summed PHQ-2 scores. For robustness check, the second column shows the results predicting dichotomized PHQ-2 scores using a cut-off of 3 (Kroenke et al., 2003), while the third column presents results for PHQ-2 scores using 2 as a cut-off (Manea et al., 2016). We found that an increase in COVID-19 risk perceptions between Wave 1 and Wave 2 predicted worse depressive symptoms in Wave 2 for the PHQ-2 ≥ 2 threshold (b = 0.27, 95% CI, 0.02, 0.51), and for the PHQ-2 ≥ 3 cutoff (b = 0.23, 95% CI, −0.04-

Table 1
Descriptive statistics.

	N	Mean	SD	Min	Max
Wave 1					
Age	3773	40.75	16.01	18	102
Male	3773	0.38	0.49	0	1
African	3773	0.88	0.32	0	1
House/Flat	3773	0.77	0.42	0	1
Traditional house	3773	0.13	0.34	0	1
Informal housing	3773	0.09	0.29	0	1
Household size	3773	5.67	3.41	1	32
Able to avoid coronavirus?	3773	0.85	0.36	0	1
Food insecurity	3773	0.27	0.44	0	1
Has Chronic illness	3773	0.22	0.41	0	1
Received gov't grant	3773	0.23	0.42	0	1
Traditional	3773	0.21	0.4	0	1
Urban	3773	0.75	0.44	0	1
Farm	3773	0.05	0.21	0	1
Electricity	3773	0.95	0.22	0	1
Water	3773	0.74	0.44	0	1
Household lost income	3773	0.42	0.49	0	1
Tertiary education	3773	0.23	0.42	0	1
Unemployed	3773	0.65	0.48	0	1
Poor health	3773	0.28	0.45	0	1
Wave 2					
Depression	3773	1.15	1.58	0	6
PHQ-2 ≥ 2	3773	0.33	0.47	0	1
PHQ-2 ≥ 3	3773	0.2	0.4	0	1
Perceived COVID-19 risk	3773	0.32	0.46	0	1
Partner	3773	0.45	0.5	0	1
# of preventative behaviours	3773	2.55	1.13	0	8

Table 2
Regression model predicting adult depressive symptoms.

	Dependent variable:		
	OLS	*Logistic*	*Logistic*
	PHQ-2 scores	PHQ-2 ≥ 3	PHQ-2 ≥ 2
	(1)	(2)	(3)
Constant	0.66	-1.84^{*}	-1.45^{*}
	(−0.40, 1.73)	(−3.58, −0.09)	(−2.87, −0.02)
Risk perception	0.23^{*}	$0.23^{\dagger}$	0.27^{*}
	(0.05, 0.42)	(−0.04, 0.51)	(0.02, 0.51)
Age	0.01	0.004	0.02
	(−0.03, 0.04)	(−0.05, 0.06)	(−0.03, 0.07)
Age squared	−0.01	−0.01	−0.03
	(−0.06, 0.03)	(−0.07, 0.05)	(−0.08, 0.02)
Male	0.12	0.22	$0.25^{\dagger}$
	(−0.08, 0.32)	(−0.07, 0.52)	(−0.01, 0.51)
African	-0.64^{**}	-0.81^{**}	-0.67^{**}
	(−0.93, −0.35)	(−1.20, −0.42)	(−1.03, −0.30)
Flat (dwelling)	0.24	0.36	0.27
	(−0.08, 0.55)	(−0.15, 0.87)	(−0.18, 0.72)
Traditional (dwelling)	0.24	0.27	0.16
	(−0.17, 0.66)	(−0.37, 0.92)	(−0.40, 0.72)
Household size	0.01	−0.01	0.02
	(−0.01, 0.03)	(−0.05, 0.03)	(−0.01, 0.06)
Avoid COVID-19	−0.07	-0.43^{*}	−0.17
	(−0.32, 0.18)	(−0.80, −0.06)	(−0.50, 0.17)
Household hunger	$0.21^{\dagger}$	0.17	0.16
	(−0.03, 0.46)	(−0.16, 0.49)	(−0.12, 0.44)
Chronic illness	0.34^{**}	0.36^{*}	0.47^{**}
	(0.10, 0.57)	(0.02, 0.70)	(0.18, 0.76)
Receive Govt grant	−0.10	−0.07	−0.07
	(−0.32, 0.12)	(−0.43, 0.30)	(−0.38, 0.24)
Traditional (area)	0.11	0.002	0.03
	(−0.34, 0.56)	(−0.70, 0.70)	(−0.53, 0.59)
Urban (area)	0.20	0.05	0.20
	(−0.16, 0.55)	(−0.54, 0.64)	(−0.28, 0.68)
Electricity	0.16	0.48	0.09
	(−0.14, 0.46)	(−0.15, 1.11)	(−0.48, 0.66)
Water	0.16	$0.32^{\dagger}$	0.02
	(−0.06, 0.38)	(−0.04, 0.69)	(−0.30, 0.35)
Household lost income	0.32^{**}	0.41^{**}	0.30^{*}
	(0.13, 0.51)	(0.13, 0.70)	(0.05, 0.55)
Tertiary Educ	0.06	0.08	0.18
	(−0.16, 0.28)	(−0.24, 0.40)	(−0.11, 0.47)
Employment status	0.32^{**}	0.49^{**}	0.38^{**}
	(0.09, 0.55)	(0.15, 0.82)	(0.10, 0.66)
Poor health	−0.09	$-0.27^{\dagger}$	−0.16
	(−0.29, 0.10)	(−0.57, 0.04)	(−0.42, 0.11)
Has partner	−0.03	0.10	0.03
	(−0.22, 0.16)	(−0.19, 0.40)	(−0.23, 0.29)
No of preventative measures	−0.01	−0.06	−0.004
	(−0.09, 0.07)	(−0.17, 0.06)	(−0.11, 0.10)
Observations	3773	3773	3773
R^2	0.06		
Adjusted R^2	0.06		
F Statistic	$11.16^{\dagger}$ (df = 22; 3750)		

Note: Columns (1) present the result for raw PHQ-2 scores, while (2) and (3) present similar result when PHQ-2 is dichotomised i.e., PHQ-2 ≥ 3 and PHQ-2 ≥ 2 respectively. All calculations use robust standard errors.

† Indicates that the F statistic is significant at 1%.

** $p < 0.01$.

* $p < 0.05$.

† $p < 0.1$.

[2] We note that an alternative to the CIA assumption relied upon in this study is the instrumental variable approach. However as with many empirical applications it is profoundly difficult to find appropriate instruments to identify causal effects; and even where these can be found identification often leads to very localized treatment effects which suffer from a lack of generalizability (Jacob et al., 2021).

0.51), albeit this estimate is only significant at the 10% level. Having a chronic illness (b = 0.47, 95% CI, 0.18–0.76), unemployment (b = 0.38, 95% CI, 0.10–0.66), and a loss of household income between Waves 1 and 2 (b = 0.30, 95% CI, 0.05–0.55) were risk factors for worse depressive symptoms, while being African was associated with lower levels of depression (b = −0.67, 95% CI, −1.03, −0.30). We note that the finding on African race group is counterintuitive given that depressive symptoms are more prevalent among those of lower socioeconomic status (SES) before the pandemic. Since SES is correlated with race in South Africa the expectation would be that the pandemic will exacerbate the existing inequality in depressive symptoms that disadvantage the (black) African population (Burger et al., 2017). While this is obviously a paradox that requires more investigation, we note that this finding is not peculiar to our analysis. Other studies based on NIDS-CRAM data reports similar finding (Oyenubi and Kollamparambil, 2020; Posel et al., 2021). Further, independent data collected by the Human Sciences Research Council (in South Africa) show that Black Africans report significantly less psychological distress than other population groups (Human Sciences Resaerch Council, 2020). Lastly evidence from the literature suggests similar pattern has been picked up in the USA. For example, the Axios-Ipsos poll reports that 47% of Americans of higher SES indicated their emotional well-being had gotten worse as a result of the pandemic, compared to only 34% of lower SES (Talev, 2020). A recent study (Wanberg et al., 2020) also confirms this result, showing that higher education was associated with greater decreases in well-being during the pandemic (indicated by a stronger increase in depressive symptoms and decrease in life satisfaction). The authors argue that this may be a consequence of the Conservation of Resource (COR) Theory (S. Hobfoll, 1989, 2010; S. Hobfoll et al., 2003; S. E. Hobfoll et al., 2016). The COR posits that reduction in wellbeing in a specific context depends on how one's resource is perceived to have contracted. Therefore, it is possible for differences in perceived loss associated with the COVID-19 pandemic and associated disruptions to disproportionately affect individual of higher socioeconomic status.

4. Discussion

In this nationally representative analysis of South African adults living through the first five months of the 2019 coronavirus pandemic, we found that worsening risk perceptions of COVID-19 infection predicted worse depressive symptoms. The causal impact of worse COVID-19 risk perceptions on depressive symptoms remained after adjusting for a wide range of demographic, socioeconomic, and household characteristics. This analysis is, to our knowledge, the first to longitudinally assess the impacts of COVID-19 risk perceptions on depressive outcomes. Our results emphasize the importance of attending to the mental health impacts of the COVID-19 pandemic, particularly in low- and middle-income contexts with elevated rates of psychiatric illness and limited mental health resources (Kola et al., 2021).

Table 3
Covariate balance before and after CBPS matching.

Variable	Type	Difference unadjusted	Difference adjusted
Propensity score	Distance	0.3105	0.0065
Age	Contin.	−0.0231	−0.0007
Age squared/100	Contin.	−0.0563	−0.0009
Male	Binary	−0.0402	−0.0002
African	Binary	−0.0955	−0.0005
House/flat	Binary	0.1018	0.0001
Traditional house	Binary	−0.0589	−0.0001
Informal housing	Contin.	0.0271	<0.0001
Household size	Binary	0.0091	0.0003
Able to avoid coronavirus?	Binary	0.0784	0.0003
Food insecurity	Binary	0.0047	<0.0001
Has chronic illness	Binary	−0.0591	−0.0004
Received gov't grant	Binary	−0.0697	−0.0005
Traditional	Binary	0.0784	0.0004
Urban	Binary	0.0174	−0.0001
Farm	Binary	0.0851	0.0003
Electricity	Binary	0.0399	0.0005
Water	Binary	0.1363	0.0006
Household lost income	Binary	−0.1759	−0.0006
Tertiary education	Binary	0.0306	−0.0001
Unemployed	Binary	0.0364	−0.0002
Poor health	Contin.	0.0085	0.0003

The relationship between greater perceived COVID-19 infection risk and depressive symptoms is consistent with the growing global literature on the mental health impacts of the COVID-19 pandemic, which consistently reports strong associations between worse risk perceptions and greater psychiatric morbidity (Ding et al., 2020; Kim et al., 2020; Olagoke et al., 2020). Specifically, our results reported that an increase in an individual's perceived risk of COVID-19 infection over a two-to-four-month period predicted worse depressive symptoms. The depressive impacts of increased risk perceptions over the three-month study period corresponded with the worsening of the COVID-19 pandemic in South Africa. The first measure of risk perceptions (Wave 1) occurred during the onset of the pandemic and associated lockdown during a time where public understanding of COVID-19 was limited and cases were low, particularly in rural areas. However, by the second assessment of risk perceptions during Wave 2, the country not only experienced the height of its first wave of COVID-19 infections, but also transitioned into less stringent lockdown regulations, leading to greater population movement and possible COVID-19 transmission.

Considering the sustained nature of the COVID-19 pandemic in South Africa, limited access to mental healthcare resources and COVID-19 vaccines, and evidence of elevated and sustained perceived COVID-19 infection risk in South Africa (Fig. 1), the depressive impacts of increased COVID-19 risk perceptions may remain a public mental health concern in the future and well after the end of pandemic. Sustained COVID-19 risk may serve as a form of chronic stress, which is a well-known determinant of depression and other psychopathologies (Hammen, 2005). Additionally, the presence of additional risk factors relevant to our context, such as the uncontrollable nature of COVID-19 stressors and poverty, are known to exacerbate the biological and health impacts of chronic stress (Lund et al., 2010; Miller et al., 2007). Public mental health planning agencies may consider promoting further educational campaigns around COVID-19 and advocating for structural changes to provide equitable access to risk mitigation resources and strategies, as past research has shown that these resources are associated with ameliorating COVID-19 risk perceptions (Ekumah et al., 2020; Kim et al., 2020).

We utilized a variety of statistical methods to estimate the causal effects of worsening COVID-19 risk perceptions on depressive symptoms and reduce bias. Covariate balanced propensity scores minimized the bias from treatment assignment to estimate average causal effects. Furthermore, we considered a wide range of possible confounding factors that may have compromised our estimates due to omitted variables bias. Most studies in the current literature on the mental health impacts of COVID-19 risk perceptions use community-based sampling and assess cross-sectional associations to estimate these effects. To our knowledge, this analysis is the first to estimate the impacts of COVID-19 risk perceptions on depressive outcomes using a causal inference framework and also extends the literature by using a nationally-representative sample. Our analysis is not without limitations. While controlling for an extensive set of covariates mitigate the risk of unobserved factor influencing the results, the risk of omitted variables bias remains given that the CBPS relies on the conditional independence assumption. However, this risk is limited by our longitudinal approach.

5. Limitations

This study is not without its limitations, some of the limitations are discussed in this section. PHQ-2 is designed to screen for depression as a "first step" approach. Ideally respondents that screen positive for depressive symptoms under the PHQ-2 scale are recommended to be further evaluated using the PHQ-9 scale (Levis et al., 2020; Rancans et al., 2018).[3] There are also studies that argue that although PHQ-2 is valid, PHQ-9 (for example) is a superior screening instrument when compared to PHQ-2 (Allgaier et al., 2012; Anand et al., 2021). Even though the ultrashort format of the PHQ-2 makes it desirable in time constrained setting (such as the one in this study), this raises question of misclassification error. For example, the weakness of the PHQ-2 score might lead to compounding misclassification over the two periods of time considered in this study. Further, the risk perception measure may also be susceptible to random error because it is based on one dummy variable.

However, we note that there is no reason to suspect that such error will be systematically different between the treatment and comparison groups. Further, the balancing method used in this study is likely to mitigate bias steaming from misclassification error especially when the covariates controlled for are correlated with the reason for the misclassification. For example, spatial differences and differences in socioeconomic condition might amplify the weakness of the risk perception measure. But controls for household income loss, hunger and geographic area in the matching strategy is likely to mitigate bias related to these measures.

Concerning our identification strategy, we note that although the groups are similar at baseline, depressive symptoms might still have been antecedent to perceived risk. This is because such symptoms might have developed in the period between the two time points. However, we note that while this is possible it is unlikely given the short period of time between the two periods. Furthermore, given the widespread mental health consequences of the pandemic previously documented in South Africa and other countries worldwide and the novelty of pandemic-related stressors, we believe that perceived risk of COVID-19 infection likely preceded the expression of adults' depressive symptoms in a major portion of our sample.

6. Conclusion

In this nationally representative analysis of South African adults, our results suggest that there is a causal relationship between increases in COVID-19 risk perceptions and worse depressive symptoms during the first five months of the COVID-19 pandemic (under the CIA assumption). The point prevalence of perceived COVID-19 infection risk increased between the third and fifth months of the pandemic, which corresponded with elevations in national COVID-19 infection rates. Additionally, various forms of personal and household adversity, including having a chronic illness, unemployment, and a loss of household income were risk factors for worse depressive symptoms, while being African was associated with lower depressive symptoms. These findings highlight the widespread mental health burdens of the COVID-19 pandemic and emphasize the importance of greater psychological resources and structural changes to promote equitable access to COVID-19 risk mitigation policies.

Data sharing

The data that support the findings of this study are openly available in The World Bank Microdata Library at https://doi.org/10.25828/5z2w-7678, reference number ZAF_2020_NIDS-CRAM-W2_v01_M.

CRediT authorship contribution statement

AO conceptualized the paper, procured the data, conducted the analysis, contributed to writing, and edited the final draft.

AWK conceptualized the paper, drafted the manuscript, contributed to analysis, and edited the final draft.

UK conceptualized the paper, procured the data, and edited the final draft.

All authors have approved the final article.

Funding source

AWK is supported by the National Science Foundation Graduate Research Fellowship, the Fogarty International Center, and the National Institutes of Health under Award Number D43 TW010543. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Declaration of competing interest

The authors report no conflicts of interests to report.

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