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Socioeconomic-related inequalities in COVID-19 vulnerability in South Africa

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Abstract: To contain and mitigate the coronavirus (COVID-19) pandemic, African governments have implemented non-pharmacological interventions (NPIs), such as imposing travel bans, confining people to their homes and closing schools, shops and workplaces. These NPIs are likely to be less effective in circumstances where people need to leave their homes to work, collect food, water and cooking fuel or where people cannot maintain distancing due to overcrowded living environments. Using data from the nationally representative South African General Household Survey 2019, we examined individuals' vulnerability to the risk of COVID-19 infection due to their health, socioeconomic and living circumstances. We explored socioeconomic-related inequalities in COVID-19 using concentration curve and concentration index methods. Our results showed that vulnerability to COVID-19 was disproportionately concentrated among those with low socioeconomic status. Using the Recentered Influence Function decomposition approach, we found that higher income and education had a significant and positive impact on reducing socioeconomic-related COVID-19 vulnerability. Conversely, people with lower socioeconomic status were more likely to live in circumstances that made compliance with NPI requirements almost impossible, and they were also more likely to have pre-existing health conditions that made them more vulnerable to COVID-19.

Keywords: COVID-19 prevention; vulnerability index; inequality; concentration index; South Africa

1. Introduction

Non-pharmaceutical interventions (NPIs), such as social distancing, isolation and regular handwashing, were effective strategies to restrict the spread of the COVID-19 virus before vaccinations were available. Even after introducing a vaccine, such interventions are still necessary, especially in developing countries, where vaccination coverage is relatively low. However, overcrowding, a lack of access to adequate water and sanitation and a lack of protective equipment plague a large proportion of households in developing countries [1]. A growing number of studies, mostly from developed countries, found that the risk of infection and death from COVID-19 was disproportionately higher for people from disadvantaged socioeconomic backgrounds [2-4]. Variations in the capacity to implement NPIs are proposed as the primary mechanism for social inequalities in pandemic morbidity and mortality [5]. Due to a lack of data on individual-level COVID-19 infection and mortality, research examining societal disparities in COVID-19 risk and NPI compliance is mainly limited to OECD countries.

Using nationally representative survey data from South Africa, this paper aims to fill in this knowledge gap, investigating the extent to which individuals are vulnerable to COVID-19 infection due to their health, socioeconomic and living circumstances. South Africa is one of the African countries most affected by COVID-19 [6], and it is characterised by a high level of socioeconomic inequality [7]. We measured COVID-19 vulnerability using living conditions indicators that are likely to affect South African families' ability to implement NPIs.

Previous research in South Africa and elsewhere has shown that lower socioeconomic status is associated with poorer health [8-11]. Our study contributes to this research by examining socioeconomic-related inequalities in vulnerability to infectious diseases such as COVID-19. The few existing works on COVID-19 vulnerability in South Africa did not investigate socioeconomic-related inequalities [1, 7, 12].

There are several reasons why people from lower socioeconomic backgrounds suffer the most severe health consequences during pandemics, even in 21st Century South Africa with its modern social security system and advanced medical care. First, people living in less affluent areas are more likely to get COVID-19. They are more likely to work in jobs that involve high amounts of social contact (e.g., factory workers, construction workers, care assistants, shop assistants and bus drivers) and, as a result, are more likely to come into contact with infected people than those who may live in more affluent areas and can work from their homes. Moreover, individuals in deprived areas are more likely to rely on public transport than those in more affluent areas, thus having more contact with infectious people. Also, the higher the population density, the more difficult it is to maintain social distancing and urban areas in which deprived individuals reside tend to have higher population densities than wealthier areas. Therefore, people in deprived areas are more likely to come into contact with infected persons when they leave home for medical care, food shopping and other activities.

Secondly, people with a COVID-19 infection in poor areas are more likely to die. There is a higher risk of severe disease and death from a COVID-19 infection if a person already has underlying health issues, such as hypertension, diabetes, cardiovascular disease, chronic respiratory disease and cancer [13]. People in deprived areas are more likely to suffer from these health issues than those in more affluent areas for various reasons, including but not limited to greater pollution levels, greater stress levels, greater inflammation levels and greater risk of getting *Helicobacter pylori (H. pylori)* infections in childhood [14]. Unfortunately, the *Inverse Care Law* reveals that health care quality is often inversely related to health needs. Consequently, deprived areas, on average, have worse health care than more affluent areas [15].

1.1. Slowing and suppressing the pandemic

Vaccines against SARS-CoV-2 were developed and received regulatory approval for emergency use in less than nine months [16]. The global COVID-19 vaccination programme first started in the United Kingdom on the 8th December 2020 and began in South Africa on the 17th February 2021. By the end of May 2022, more than 36 million vaccinations had been administered in South Africa, and approximately half of the adult population had received at least one vaccination.[1]

Nevertheless, this still leaves a large percentage of the South African population unvaccinated, and NPIs remain one of the most effective ways to prevent community transmission [17]. Common NPIs include social distancing, facemask wearing, increased ventilation, frequent handwashing with soap and water, etc. The primary purpose of NPIs is to reduce and mitigate the impact of the pandemic by slowing "*the spread of infections in the community, delaying the peak in infections, reducing the size of the peak and spreading infections over a longer period of time*" as illustrated by Figure 1 ([18], pp.1). This flattening-the-curve strategy aims to prevent the country's health service from being overwhelmed by an exponentially increasing number of patients and provide more time for the population to be vaccinated and new treatments to be developed [19].

[1] See https://sacoronavirus.co.za/latest-vaccine-statistics/

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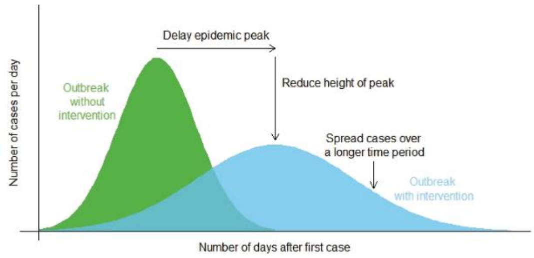

Figure 1. NPIs aim to reduce the rate of infection.

Source: World Health Organization [18] (License: CC BY-NC-SA 3.0 IGO, pp.1).

The purpose of NPIs is to reduce the rate at which the disease spreads (i.e., the disease effective reproduction number "***R***"), defined as the average number of secondary cases per infectious case in a population made up of both susceptible and non-susceptible people [20]. Since SARS-CoV-2 is a new virus, it is assumed that everyone is initially susceptible to contracting a COVID-19 infection [13]. People only gain immunity by being vaccinated or contracting and recovering from COVID-19.

If the effective reproduction number, ***R***, is less than 1, the number of infected people will fall. If ***R is*** 1, the number of people with COVID-19 will stay static, and if ***R*** is larger than 1, the number of infections will increase [21]. The reproduction number equals the rate of infection divided by the recovery rate (i.e., ***R*** = Infection rate/Recovery rate). Thus, it can be reduced by either lowering the infection rate (e.g., through social distancing, vaccination) or increasing the recovery rate (e.g., through effective treatments which speed recovery).

The course of a pandemic can be predicted using SEIR (Susceptible, Exposed, Infectious and Recovered) models. In these models, a key parameter is the *basic reproduction number* (R_0), defined as the average number of people in the susceptible population who will catch the disease from an infected person [22]. However, to implement effective policies for controlling a pandemic, it is crucial to know the average infection rate and "*whether specific situations and settings might be driving the outbreak*" [23]. For example, in Guangzhou (China), the risk of catching COVID-19 at home (from an infected household member) was approximately ten times greater than the risk of acquiring it in hospital and 100 times greater than the risk on public transport [24, 25]. In Japan, contact tracing data showed that the risk of an infected person transmitting the virus was, on average, 18.7 times higher in a closed environment (such as a building or a house) than in an open-air environment [26]. Hence, it is essential for policy purposes to decompose R_0 into a series of *Secondary Attack Rates* (2^0AR), i.e., the proportion of people exposed to an infected person that develops the disease within a specific group (e.g., the household or a group of friends). Thereby,

R_0 = 2^0AR [Household] x Number of contacts [Household]
+
2^0AR [Neighbours/Friends] x Number of contacts [Neighbours/Friends]
+
2^0AR [Community/Strangers] x Number of contacts [Community/Strangers]

Lockdown and social distancing policies mainly reduce contacts and the probability of being infected outside the household. However, a quarantine (that is, not allowing people to leave their homes) is likely to increase the secondary attack rate [27] *within* the household, i.e., where a household member has been infected with the virus before the lockdown.

The increased household attack rate may vary by the age and relationship of household members. A meta-analysis of 44 studies by Madewell and colleagues [27] estimated that the average household secondary attack rate of the SARS-CoV-2 variants at that time was 16.6% (95% CI ∈ 14.0%-19.3%); the average attack rate for family contacts was 17.4%

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(95% CI ∈ 12.7%-22.5%); the chance of catching a COVID-19 infection from an infectious household member was significantly higher for adults (28.3%; 95% CI ∈ 20.2%-37.1%) than children (16.8%; 95% CI ∈ 12.3%-21.7%), with spouses having a much higher risk of a COVID-19 infection (37.8%; 95% CI ∈ 25.8%-50.5%). It should be emphasised that serological studies (i.e., studies that measure IgG blood antibodies against COVID-19) have found much higher average household attack rates, e.g., 45% in Norway, 37% in Spain and 35% in Brazil [28-30].

The SARS-CoV-2 virus has continued to evolve to become more infectious. A recent estimate of the average household attack rate for the Delta variant (B.1.617.2), which South Africa firstly reported at the end of 2021, is 5.1 (e.g., ten people would, on average, infect another 51 people), whereas that of the original version of the virus was 2.8 [31]. The average household attack rate for the Omicron variant (B.1.1.52) is about 50% higher than for the Delta variant [32]. Thus, it becomes more critical than ever to understand who in South Africa is at the highest risk of contracting a COVID-19 infection due to health, socioeconomic and living conditions and the resulting limited capacity to implement NPIs effectively.

2. Data and Methods

2.1. Data

The South African General Household Survey (GHS) 2019, a nationally representative sample collected just before the COVID-19 pandemic, serves as the primary data source for this work. The sample was drawn using a stratified two-stage sampling method. The first stage sampled primary sampling units (i.e., Enumeration areas; EAs) using a probability proportional to size (PPS) method [33]. The second stage sampled dwelling units (DUs) using systematic sampling. In total, 22,529 DUs were sampled, containing 19,649 households and 68,986 individuals [33]. After removing individuals with missing information, we have 99.9% (i.e., n = 68,924) of individuals in our final sample. The data includes housing conditions, access to basic services, assets, income, health and demographic factors (i.e., age, gender and race).

2.2. Measuring COVID-19 vulnerability

To assess COVID-19 vulnerability in South Africa, we used a syndemic approach [34, 35]. This approach emphasises the interaction and intersection of multiple social, economic and environmental risks with biological risks to produce increased disease risks and health burdens [35]. Therefore, pre-existing health conditions and socioeconomic status can interact with SARS-CoV-2 to determine individuals' vulnerability to COVID-19.

In order to measure people's vulnerability to COVID-19, we examined an individual's pre-existing illness and household living conditions that are likely to limit their ability to implement NPIs and increase the risk of COVID-19 infection. Table 1 lists the relevant vulnerability indicators that have been validated by previous scientific findings and are applicable in local contexts. These indicators can help identify conditions likely to increase the population's secondary attack rate.

The vulnerability indicators have high face validity resulting from high scientific relevance (i.e., *Scientific Reasons* in Table 1). We further examined the vulnerability indicators' criterion validity by correlating them with aggregated case-fatality data at a district level (see Annex for details).[2] Except for the toilet-sharing indicator, the findings indicate a statistically significant positive relationship between the vulnerability indicators and the estimated case-fatality rates (i.e., the number of total deaths due to COVID-19 divided by the number of total confirmed COVID-19 cases in each district).

[2] There is no data on COVID-19 infections and mortality at the household or individual levels in GHS 2019 or other representative household surveys in South Africa.

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Table 1. COVID-19 vulnerability indicators.

Vulnerability indicators	Secondary attack rate level	Scientific reasons
Large household with six or more people	Household	Data An ill person is more likely to infect their household members than friends, neighbours or the wider community. The larger the household, the more members are likely to be infected.
People over 60 live in households with one or more younger people aged between 7 and 60 years.	Household	People aged 60 and over are more likely to die or suffer from a severe COVID-19 infection. Older people are more likely to be infected within households with younger members; i.e., older people have a higher secondary attack rate within the household
Overcrowding household with more than three people per room	Household	COVID-19 is primarily spread by contact with coughed and respired droplets and fomites. It is difficult or impossible for household members to socially distance themselves from an infected household member in overcrowded households
No refrigerator	Household	Households not having a refrigerator need to leave their homes more frequently to get food, thus are at greater risk of infection.
No access to a handwashing facility and lack of soap for handwashing	Household	Inability to wash hands regularly with soap or detergent increases the risk of contracting a COVID-19 infection.
There is a household member with a chronic health condition	Household	Individuals with chronic health conditions are more likely to suffer from a more severe Covid-19 infection and remain infectious for longer.
No access to a radio or TV	Household	Effective risk communication and community engagement are crucial to controlling infectious disease epidemics. It is much harder for households without access to broadcast media to get the correct public health information to stay safe, as misinformation and rumour during a pandemic can be extensive and dangerous.
Sharing a toilet with other households or not having a toilet facility	Wider community	Sharing a toilet increases the risk of catching COVID-19 from infected people in neighbours' households either by faecal/oral transmission or from close contact in or near the shared toilet, e.g., while waiting/queuing.
Water source not in house or yard/plot of dwelling	Wider community	Collecting water from a public supply increases the risk of catching COVID-19 from infected people in other households due to close contact while queuing to collect water or touching contaminated water supply equipment, e.g., stand-pipe taps, pump handles, well buckets.

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We next created an overall vulnerability index based on the nine indicators listed in Table 1. We used two methods to aggregate the nine indicators for each individual to obtain a summary measure of the indicators. First, we calculated a weighted Average Vulnerability Index (AVI) for each person, with each indicator weighted equally. Second, following previous research (e.g., [7, 12]), we used a counting approach to aggregate the nine indicators for each individual to assess the Intensity of Vulnerability (IV). We presented results based on both methods of aggregation. The AVI ranges from 0 to 1, and the IV scales from 0 (no vulnerability in any of the indicators) to 9 (vulnerable in all nine indicators). Higher AVI and IV values indicate a higher vulnerability to COVID-19 infection.

2.3. Socioeconomic-related inequalities in COVID-19 vulnerability

This section discusses the empirical strategies used to analyse socioeconomic-related inequality in COVID-19 vulnerability. The relationships between COVID-19 vulnerability and socioeconomic and demographic factors were investigated using regression analysis. The concentration curve and concentration associated index were used to investigate socioeconomic-related inequality in COVID-19 vulnerability. Decomposition analysis was adopted to identify factors contributing to socioeconomic-related inequalities in COVID-19 vulnerability.

2.4. Regression model

To investigate the association between COVID-19 vulnerability and socioeconomic (education and income) and demographic factors (i.e., age, race, gender), we specify the following model:

$$Y_i = X'\beta + \varepsilon_i$$

Where Y_i is individual i's COVID-19 vulnerability score (i.e., AVI and IV, respectively), X' is a vector of explanatory variables, β is a vector of coefficients of the explanatory variables and ε_i is the error term, assumed to have a conditional mean of zero.

Ordinary least squares (OLS) regression was applied to estimate the model. A fractional probit regression was also conducted since the AVI ranges from 0 to 1. Although IV ranges from 0 to 9, only a few people have reported being vulnerable in eight or nine indicators. As a result, scores 8 and 9 were combined with 7 for the regression analyses.

2.5. The concentration curve and concentration index

We estimated socioeconomic-related inequalities in COVID-19 vulnerability using the concentration curve and the concentration index, which are widely adopted to measure socioeconomic-related health inequality [36-39]. The concentration curve plots the cumulative percentage of a health variable on the vertical axis against the cumulative share of the population ranked by socioeconomic status (from lowest to highest socioeconomic status; SES) on the horizontal axis. A concentration curve above the line of equality (i.e., the 45-degree line) indicates greater COVID-19 vulnerability amongst the poor, while a concentration curve below the line of equality indicates greater vulnerability amongst the rich. If everyone had the same level of vulnerability, regardless of socioeconomic status, the concentration curve would intersect the 45-degree line. The greater the degree of inequality, the further the concentration curve diverges from the line of equality.

The associated Concentration Index (CI) is a summary index, defined as twice the covariance between a health variable and an SES ranking [37]. The formula for the standard concentration index is given below:

$$CI = \frac{2}{\mu_h} cov(Y_h, R)$$

Where Y_h is the individual COVID-19 vulnerability index score (i.e., AVI and IV), μ_h represents the mean of the index, and R represents the SES ranking of the individual.

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For our SES ranking, we used per capita household income. A higher value of AVI or IV indicates a higher level of vulnerability.

As AVI and IV are both bounded variables, the standard CI has limitations. For bounded health measures, for example, the magnitude of the CI differs when calculated using the good health indicator versus when calculated using the associated ill-health indicator [40]. In addition, the minimum and maximum values of the CI are dependent on the mean of the health indicator [41]. To account for the specific issues they raised, Erreygers [40] and Wagstaff [41] each proposed a "corrected" CI for use when the health measure is bounded [37]. However, there is no agreement on which of the two normalisations is preferable. According to Erreygers and Van Ourti [37], Erreygers' index [40] has some desirable properties compared with Wagstaff's [41] index. We thus used the Erreygers' [40] normalised concentration index (EI). It is calculated according to:

$$EI = \frac{4\mu_h}{b_h - a_h} * \frac{2}{\mu_h} cov(Y_h, R)$$

The CI ranges from -1 to +1, with a negative value indicating that COVID-19 vulnerability is disproportionately concentrated among the poor and a positive value indicating that COVID-19 vulnerability is disproportionately concentrated among the rich. The index assigns a value of zero if the distribution of vulnerability is equal.

2.6. Decomposing the concentration index of COVID-19 vulnerability

Recentered Influence Function (RIF) regression was used to decompose the concentration indices of COVID-19 vulnerability. RIF regression is recommended for decomposing bivariate rank-dependent indices like the CI to identify factors contributing to SES-related health inequalities [42]. The main limitation of the most commonly used alternative decomposing methods, such as the Wagstaff decomposition method, is that it only explains the degree of variation in health while ignoring the covariance between SES rank and health [42].

The RIF method uses standard regression techniques to estimate the unconditional partial effects of small changes in a given explanatory variable on the size of distributional statistics such as a CI [42-44]. The procedure involves two steps. First, each observation's RIF value, i.e., a transformation of the Influence Function (IF), is computed. The IF quantifies the influence of a given observation on the estimation of the CI, whereas the RIF quantifies the relative contribution of that observation to the CI [44].

The average of individual RIF is the CI itself. Under the assumption of a linear relationship between the RIF and the explanatory variables and an additive error term with a conditional zero mean value, the RIF regression can be estimated using the OLS approach, which is termed RIF-I-OLS regression. The formula for RIF-I-OLS is given below [44].[3]

$$RIF\{h, v(F_H)\} = X'\beta + \varepsilon_i$$

Where h is the COVID-19 vulnerability index, $v(F_H)$ is the distribution statistics (CI of COVID-19 vulnerability), X is the vector of explanatory variables, and ε_i is an error term assumed to have a zero conditional mean. The coefficient β is the marginal effect of the explanatory variables on the RIF of the CI.

3. Results and Discussion

3.1. Distribution of COVID-19 vulnerability

Figure 2 shows the distribution of our vulnerability indicators at national, rural and urban levels. There were remarkable differences between rural and urban areas regarding the extent of lacking on-site water, household size and the presence of older people. Approximately 62% of people (16 million) in rural areas lived in households that lacked on-

[3] Rios-Avila [44] provides a simple procedure to estimate RIF-regression using STATA software.

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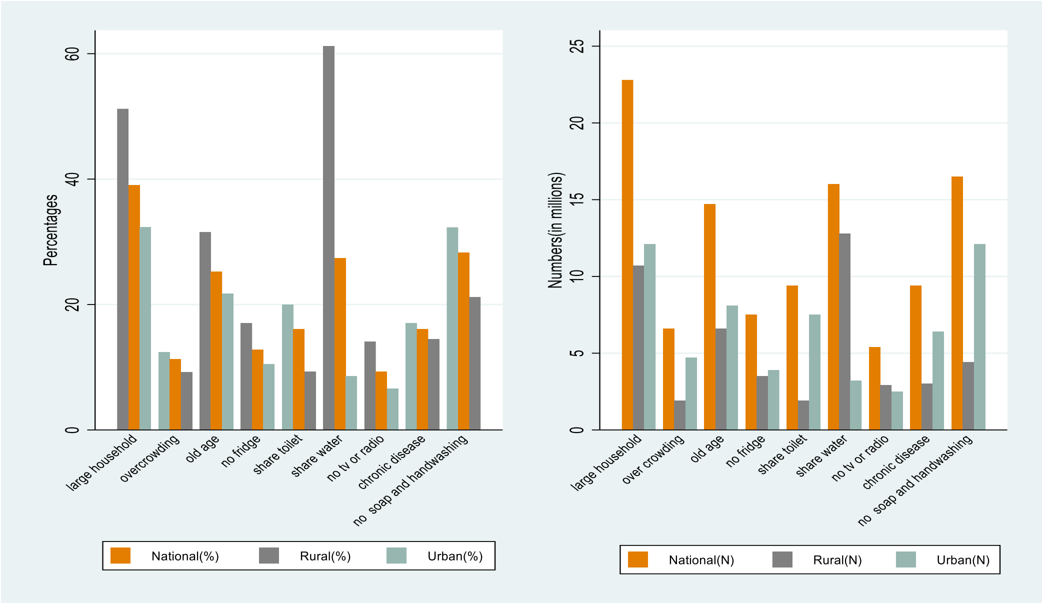
site water sources, while the figure in urban areas was only 8.6% (3.2 million individuals). By contrast, approximately 20% of people (7.5 million) in cities lived in households where a toilet was shared with another household, while only 9.3% of people in rural areas (1.9 million) lived in similar conditions. Approximately 14% of the households in rural areas lacked access to television or radio, whereas only 7% of the population in urban areas was estimated to be without access. Surprisingly, the proportion of the population without access to soap and handwashing facilities is higher in urban (32%) than in rural areas (21%).

Figure 2. Vulnerability indicators, nationally and in rural and urban areas.



Notes: 1. Source GHS (2019); 2. Authors' calculation.

The distribution of the two vulnerability indices (i.e., AVI and IV) by demographic and socioeconomic factors is shown in Table 2. Individuals from lower-income households were more vulnerable than those from higher-income households. Those in the lowest income quintile had an AVI of 0.26 compared with 0.12 for those in the highest quintile. Members of female-headed households were more vulnerable than those from male-headed households. Similarly, older people were more likely to live in homes with limited capacity to comply with NPIs and had pre-existing health conditions, contributing to their vulnerability. These findings are consistent with previous research indicating a link between older age and female-headed households and poverty in South Africa [45, 46].

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Table 2. Vulnerability indices by demographic and socioeconomic factors.

	AVI (0-1)	IV (0-9)
Old (age >60 years)		
No	0.20	1.82
Yes	0.27	2.41
Head gender		
Male	0.19	1.72
Female	0.23	2.04
Income		
Quintile 1	0.26	2.33
Quintile 2	0.24	2.18
Quintile 3	0.22	2.00
Quintile 4	0.19	1.70
Quintile 5	0.12	1.04
Race		
African/Black	0.22	1.99
Coloured	0.18	1.60
Indian/Asian	0.13	1.15
White	0.10	0.93
Education		
No Education	0.23	2.09
Primary	0.24	2.14
High School	0.20	1.79
Tertiary	0.13	1.15
Region		
Urban	0.18	1.61
Rural	0.25	2.29

Notes: 1. Source GHS (2019); 2. Authors' calculation.

3.2. SES-related inequalities in COVID-19 vulnerability

Table 3 displays the regression analyses in which AVI and IV are dependent variables. An increased risk of COVID-19 vulnerability was associated with having a lower level of education and income and being African/Black. There is no significant difference between having a primary education and not having any education. Having a secondary or tertiary education, on the other hand, is significantly associated with a lower risk.

Table 3. Regression of COVID-19 vulnerability indices.

	(1) AVI (OLS)	(2) AVI (Fractional Regression)	(3) VI (OLS)
Old (age > 60 years)	0.07***	0.25***	0.66***
	(0.00)	(0.00)	(0.00)
Female	0.00	0.01	0.02
	(0.39)	(0.37)	(0.40)
Reference = African/Black			
Coloured	-0.03***	-0.11***	-0.26***
	(0.00)	(0.00)	(0.00)
Indian/Asian	-0.04***	-0.21***	-0.39***
	(0.00)	(0.00)	(0.00)
White	-0.06***	-0.28***	-0.52***
	(0.00)	(0.00)	(0.00)
Log pc income	-0.03***	-0.10***	-0.25***
	(0.00)	(0.00)	(0.00)
Reference = No education			
Primary	0.00	0.01	0.01
	(0.42)	(0.31)	(0.41)
Secondary	-0.02***	-0.05***	-0.14***
	(0.00)	(0.00)	(0.00)
Tertiary	-0.04***	-0.16***	-0.34***
	(0.00)	(0.00)	(0.00)
Urban	-0.05***	-0.18***	-0.48***
	(0.00)	(0.00)	(0.00)
Constant	0.46***	0.08*	4.14***
	(0.00)	(0.02)	(0.00)
R-squared/Pseudo R^2	0.17	0.02	0.17
N	67733	67733	67733

Notes: 1. Source GHS (2019); 2. Authors' calculation. Notes: 1. Source GHS (2019); 2. Authors' calculation; 3. Columns (1) and (3) show estimates of the AVI and IV dependent variables using the OLS regression approach, while column (2) shows the estimates of AVI using the fractional regression method; 4. All models included province fixed effects; 5. * $p < .05$, ** $p < .01$, *** $p < .001$.

In contrast to the descriptive results, holding other factors constant, the gender of the head of household became statistically insignificant. Gender becomes insignificant once income is controlled for due to the correlation between low income and female headship. Individuals living in rural areas are more vulnerable to COVID-19 than those in urban areas due to their living conditions. The findings imply that people with higher socioeconomic status are more likely to live in houses that can comply with NPIs and are less likely to have pre-existing health conditions than people with lower socioeconomic status, making them less vulnerable to COVID-19.

Figure 3 depicts the concentration curves for the AVI and IV measures. The concentration curves are above the 45-degree line, suggesting that those with low per capita household income are disproportionately vulnerable to COVID-19 infection.

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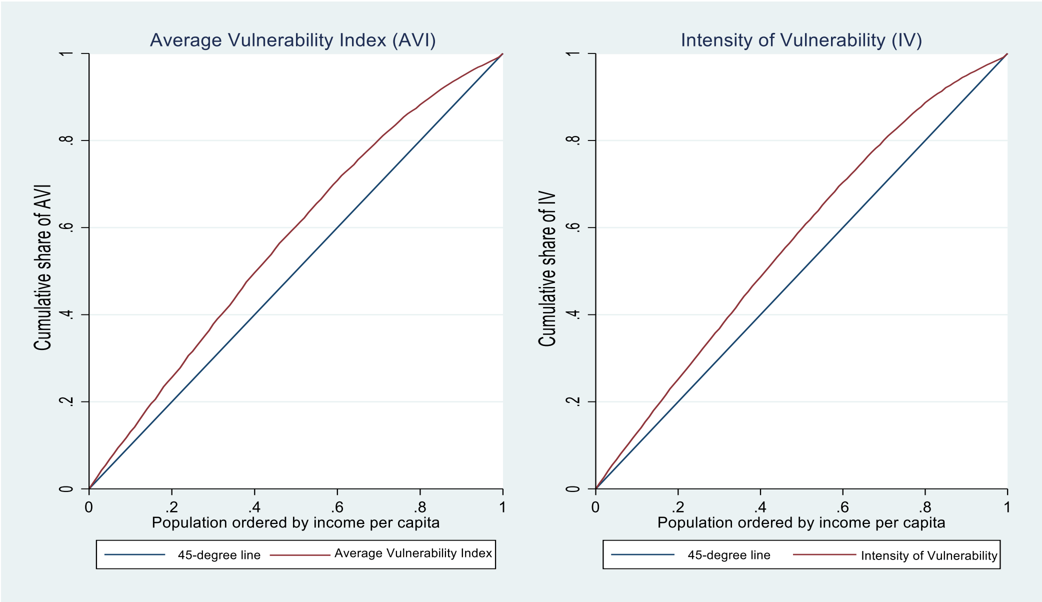

Figure 3. Concentration curves for COVID-19 vulnerability.

Notes: 1. Source GHS (2019); 2. Authors' calculation.

We also used a wealth index as an alternative SES ranking variable to per capita household income as a robustness check. The wealth concentration curves are similar to the per capita household income ranking.[4]

Table 4 shows the estimates of the CI using income (columns 1 and 2) and wealth index (columns 3 and 4) as SES ranking variables. The CI estimates were all negative and highly significant ($p < .01$), indicating that vulnerability to COVID-19 was more concentrated among the poor, which is consistent with the concentration curve analysis. It again indicates that the rich, compared with the poor, can afford to live in houses that allow them to implement NPIs and have better health conditions, potentially due to the social determinants of health and their access to better health care [47].

Table 4. Concertation index of SES-related vulnerability to COVID-19.

	(1)	(2)	(3)	(4)
	Income-Ranking		Wealth-Ranking	
	AVI	IV	AVI	IV
EI	-0.118***	-0.152***	- 0.149***	- 0.192***
	(0.0037)	(0.0048)	(0.00367)	(0.0046)
N	68254	68254	68923	68923

Notes: 1. Source GHS (2019); 2. Authors' calculation; 3. Standard errors are in parentheses; 4. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 5 shows the outcome of the concentration index decomposition based on the RIF-I-OLS regression. Except for gender, the findings showed that all factors significantly impacted inequality in SES-related COVID-19 vulnerability. Higher-income reduced ine-

[4] We used the uncentered PCA (UCPCA) method to create our wealth index from a set of household asset indicators [48]. The asset set included a stove, a vacuum cleaner, washing machines, a phone, a table, a personal computer, a satellite dish, a car, a DVD player, a home theatre, a microwave, a geyser and air conditioning.

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quality in SES-related COVID-19 vulnerability as increased income improves living conditions. Only completing primary or secondary education was associated with increased COVID-19 vulnerability inequality, whereas tertiary education significantly reduces COVID-19 vulnerability inequality. In other words, increasing the percentage of people with a tertiary education can reduce income-related inequalities in COVID-19, probably because tertiary education is associated with higher earnings in South Africa than lower educational attainment levels [49] and graduates are also likely to be better off in other dimensions of wellbeing.

Table 5. RIF-I-OLS regression for COVID-19 vulnerability indices.

	(1) EI_AVI	(2) EI_IV
Old (age >60 years)	0.03***	0.31***
	(0.00)	(0.00)
Female	0.01	0.10
	(0.05)	(0.05)
Reference = African/Black		
Coloured	-0.03**	-0.27**
	(0.00)	(0.00)
Indian/Asia	-0.12***	-1.10***
	(0.00)	(0.00)
White	-0.18***	-1.61***
	(0.00)	(0.00)
Log pc income	-0.02***	-0.21***
	(0.00)	(0.00)
Reference = No education		
Primary	0.01	0.07
	(0.05)	(0.05)
Secondary	0.03***	0.28***
	(0.00)	(0.00)
Tertiary	-0.04***	-0.35***
	(0.00)	(0.00)
Urban	0.03***	0.23***
	(0.00)	(0.00)
Constant	0.04	0.39
	(0.13)	(0.13)
R-squared	0.05	0.05
N	67733	67733

Notes: 1. Source GHS (2019); 2. Authors' calculation; 3. All models included province fixed effects; 4. * $p < .05$, ** $p < .01$, *** $p < .001$.

Individuals from other races were more likely than African/Blacks to be negatively associated with inequality in SES-related COVID-19 vulnerability. This suggests that African/Blacks were the main contributors to the high inequality in SES-related COVID-19 vulnerability. This could be because, compared with other race groups, African/Blacks are more likely to live in areas with poor housing conditions [50], increasing SES-related inequality in COVID-19 vulnerability between the rich and the poor.

Older age had a significant positive impact on inequality in COVID-19 vulnerability, suggesting that an increase in the number of older adults increases inequality in SES-related COVID-19 vulnerability. Similarly, living in urban areas had a significant positive impact on inequality in COVID-19 vulnerability compared to living in rural areas. As a result, increasing the proportion of people living in urban areas increases inequality in SES-related COVID-19 vulnerability.

4. Conclusion

The COVID-19 pandemic affects everyone, but people already in vulnerable conditions (e.g., those with poor living conditions) are disproportionately affected. According to the Global Dashboard for Vaccine Equity5, over 71.3% of people in high-income countries had received at least one dose of vaccine as of the 9th March 2022. However, the percentage drops to only about 14.3% in low-income countries. In South Africa, about 45% of the adult population were fully vaccinated[6] with noticeable sub-regional variations.

While undoubtedly, governments should prioritise providing sufficient and equal access to vaccinations, informing and supporting individuals and households already in vulnerable conditions to ensure that they can implement the recommended NPIs should also be prioritised. One significant finding of this study is that millions of people in South Africa live in households without basic facilities to maintain a reasonable standard of living or adequate living space and yet contain members especially vulnerable to COVID-19 infection due to old age or health issues. Given that the 2019 GHS data were collected before the pandemic, the situation might be even worse because many individuals have lost jobs, incomes and resources due to the pandemic (e.g., [51]).

A second main finding of this study is that economic and demographic factors such as age, race, income and education are significant predictors of COVID-19 vulnerability and have an impact on SES-related inequalities in COVID-19 vulnerability. This suggests that South Africa's vulnerability to COVID-19 results from the interactions between multiple socioeconomic and environmental risk factors and biological risk factors. This necessitates the South African government to take rapid steps to tackle the intersectionality between COVID-19 vulnerability and other forms of poverty, inequality and social exclusion resulting from ethnicity, income and location.

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[5] See https://data.undp.org/vaccine-equity/
[6] See https://sacoronavirus.co.za/latest-vaccine-statistics/

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Appendix A

The vulnerability indicators used in this paper have high face validity due to their high scientific relevance (see Table 1). It is also important to test the indicators' criterion validity to determine how closely they are related to the risk of COVID-19 infections and mortality. Criterion validity analysis requires information on COVID-19 infection and mortality at the household or individual level as well as socioeconomic status. Such data is difficult to obtain in countries such as South Africa. COVID-19 infection and mortality data are also scarce at lower geographical levels. Therefore, we were only able to obtain data on cumulative COVID-19 cases and deaths at the district level for seven out of the nine provinces in South Africa. This information was analysed to evaluate the criterion validity of some of the COVID-19 vulnerability indicators used in this paper. Our analysis included 41 districts out of the country's 52 districts. Western Cape and Free State were two provinces with no available data.

Given that our sample from the 2019 GHS was not representative at the district level, we used data from the 2016 community survey (CS) to measure COVID-19 vulnerability based on similar indicators used in the 2019 GHS. However, the 2016 CS only includes six of the nine indicators used to assess COVID-19 vulnerability. Thus, our criterion validity test was based on the six vulnerability indicators from the 2016 CS. Shifa et al. [7] demonstrated that measuring COVID-19 vulnerability using indicators from the 2016 CS and the 2018 GHS produced similar results. Hence, we do not anticipate a significant difference in COVID-19 vulnerability measures based on the 2016 CS and the 2019 GHS.

Given that reported cases and death numbers are a function of testing rates and practices that vary over time and space, we considered using the case-fatality rate (i.e., the number of total deaths due to COVID-19 divided by the number of total confirmed COVID-19 cases for each district) for criterion validity analysis. The total number of COVID-19 cases and a total number of COVID-19 deaths reported by each province between 16th and 22nd January 2022 were used to calculate the case-fatality rates. Figure A1 depicts the district-level relationship between the case-fatality rates and vulnerability indicators from the 2016 CS. Except for the toilet sharing indicator, the findings showed a positive and statistically significant relationship between the vulnerability indicators and the COVID-19 case-fatality rates. Further research should be conducted to understand why the expected positive linear relationship was not found for the toilet sharing indicator.

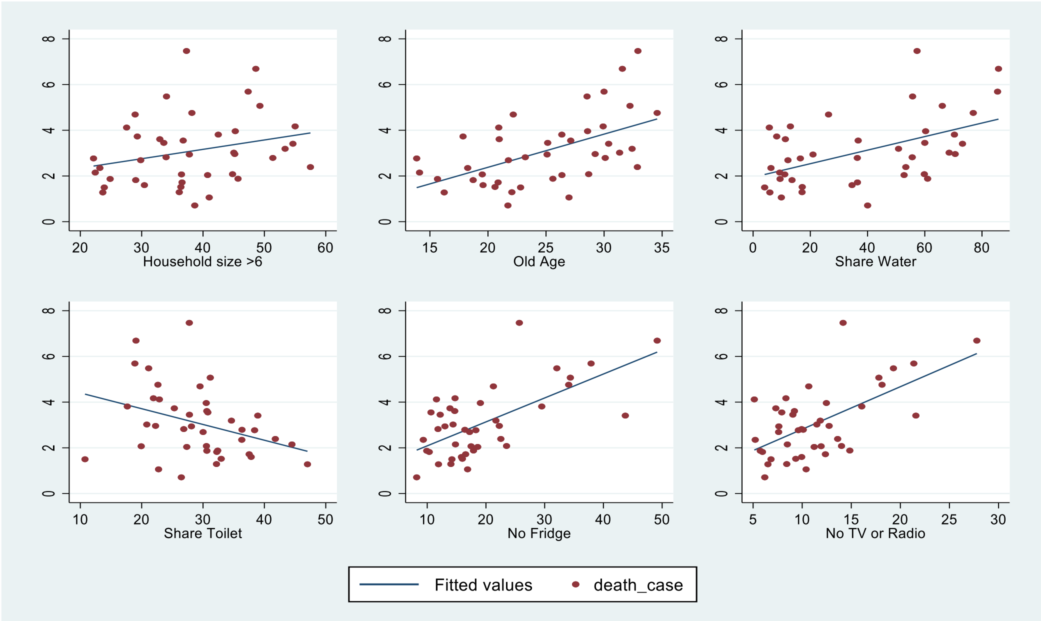

Figure A1. COVID-19 Deaths/Cases vs COVID-19 vulnerability indicators (by district).
Notes: 1. Source CS (2016) and provincial health department websites; 2. Authors' calculation.

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