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WAVE 2

National Income Dynamics Study (NIDS) – Coronavirus Rapid Mobile Survey (CRAM)

COVID-19 and Depressive symptoms in South Africa

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COVID-19 and Depressive symptoms in South Africa

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Abstract

The negative impact of the COVID-19 pandemic suggests that it disproportionately affects vulnerable groups in terms of income and health. One aspect of health that is often less researched but is particularly important in the context of the pandemic is mental health. We explore how the distribution of depressive symptoms (as a proxy for the state of mental health) and the variables associated with depressive symptoms in existing literature have changed relative to the pre-COVID period (2017). We also estimate the relationship between employment transition (between February and April, 2020) and depressive symptoms.

While we exercise caution in comparing the depressive symptoms between 2017 and 2020 because of the difference in instruments, under reasonable assumptions our analysis suggests that depressive symptoms has increased significantly in 2020 relative to 2017. Furthermore, our results show that the pandemic has actually narrowed existing inequalities due to some factors that are known to influence depressive symptoms (e.g. gender and income). However, this equality occurs at a higher level relative to 2017. While higher subjective risk perception is associated with increase in depressive symptoms for the affluent, depressive symptoms for the poor is related to financial concerns and social grants. We find that employment shock that occurred between February and April 2020 is associated with increased (decreased) depressive symptoms for those who lost (gained) employment. This relationship also differs by gender with the effect of job loss being stronger for males workers.

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Executive summary

Introduction & Motivation

The negative impact of the COVID-19 pandemic suggests that it disproportionately affects vulnerable groups in terms of income and health. One aspect of health that is often less researched but is particularly important in the context of the pandemic is mental health. We explore how the distribution of depressive symptoms (as a proxy for the state of emotional wellbeing and mental health) has changed relative to the pre-COVID-19 period (2017) and how variables known to be correlated with depressive symptoms (e.g. gender and employment status etc) explain the change, if any. We also explore the relationship between employment transition due to the pandemic related labour market shock (of February to April, 2020) and depressive symptoms.

The consensus in the literature suggests that mental health would have worsened relative to the pre-COVID-19 period (see Galea et. al, 2020; Vindegaard & Benros, 2020) (in this paper mental health is measured by depression scores). This is because the pandemic and the associated lockdown introduces new stressors. The other important aspect is that the additional burden in terms of mental health is likely to be unevenly distributed given the socio-economic landscape of South Africa.

Broadly, the pandemic precipitated (i) health and (ii) financial concerns which may have an adverse effect on mental health. Within these broad factors, we identify risk perception, social grants, household structure, COVID-19 related employment transition and employment status as some of the factors that are associated with depressive symptoms. These factors can operate through a number of channels. First, the relationship between health concerns around COVID-19 and psychological distress is likely to be mediated by risk perception. Literature has shown that affluent South Africans tend to have higher (subjective) infection risk perception compared to poor South Africans (Burger et al, 2020). This implies that the channel that has to do with health concerns itself may have a greater negative relationship with depressive symptoms of affluent individuals.

Second, the associated lockdown implies increased labour market disengagement, especially for people who are unable to perform their work task from home. It turns out that women, those with lower levels of education, those in manual occupations, informal workers, and the poor in general face the greatest net employment losses (Jain et al, 2020). Therefore, financial related stress is expected to affect vulnerable groups more. Third, individuals with different socio-economic status will experience the lockdown differently. While more affluent individuals may be more comfortable under lockdown because of their living condition, the living condition of the poorer section of the society is likely to introduce additional psychological pressure. For example, preventative measures like social distancing and handwashing may be harder to observe in overcrowded spaces and places with poor service delivery. On the flip side, poorer households tend to have larger household size, and during the hard lockdown, loneliness is a factor (Vindegaard & Benros, 2020). So, while the living condition of the poor may not be ideal, the fact that they live in larger households may make the lockdown more bearable.

Key Questions

Considering all these factors, does South African data support the hypothesis that the likelihood of screening positive for depressive symptoms has increased during the pandemic relative to the pre-pandemic period? If so, how has the extra health burden been redistributed in relation to variables that are known to be associated with depressive symptoms? For example, existing South African literature points to higher risk of depressive symptoms amongst women and those with low socio-economic status (Burger et al, 2017). Has this relationship changed, and in what way? In this paper we provide some answers.

Data & Results

Using Wave 5 of the National income Dynamic Study (NIDS) and Wave 2 of the NIDS-Coronavirus Rapid Mobile Survey (NIDS-CRAM), we compare the prevalence of depressive symptoms in 2017 (pre-COVID-19 era) and 2020 (COVID-19 era). To answer the question about how mental health has changed across these years, we restrict the analysis to individuals that appear in both waves. All analysis is weighted to be nationally representative of the adult population aged 18 and older.

We found that the likelihood of screening positive for depressive symptoms has increased in the COVID-19 era relative to the pre-COVID-19 era. Furthermore, our results indicate that the likelihood of screening positive for depressive symptoms has changed across key demographic variables. For example, while the literature and the 2017 data show that the prevalence of depressive symptoms is higher for women relative to men, our result shows that this is not the case in 2020. We found no significant difference between the likelihood of screening positive for depressive symptoms across gender. Similarly, in the 2017 data, we found statistically significant evidence for the health-income gradient that favours the rich. In contrast, the likelihood of screening positive for depressive symptoms is not significant across per capita income quintiles in 2020.

The same argument can be made for possession of tertiary education. Specifically, these results show that demographic indicators that point to a higher level of wealth are associated with higher likelihood of screening positive for depressive symptoms in the COVID-19 era. While the gap in depressive symptoms across some variable categories (such as gender) has reduced, it is of concern that the level of depressive symptoms have increased in general. For example, it is not the case that depressive symptoms have reduced for women, rather what we observe is that depressive symptoms have increased for men to equalize the prevalence across gender. The same argument can be made in terms of the likelihood of screening positive for depressive symptoms across income quintiles: It is not that the case that the poor are now less likely to screen positive for depressive symptoms, but rather the likelihood of screening positive has increased amongst the rich to equalise the prevalence across income quintiles.

We identify a number of competing factors that explain the pattern observed in the COVID-19 era:

- Risk perceptions of contracting COVID-19 is higher amongst the rich and this is correlated with the increase in depressive symptoms for the rich under the pandemic.
- While factors like hunger, poverty and loss of income are positively associated with increase in depressive symptoms for the poor, factors like social grants and household size mitigate these effects. For example, both hunger and hunger severity increase the likelihood of screening positive for depressive symptoms while this likelihood reduces with the number of social grants a household receives. As expected, this trend is stronger for households in the bottom quintiles.
- Net of the above effects, loss of employment is an important correlate of depressive symptoms. Specifically, losing a job between February and April 2020 is correlated with higher depression scores on average relative to those whose employment status did not change in that period. Similarly, gaining a job in the said period is correlated with lower depression scores.
- Lastly, we find that the relationship between employment transition and depressive symptoms is mediated by gender. Specifically, the relationship between getting a job and lower depression score is significant for men.
- One implication of this result is that while the health problem (COVID-19) is the reason for the economic problem (in the form of job and income losses), fixing the health problem will not necessarily take care of the economic problem and its implications. Even if a vaccine for the virus is available in the near future, this will only address the risk perception problem that affects the rich. For the poor, economic recovery is key to resolving the mental health issues the pandemic has inadvertently created.

Policy Recommendations

- Policymakers need to pay attention to the impact of the pandemic on emotional wellbeing and mental health and make adequate provision for what may be an upsurge in acute mental health issues that could, if not addressed, become chronic and prolonged. This should come in the form of increased budget allocation to allow for an increase in capacity of the health sector to deal with mental illness.
- There is need to create awareness around mental health problems. This will help tackle cultural barriers that prevent those affected from seeking help.
- Tackling unemployment is key to addressing pandemic-related mental health problems. Therefore, policies such as the public works programme being contemplated by the government (if executed properly) can provide an immediate counter-shock that may help recover some of the jobs lost as a result of the pandemic. Providing incentives for employers to pull employment back to their pre-COVID-19 levels can also assist in this effort. Such a policy can be implemented in the same way to the Employment Tax Incentive (ETI) that focuses on the youth.

1. Introduction

There have been concerns about the mental health consequences of COVID-19 and the associated lockdown. The additional stress that comes from health concerns about contracting or transmitting the virus aside, Galea et. al (2020) noted that the response to the pandemic in terms of full or partial lockdown will likely result in a substantial increase in the incidence of depression, substance use, loneliness, and domestic violence (also see Vindegaard & Benros, 2020). High-income inequality in South Africa suggests that there will be substantial differences in the way that people in South Africa experience the lockdown.

For a minority of comparatively well-off families living in the suburbs, the restriction of movement and the need to change behaviour (e.g. social distancing) may introduce extra stressors. However, for poor families living in the townships and informal settlements, who depend on the informal economy for their livelihood, loss of income, as a result of forced disengagement from the labour market will create considerable financial pressure.[3] In the case of the former, loneliness may contribute to depression (Erzen and Çikrikci, 2018). For the latter, poverty and mental illness are widely understood to work in a vicious cycle – with the stress associated with poverty predisposing individuals to mental illness (including depression), while mental illness, in turn, increases the risk of falling into, or remaining, in poverty (Lund et. al, 2011).[4] Furthermore, the absence of reliable service delivery in poor areas of South Africa means that preventative measures like hand washing and social distancing can be tricky for the poor. Therefore, apart from the concerns around contracting or transmitting the virus, the net effect of these various factors will shape the prevalence of depressive symptoms in the COVID era.

Given the aforementioned, mental health problems are likely to have increased relative to the pre-COVID period in South Africa. Before the pandemic, Common Mental disorders (CMD) that include depression and anxiety, accounted for about 14% of the global burden of disease (Prince et. al, 2007). In sub-Saharan Africa, the figure is about 10% (Lopez et. al, 2006). However, similar to the impact of the pandemic in other spheres of the economy, the distribution of the extra burden imposed by the pandemic and associated lockdown is likely to be unequal given the social-economic landscape of South Africa. Prior to the pandemic, problems related to mental health generally receive little attention in developing countries and South Africa is not an exception. This has to do with resource constraint, cultural barrier and cost of training clinicians (Kagee, et. al, 2013)[5]. It is, therefore, important for policymakers to pay attention to the short- and long-term effects of the pandemic on mental health, including that associated economic costs. Evans-Lacko and Knapp (2016) estimate the economic cost of depression in Brazil, Canada, China, Japan, South Korea, Mexico, South Africa and USA, finding it to be between 0.1% and 4.9% of a country's GDP. This is substantial given the prevailing economic situation of South Africa.

Existing studies show that the impact of the pandemic in terms of job and income loss vary by factors of gender, race and type of employment (Spaull & the NIDS-CRAM team). The same report shows that the poor, women and informal workers are disproportionately affected. In terms of health, Nwosu and Oyenubi (2020) show that poor health is more concentrated among the poor relative to the pre-COVID period with hunger, income inequality and employment status explaining the inequality. Based on this, one will expect that the extra burden associated with the pandemic in terms of depression may exacerbate health inequality in terms of the prevalence of depressive symptoms.

On the other hand, the steps that have been taken by the government to alleviate the impact of the pandemic may assist in addressing financial concerns for the poor. For example, the government increased the amount paid as social assistance to help families cope during the pandemic. The government also introduced a COVID-relief grant to assist those who don't qualify for existing social grants but are unemployed.

3 Such families are also likely to have lower level of saving thus increasing the financial pressure.

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

5 Docrat et al (2019) found that in the 2015/16 financial year Mental Health in South Africa accounts for 5% of the total health budget

In terms of health concerns, the risk perception of individuals may exacerbate the psychological impact of the pandemic. Those whose perception of the risk of contracting or transmitting the virus is higher may experience more psychological distress. Burger et al (2020) and Kollamparambil and Oyenubi (2020) showed that affluent South Africans have higher (subjective) infection risk perceptions compared to poor South Africans. This underscores the importance of re-evaluating what has happened to the prevalence of depressive symptoms in relation to demographic factors that are correlates of depressive symptoms.

Our analysis is separated into two parts. First, we compare the prevalence of depressive symptoms between 2017 (pre-COVID period) and 2020 along the distribution of variables that are known to be correlated with depressive symptoms. This analysis will reveal whether our data supports the hypothesis that prevalence of depressive symptoms has increased during the pandemic, as well as provide an indication of how the extra burden might be redistributed with respect to variables that are known to mediate the prevalence of depressive symptoms across demographic groups.

In the second analysis, we focus on a specific mechanism, that is, how job and/or income loss is correlated with depressive symptoms controlling for other relevant factors in a multivariate regression setting. We acknowledge that there is a bilateral relationship between depressive symptoms and employment status (Bubonya et al, 2017). However, due to data limitations,[6] we rely on regression analysis to capture the relationship between COVID-19 related employment transition and depressive symptoms. We note that even before the pandemic, a sizable subset of the workforce experienced employment as a transient state; that is, experienced a high level of volatility between employment states (Zizzamia and Ranchhod, 2019). This combined with the employment shock of the pandemic means that this subset of workers will be more vulnerable in terms of employment and income loss.

Having declared a State of National Disaster on March 15, South Africa went into a total lockdown on March 26. Therefore, for our second analysis, we focus on the relationship between employment transition between February and April 2020[7] and depressive symptoms. An estimate by Jain et al, (2020) for this period indicates that there has been about a 40% net decline in active employment compared to the pre-lockdown period, with an estimated 3 million people pushed into poverty as a result of the labour market shock. Given the relationship between depression, employment and poverty, it is expected that the labour market shock will be negatively associated with the depressive symptoms of affected workers net of the effect of other factors. Furthermore, given that gender has been shown to mediate the relationship between depression and employment (Oyenubi & Ajefu, 2020; Bubonya et al, 2017) we further disaggregate our analysis by gender.

2. Brief Review

Apart from the anticipated increase in the prevalence of depressive symptoms and possible inequality in the distribution of the extra health burden, increases in depressive symptoms also have implication for people living with chronic illnesses. The World Health Organization (WHO, 2008) estimates that the burden of non-communicable diseases in South Africa is about two to three times higher than that of developed countries. Furthermore, age-specific mortality rates from chronic disease as a whole are higher in sub-Saharan Africa than elsewhere (WHO, 2005). Therefore, paying attention to the evolution of CMDs and chronic illnesses is important because depression has been found to be co-morbid with a range of chronic diseases including HIV/AIDS (Brandt, 2009; Moussavi et al, 2007). The reciprocal relationship between depression and chronic physical health problems suggests that a negative shock in the prevalence of depression will have implications for people living with chronic illnesses. This is especially important given the expectation that COVID-19 will worsen the mental state of individuals across the board.

6 Our initial approach is to use a variable that captures the ability of an individual to work from home as an instrument for their employment status. This will help break the reverse causality between employment and depression. However due to implementation concerns the variable cannot be used as proposed.

7 data sourced from wave 1 of NIDS-CRAM

Considering all these factors, the question of how the extra burden in terms of depressive symptoms will be mediated by variables known to be correlated with depressive symptoms remains open. For example, the prevalence of depressive symptoms is traditionally higher amongst women and the poor compared to men and the rich. Has this relationship changed, and in what way? We hope to provide some answers in this paper.

In terms of what we know from available literature, a recent online survey[8] conducted by the Centre for Social Change (University of Johannesburg) in collaboration with the HSRC (Human Science Research Council) show that about a third (33%) of South Africans are depressed[9] (or experience depressive symptoms). It is important to note that an online survey may not be effective at capturing what is going on in the country as a whole as only a section of the populace will have access to online surveys. However, compared with clinically determined prevalence rates of 18% to 27% (Rumble et. al, 1996) in small rural-based studies and 25.2% in urban settings (Gillis et al, 1991), this figure represents an increase in the prevalence of depressive symptoms compared to less unusual times. In terms of mediating factors, women reported experiencing more depressive symptoms than men (36% vs 33%), and despite racial income inequality, Black Africans reported significantly less psychological distress compared to other population groups.[10]

Existing literature also suggests that there are differences in how people internalize the stress that may be associated with contracting or transmitting the virus. For example, Barzilay et al (2020) found in their survey that respondents were significantly more worried about a family member contracting COVID-19 or about unknowingly infecting others than about getting COVID-19 themselves. Therefore, understanding the local dynamics in terms of the expected and unexpected differences in the prevalence of depressive symptoms and factors that may contribute to it in the COVID era is important for policymakers.

3. Methods

3.1. Data

Our data was sourced from the last wave of the National Income Dynamic Study (NIDS) and the second wave of the NIDS-Coronavirus Rapid Mobile Survey (NIDS-CRAM).[11] NIDS is a nationally representative dataset collected every two years with the first wave conducted in 2008 and the last wave (Wave 5) collected in 2017. Two-stage stratified cluster sampling was used in the sampling design. For a full description of NIDS and NIDS-CRAM sampling process see Brophy et al (2018), Ingle et al (2020) and Kerr et al (2020). NIDS-CRAM is a nationally representative survey based on the NIDS wave 5 adult sample that initially targeted more than 17 000 adult individuals. In the first wave of NIDS-CRAM, approximately 7 000 successful interviews were conducted. High-frequency Computer Assisted Telephone Interviewing (CATI) is used to collect monthly information as a series of panel surveys between May and October 2020. Wave 2 of NIDS-CRAM was conducted between 13th July and 13th August 2020. The survey covers income and employment, household welfare, grant receipt, and knowledge and behaviour related to COVID-19.

3.2. Comparing Depressive symptoms between Wave 5 of NIDS and wave 2 of NIDS-CRAM

Our outcome of interest is depression scores. Therefore, in our first analysis we compare the prevalence of depressive symptoms in Wave 5 of NIDS (2017) to the one observed in Wave 2 of NIDS-CRAM (2020). We could not use Wave 1 of NIDS-CRAM for this analysis because items referring to emotional wellbeing and depression were not asked.

8 which ran from 13 April to 4 May

9 As described in the article, this is a one shot question on depressive symptoms so the term used may not be appropriate.

10 See http://www.hsrc.ac.za/en/news/media-and-covid19/the-hidden-struggle for a detailed report.

11 Note that wave 1 of NIDS-CRAM does not ask about depressive symptoms.

A further complication is the fact that depression scores in Wave 5 of NIDS and Wave 2 of NIDS-CRAM are not directly comparable because of the difference in the screening tools used. NIDS sourced information about depression using the 10-item Centre for Epidemiological Studies Depression Scale (CESD-10) (Radloff, 1977) while NIDS-CRAM—being a telephonic interview—made use of the 2-question version of the Patient Health Questionnaire (PHQ-2).[12] One way around this is to use the dichotomised version of these variables. In practice, these screening instruments are validated against clinical diagnosis (performed by professionals) to evaluate their accuracy. The validation yield cut-offs that can be used to determine if the respondent screen positive for possible depression, in which case further assessment by a professional is recommended.

The range of possible scores for PHQ-2 is 0 to 6, and the recommended cut-off is PHQ-2 >=3 (Kroenke et. al, 2003). CESD-10 ranges from 0 to 30, and Andresen et al (1994) recommend cut-offs that range from 8 to 10. However, a number of studies that have used the CES-D10 provided in the NIDS data use a cut of 10 (see Tomita & Burns,2013; Ardington & Case, 2010). Furthermore, recommended cut-offs can vary by locality. In the case of CES-D10, Bhana et al (2019) recommend cut-offs of 11-13 depending on language in a validation study done in South Africa. Lastly, Manea et al (2016) argue that because of the low sensitivity of PHQ-2, a cut-off of 2 might be preferable. In this study, we use cut-offs of PHQ-2 >=3 and CES-D10>=10 to identify people that can be regarded as screening positive for possible depression/depressive symptom. We note that both PHQ-2 and CES-D10 are screening tools (as against clinically determined diagnosis), and while we believe they provide a useful way of comparing the prevalence of depressive symptoms, they cannot be as accurate as clinically determined values.

3.3. What we know about the prevalence of Depressive symptoms and why it may have changed

Apart from comparing the prevalence of depressive symptoms (in general) between 2017 and 2020, we also examine how the distribution of factors known to influence depressive symptoms changed in the COVID era. This expectation is based on the fact that new stressors have been introduced as a result of the pandemic, and these new factors may have different implications for different groups.

First, the relationship between health concerns around COVID and psychological distress is likely to be mediated by risk perception. As shown by Burger et al (2020) and Kollamparambil and Oyenubi (2020), affluent South Africans tend to have higher infection risk perceptions compared to poor South Africans. This implies that the channel that has to do with health concerns itself may have a greater negative impact on the depressive symptoms of affluent individuals.

Second, the associated lockdown implies increased labour market disengagement, but only for people who are unable to perform their work task from home. It turns out that women, those with lower levels of education, those in manual occupations, informal workers, and the poor in general face the greatest net employment losses. Therefore, financial related stress is expected to affect vulnerable groups more.

Third, individuals with different socio-economic status will experience the lockdown differently. While more affluent individuals may be more comfortable under lockdown because of their living condition, the living condition of the poorer section of the society is likely to introduce additional psychological pressure. For example, preventative measures like social distancing may be harder to observe in overcrowded spaces. On the flip side, poorer households tend to have larger household size, and during the hard lockdown, loneliness may be a factor as it is known to be correlated with depression (Erzen & Çikrikci, 2018). So, while the living condition of the poor may not be ideal, the fact that they live in larger households may make the lockdown more bearable.

The above-mentioned factors can change the prevalence of depressive symptoms across factors that are known to be correlated with depression. The implication of this is that in addition to the expected general increase in the prevalence of depressive symptoms, there might be shifts in the

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

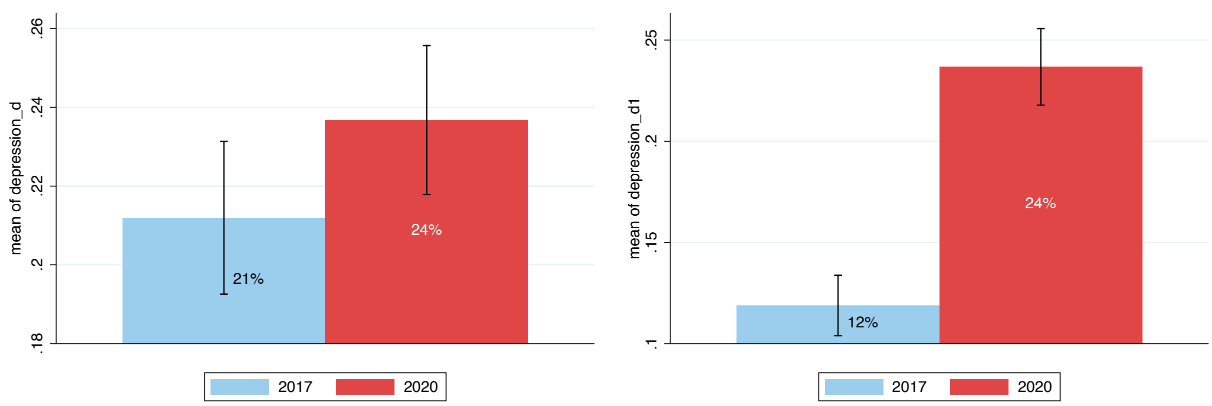
distribution across different demographic groups. Some of what is known about the prevalence of depressive symptoms across demographic groups can be summarised as follows: Burger et al (2017) identified the risk of depressive symptoms to be higher for women, unemployed and urban dwellers. Furthermore, Ten et al (2017) showed that education reduces the risk of depression. While the list is not exhaustive, these points summarise some of what we know about depressive symptoms.

4. Results

We first address the question about the prevalence of depressive symptoms between 2017 and 2020. It is important to note that the reported figure is for the matched sample; that is, the results are for the same individuals that appear in both the NIDS Wave 5 and NIDS-CRAM Wave 2 samples. Also note that all analysis is weighted using the Wave 5 post-stratified weights (for 2017) and NIDS-CRAM Wave 2 (panel) weight for 2020. To determine the sensitivity of the results to the choice of cut-off we use 3 different cut-offs. The first set of cut-offs consist of the widely accepted cut-offs: 10 and 3 for CES-D10 and PHQ-2, respectively. The result shown in panel 1 of *Figure 1* suggests that the likelihood of screening positive for depressive symptoms increased in 2020 relative to 2017 (even though the difference is not statistically significant). The proportion of those who screened positive for depressive symptoms increased from 21% in 2017 to 24% in 2020. Following Bhana et al (2019), panel 2 (of *figure 1*) uses a cut-off of 12 for CES-D10 (i.e. the midpoint of the recommended 11 to 13) while keeping the PHQ-2 at 3. The result is consistent with panel 1, although the difference is statistically significant (12% vs 24%).

Figure 1: Proportion of the population that screened positive for depressive symptoms (2017 & 2020)

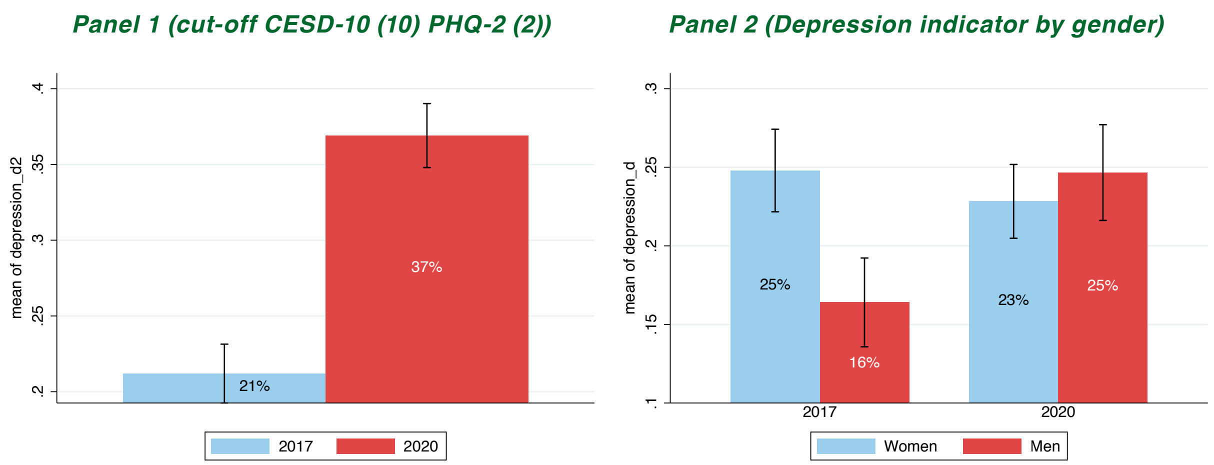
Panel 1 (cutoff CESD-10 (10) PHQ-2 (3)) ***Panel 2 (cutoff CESD-10 (12) PHQ-2 (3))***



Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. 95% confidence intervals are shown

Figure 2 (panel 1) shows that following Manea et al (2016) and dropping the cut-off of PHQ-2 to 2 while keeping CESD-10 at 10 leads to the same result: those who screened positive for depressive symptoms increased from 21% to 37%, and this difference is statistically significant. For the remainder of the analysis, we use the cut-off of 10 and 3 for CES-D10 and PHQ-2, respectively. We, therefore, regard the pattern observed under this set of cut-offs as the conservative estimate of what has happened to the prevalence of depressive symptoms between 2017 and 2020.

Figure 2: Proportion of the population that screened positive for depressive symptoms by year (2017 & 2020) and Gender



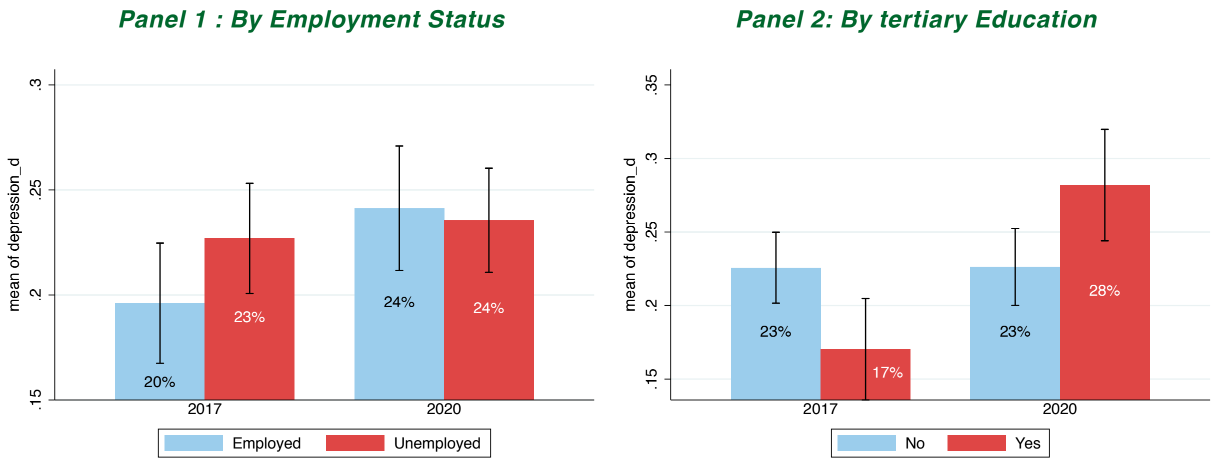
Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. 95% confidence intervals are shown

Next, we disaggregate the prevalence by gender; the result is shown in panel 2 of *Figure 2*. From this result, it is clear that the inequality in the prevalence of depressive symptoms that favour men has narrowed. While the prevalence is significantly higher for women in 2017, the difference is no longer significant in 2020. A similar result is observed when the result is disaggregated by employment status (see *Figure 3, panel 1*): while in 2017 those who are employed are less likely (although not statistically significantly so) to screen positive for depressive symptoms, this is no longer the case in 2020.

Further disaggregating the result in panel 1 of *Figure 3* shows that the employment trend has a gender dimension to it (see *Figure A1* in the appendix). Most of the difference observed by employment status is accounted for by male workers: the likelihood that a male worker will screen positive for depressive symptom has increased from 15% in 2017, to 25% in 2020. The difference for unemployed men is large but not significant (18% versus 25%) while those for women are much lower irrespective of employment status (see *Figure A1* in the appendix for details).

In terms of education, again the inequality seems to have narrowed (see panel 2 of *Figure 3*). While those who have tertiary education are less likely to screen positive for depressive symptoms in 2017 (17% versus 23%), in 2020 those with tertiary education are more likely to screen positive for depressive symptoms.

Figure 3: Proportion of the population that screened positive for depressive symptoms by Employment status and Education



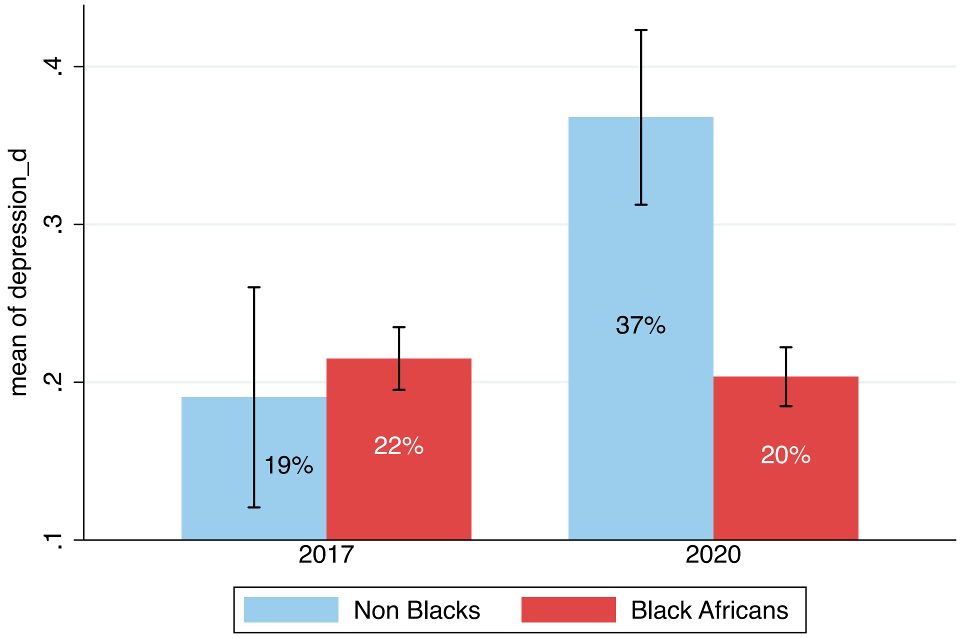
Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. 95% confidence intervals are shown

What the results so far suggest is that demographic indicators that point to a higher level of wealth (in the South African context) tend to increase the likelihood of screening positive for depressive symptoms relative to the pre-pandemic period. In the contexts of South Africa, this suggests that the likelihood of screening positive by previously identified factors in the literature may have changed. This is exactly what we observe in the data. *Figures 4* and *5* disaggregate those who screen positive for depressive symptoms in 2017 and 2020 by race and household per capita income quantile.

While the likelihood of screening positive for Black African respondents has hardly increased, those for other race groups has increased much more with the increase being statistically significant (19% versus 37%).[13] Note that this result should be interpreted with caution because race and socioeconomic status are correlated in the South African context. This relationship may be due to differences in, for example, income and occupation or other unmeasured factors (especially since *Figure 4* shows a bivariate relationship).

13 We choose to re-categorise the four race groups into two given sample size issues for the other race groups.

Figure 4: Proportion of the population that screened positive for depressive symptoms by race

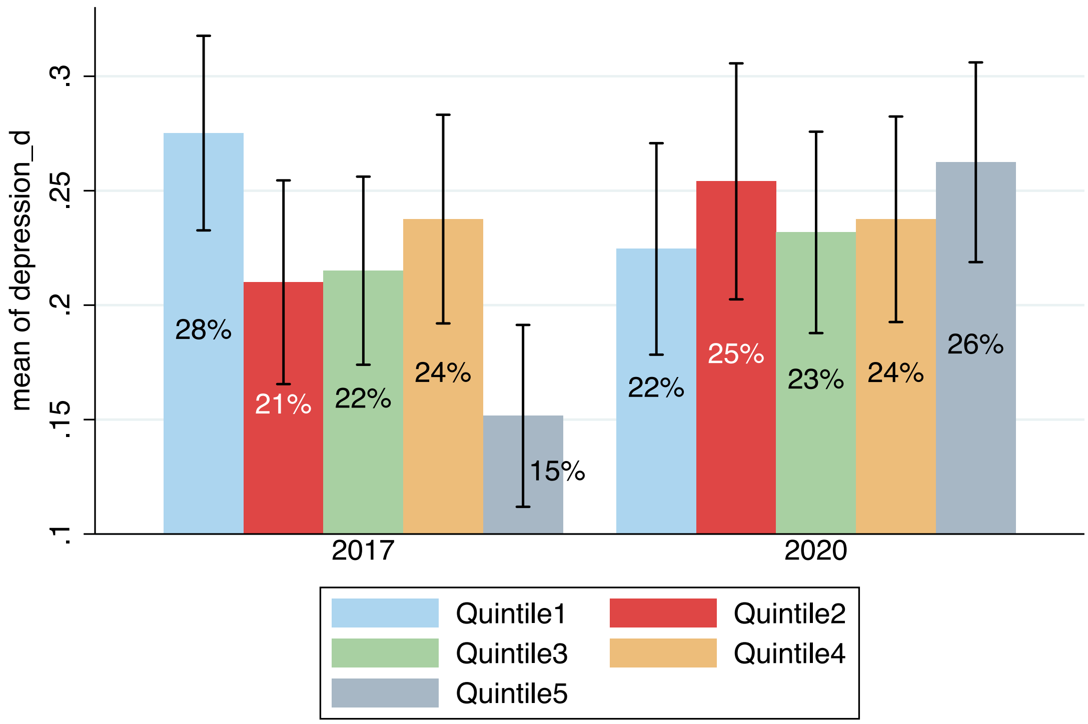


Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. 95% confidence intervals are shown

Next, we disaggregate by per capita income quintile (*Figure 5*). In 2017, being in quintile 5 was associated with a significantly lower likelihood of screening positive for depressive symptoms relative to quintile 1; this is not the case in 2020. We also compare how those who screen positive for depressive symptoms are distributed by geo-location. The result is presented in *Figure A2* in the appendix, and shows that the likelihood of screening positive for depressive symptoms in an urban area remains higher than the likelihood in other geo-locations.

The emerging patterns appear to contradict what one would expect in terms of the relationship between income and health. We go a step further in an attempt to confirm the results. Even though the chances are slim (given the results in *Figure 1*), it is possible that the choice of cut-offs for CES-D10 and PHQ-2 are influencing the results. Since in summary, the results suggest that higher depressive symptoms are concentrated amongst the affluent in 2020 relative to 2017, one can confirm the result using a concentration index (O'Donnell et al, 2008). To avoid relying on the cut-offs, we use the raw depression scores to calculate the concentration index. The result is shown in *Table 1*. It is evident from *Table 1* that in 2017 depressive symptoms were significantly pro-poor, while in 2020 they are pro-rich (although the estimate is smaller and not statistically significant). This confirms our earlier results: the income health gradient in terms of depressive symptoms is weaker during the pandemic.

Figure 5: Proportion of the population that screened positive for depressive symptoms by household per capita income quintile



Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. 95% confidence intervals are shown

Table 1: Concentration Index

2017	2020
-0.0483***	0.0015

Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted.
*** p<0.01, ** p<0.05, * p<0.1

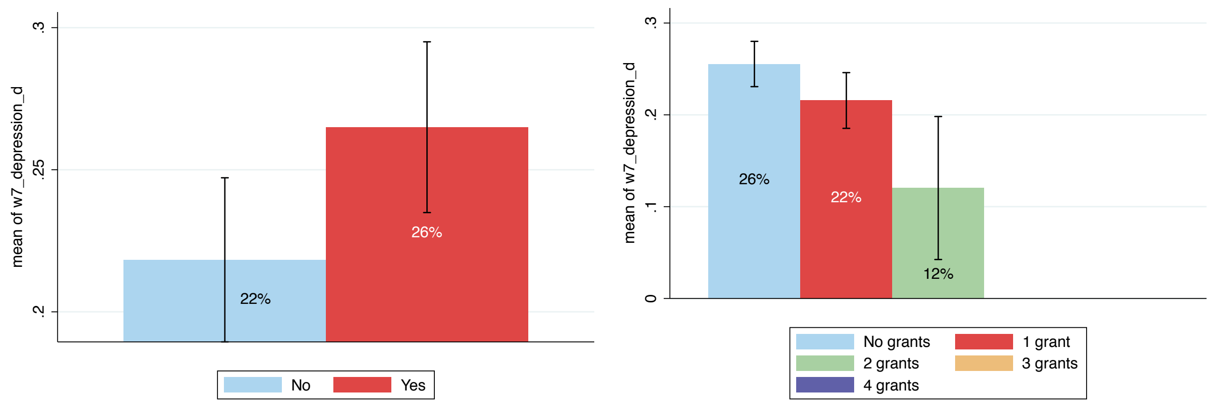
4.1. 4.1. Explaining the results

In this section, we explore possible explanations for the trends observed. We note that the narrowing of the gap between various demographic groups does not mean the likelihood of screening positive for depressive symptoms in 2020 has reduced. The reason being that, although inequality in depressive symptoms is narrower in the COVID-19 era, this reduction emerges given higher depression scores for demographic groups that in more usual times showed lower depression scores. For example, in *Figure 2 (panel 2)* it is not the case that the depressive symptoms for women have reduced, but rather equality appears to stem from an increase in the depressive symptoms amongst men.

One possible explanation for prevalence observed in 2020 (relative to 2017) is that risk perception differs by socioeconomic status. *Figure 6 (panel 1)* shows that those who think that they are at risk of contracting the virus are more likely to screen positive for depressive symptoms. This is important because, as noted earlier, Burger et al (2020) argued that affluent South Africans have higher infection risk perception compared to poor South Africans. Furthermore, Kollamparambil and Oyenubi (2020) showed that risk perception is significantly concentrated among higher income groups, the educated and older respondents. Therefore, higher levels of depressive symptoms amongst these groups is correlated to risk perception.

Figure 6: Proportion of the population that screened positive for depressive symptoms by Risk perception and number of Government grant receipt

Panel 1: By COVID risk *Panel 2: By number of Grants*



Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. 95% confidence intervals are shown

Another plausible explanation is the receipt of grants. The government has put in place a series of fiscal interventions to ease the blow on the most vulnerable. This has taken the form of a special COVID-19 Social Relief of Distress payout of R350 per month for the period from May until October 2020. This grant is for individuals above the age of 18 years with no other income and not receiving any another grant or form of social support from the government. The additional measures put in place includes topping-up of the Child Support grant (CSG) to an additional R300 (per child) in May and from June to October a per caregiver top-up of R500 each month. All other grant beneficiaries such as the old-age pension (OAP) will receive an extra R250 per month for the six-month period May-October 2020. *Figure 6 (panel 2)* shows that respondents that receive more grants are less likely to screen positive for depressive symptoms.

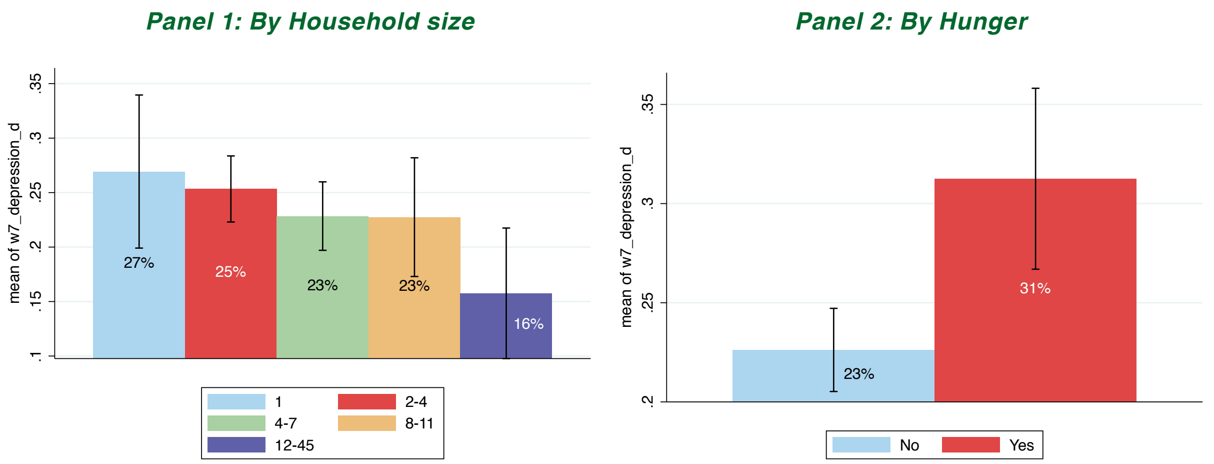
Figures A3 and *A4* in the appendix show that the relationship between the likelihood of screening positive and the number of grants received is stronger when the analysis is restricted to the bottom 2 income quintiles and when the CSG alone is considered. However, we did not observe the same effect for the COVID-relief grant and the OAP. In general, this result suggests that the anticipated increase in the depressive symptoms of vulnerable groups may have been mitigated by the increase in social grants.

Household size is another factor, as alluded to earlier. *Figure 7 panel 1* show that those who live in larger households are less likely to screen positive for depressive symptoms. We note that poorer households tend to have larger household size as shown in *Figure A5* (see the appendix). Despite the protective effect of the grants, hunger which is likely to affect lower-income households is still a problem. Those who reported that someone in their household went hungry in the last seven days because there wasn't enough food are also (significantly) more likely to screen positive for depressive symptoms (see *Figure 7, panel 2*). Not only that, *Figure A6* in the appendix shows that the severity of hunger is also important: respondents that reported that people in the household go hungry more often are more likely to screen positive for depressive symptoms.

Lastly, we note that the type of employment also matters as shown in *Figure A7* in the appendix, those who have regular jobs are less likely to screen positive for depressive symptoms than those who are either casual workers/self-employed/run a business.

In summary, our results so far suggest that risk perception increases the depressive symptoms of the affluent, while social grant offers some protection for the less affluent. Despite these factors, variables such as hunger remain important in terms of the likelihood to screen positive for depressive symptoms. This suggests that the changes in the likelihood of screening positive for depressive symptoms may be driven by the net effect of these factors.

Figure 7: Proportion of the population that screened positive for depressive symptoms by household size and hunger



Source: NIDS, Wave 5 (2017) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. 95% confidence intervals are shown

4.2. Multivariate analysis focusing on employment status

We note that our analysis so far has been univariate in nature. While this analysis allows us to identify variables that are correlated with screening positive for depressive symptoms, some of these variables may not be important in a multivariate setting because of their correlation with other variables. In the next analysis, we focus on how the employment shock in the period between February and March 2020 is related to the depressive symptoms of those who are active in the labour market. The reason for this is that there was a significant shock to the labour market in terms of employment during this period, as mentioned earlier 40% net employment loss is substantial. The implication is that vulnerable workers and those that are unable to work from home will bear the brunt of the sudden labour market disengagement.

Jain et al (2020) noted that of the 40% net loss in employment February/March, almost half is accounted for by terminated employment relationships. This indicates a dramatic change in labour market structure, suggesting large longer-term effects on unemployment. Given the relationship between employment and depression, the same longer-term effects can be expected for the prevalence of depressive symptoms. Aside from employment change, we also sequentially introduce some of the variables shown to be correlated with depressive symptoms in the previous section of this paper to see if their association with depressive symptoms, as well as the coefficient on employment transition change following their introduction given multicollinearity; for example, household income and receipt of social grants may be correlated. Lastly, to remain consistent with our previous analysis, we use a dummy variable coded as 1 if respondents PHQ-2 and zero otherwise as the dependent variable.

Table 2 shows the result of our linear probability model regression analysis. The first two rows show the regression coefficient for those who lost and gained employment between February and March, respectively. It is clear that in the presence of most of the other covariates explored in the previous analysis, losing (or acquiring) a job in that period is associated with an increase (decrease) in depressive symptoms, even though the relationship is not statistically significant.[14] Note that this result is relative to those whose employment status did not change between February and March 2020 (i.e. those who were not affected jobwise which is the base category). Specifically, this means that *Figure 2 (panel 2)* that indicated no significant difference in the likelihood of screening positive for depressives symptoms by employment status does not fully reflect the effect of the employment shock for those who lost or gained employment.

The implication of this result is that the social and economic upheaval generated by the pandemic and the associated lockdown may be hard to reverse if pro-active measures are not taken. For example, even if a vaccine for the virus becomes available in the near future, this might only be effective in solving the risk perception problem that disproportionately affects the rich. For the poor, the impacts of labour market disengagement on mental health is likely to linger on, as this will likely depend on how quickly lost employment is recovered. This will be a function of how quickly the local and global economies are able to recover. In other words, even after the primary cause is solved, the effect on mental health may persist over the longer-term.

Other results show that even after partialling out the employment transitions, receipt of OAP and CSG (columns 2 and 3), tertiary education (column 4), household access to piped water (column 5), household size (column 6), risk perception (column 8), hunger severity (column 9), decrease in household income (column 10) and some categories of household income source (column 11) remain significantly correlated with risk of depressive symptoms. In general, our results suggest that higher wealth level is positively correlated with higher depressive symptoms during these unusual and unprecedented times. When covariates are included simultaneously, most of these variables become statistically insignificant except for hunger severity (see *Table 3*).

Similar to *figure 4*, we exercise caution in interpreting the significant coefficient on race in *table 3*. The multivariate analysis utilised here can, at most, pick up correlations between the outcome and covariates of interest. We further acknowledge that the significant result on race is likely driven by unobserved heterogeneity. For example, the relative deprivation hypothesis posits that differences in unobserved subjective relative wealth perceptions (that more accurately reflect personal experiences and more precisely capture social position) may account for differences in emotional wellbeing. Specifically, studies that have controlled for both objective (e.g. income, occupation, education) and subjective measures of social status have found the latter to be more strongly associated with probable depression (see, for example, Smith et. al, 2019). In the case of South Africa, Mutyambizi et al (2019) found that there is a subjective social status (SSS) related inequality in depressive symptoms. Since CRAM did not collect data on SSS, and this (as well as other omitted individual and household information) might explain the correlation with race, we do not emphasise this finding as indicative of racial differences in probable depression.

Lastly, following Oyenubi and Ajefu (2020) and Bubonya et al (2017) who suggest that the impact of employment may differ by gender, we disaggregate the analysis by gender. Bubonya et al (2017) argue that men's mental health depreciates as they exit the labour market whilst the mental health of women worsen only after they have been out of the labour force for a period of time. This suggests that the impact of a job loss may be more immediate for male workers. Oyenubi and Ajefu (2020) found that for individuals around 60 years of age depressive symptoms are higher for unemployed men relative to other groups. They argue that perhaps the traditional role of being a "breadwinner" renders being unemployed more psychologically damaging for men.[15] Our estimations show that acquiring a job in the period of interest (February to March) substantially decreases the likelihood of depressive symptoms for men, see column 3 of table 3.

5. Conclusion & Policy recommendations

This paper sought to compare the likelihood of screening positive for depressive symptoms in 2017 (pre-COVID-19 era) relative to 2020 (COVID-19-era). We find that while this likelihood has increased, the question of whether this increase is statistically significant depends on the cut-off chosen for the screening instruments. However, the finding that the likelihood has increased is in line with international evidence on this question.

Our analysis reveals that the extra burden in terms of depressive symptoms (as proxied by the screening instruments) is unevenly distributed. One may expect that since the impact of the

15 In the same paper, the authors found the opposite for women. Being employed worsens depressive symptoms for women relative to being unemployed. They suggest that due to the same tradition that imposes gender roles, employed women face a double burden of being effective as a worker and a home-maker. This is one explanation for why employed women are more prone to depression.

pandemic and associated lockdown disproportionately affected the poor in terms of income and job loss, the same would be observed for the likelihood of screening positive for depressive symptoms. However, we found that the channels through which the pandemic affects people of different socio-economic status vary. Specifically, we find that risk perception is correlated with psychological distress for more affluent individuals, while concerns that relate to finances is more important for the less affluent. Furthermore, the poor may find it difficult to adopt some precautionary measures because of the associated cost or the kind of environment they live in. However, we find that some of these negative factors are mitigated by social grants and larger households sizes. Therefore, the extra burden in terms of depressive symptoms are the net effect of a number of competing factors.

Related to this we found that the prevalence of depressive symptoms as measured by the depression instruments suggest that known inequality in depressive symptoms in some demographic factors was narrower in June 2020. For example, while there was a significant difference in the likelihood of screening positive for depressive symptoms between men and women in 2017, this difference is weaker in 2020. Furthermore, contrary to the pattern observed in more usual times, those with tertiary education were more likely to screen positive for depressive symptoms in June 2020 relative to those who do not have tertiary education. An implication of this is that the income-health gradient in depressive symptoms that existed in 2017 is weaker during the pandemic period. Given that our analysis is based on the same individuals across waves and nationally representative of the adult population (in 2017), we think this is a significant result.

Table 2: Multivariate analysis of correlates of depressive symptoms in the COVID era

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Depression dummy (PHQ-2)					
Base category (no change)											
job loss (Feb/March)	0.04	0.04	0.06	0.03	0.04	0.04	0.04	0.03	0.08	0.03	0.03
job gain (Feb/March)	-0.04	-0.05	-0.03	-0.05	-0.04	-0.04	-0.04	-0.02	-0.01	-0.05	-0.04
Social Grants											
No of OAP		-0.04**									
No of CSG			-0.02***								
Tertiary Education				0.06**							
Water					-0.04*						
Electricity					-0.04						
Household size						-0.01***					
Chronic illness							0.01				
Risk of Corona								0.05**			
Hunger Severity									0.08***		
Base Category (no change)											
Lost income (Decreased)										0.07**	
Lost income (Unchanged)										0.03	
HH Income source (Employment)											
HH source (business)											0.16**
HH source (Government grants)											-0.02
HH source (friends or family)											-0.02
HH source (Other)											0.09
HH source (no income in June)											0.01
HH source (Pension)											0.15**
Constant	0.24***	0.26***	0.27***	0.23***	0.33***	0.28***	0.24***	0.22***	0.07	0.21***	0.23***
Observations	5,351	4,955	5,012	4,073	5,351	5,324	5,332	4,448	1,004	4,797	5,049
R-squared	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.03	0.01	0.01

Robust standard errors are used to determine the p-values (*** p<0.01, ** p<0.05, * p<0.1)

Table 3: Correlates of depressive symptoms in the COVID era (by gender)

	(1)	(2)	(3)
VARIABLES	All	Female	Male
Job loss (Feb/March)A	0.0237	-0.0248	0.0747
	(0.0480)	(0.0490)	(0.0856)
Job gain (Feb/March)	-0.0181	0.0884	-0.112**
	(0.0370)	(0.0550)	(0.0445)
Age in years	-0.000746	-0.00184	0.00270
	(0.00491)	(0.00598)	(0.00703)
Square Age in years	1.44e-05	3.84e-05	-3.86e-05
	(5.23e-05)	(6.57e-05)	(7.52e-05)
Male	0.0167		
	(0.0274)		
Black African B	-0.142***	-0.161***	-0.138**
	(0.0387)	(0.0429)	(0.0664)
Has partner (yes)	-0.0221	-0.0172	-0.0219
	(0.0242)	(0.0305)	(0.0430)
Hungry (yes)	0.110***	0.142***	0.0733
	(0.0329)	(0.0367)	(0.0601)
Income quintile (2)C	0.0398	0.101**	-0.0632
	(0.0463)	(0.0505)	(0.0723)
Income quintile (3)	0.0646	0.0888*	0.0412
	(0.0400)	(0.0488)	(0.0650)
Income quintile (4)	0.0260	0.0656	-0.0278
	(0.0349)	(0.0456)	(0.0674)
Income quintile (5)	0.0634	0.109**	0.00346
	(0.0439)	(0.0549)	(0.0798)
Risk of Corona (yes)	0.0231	0.0130	0.0280
	(0.0243)	(0.0317)	(0.0401)
Urban (Geo location)	0.0156	0.0142	0.00166
	(0.0283)	(0.0325)	(0.0519)
Farms (Geo location)	-0.0454	-0.0644	0.0374
	(0.0817)	(0.0999)	(0.106)
No of children (live with)	0.00161	0.00330	-0.000849

	(0.00929)	(0.0116)	(0.0197)
Unemployed DiscouragedG	0.0696	0.119**	-0.0203
	(0.0493)	(0.0465)	(0.0982)
Unemployed Strict	0.102**	0.135**	0.0673
	(0.0442)	(0.0541)	(0.0753)
Employed	0.0350	0.0578	0.00330
	(0.0399)	(0.0426)	(0.0755)
Chronic illness	0.0257	0.0367	0.0113
	(0.0264)	(0.0314)	(0.0514)
Dwelling type (Trad/mud)D	-0.0907***	-0.0984**	-0.0704
	(0.0310)	(0.0397)	(0.0429)
Dwelling type (Informal/shack)	-0.0370	-0.0707*	0.00576
	(0.0322)	(0.0395)	(0.0605)
Household income (Decreased)F	0.0216	0.0401	0.00382
	(0.0399)	(0.0484)	(0.0689)
Household income (Unchanged)	-0.0107	-0.0153	-0.0114
	(0.0292)	(0.0336)	(0.0578)
Constant	0.246**	0.195	0.322**
	(0.103)	(0.122)	(0.147)
Observation	3 256	2 129	1 127
R-squared	0.043	0.068	0.044

Base category ANo change in employment status BBlack African CIncome quintile 1 DHouse/flat EDwelling Area
FIncome increased G Employed
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

We also examine how the forced labour market disengagement that happened in February/ March 2020 affected depressive symptoms scores. The premise is that our previous analysis suggests that the impact of employment status on depressive symptoms might be minimal given that factors such as social assistance mitigate some of the effects. However, South Africa has a relatively high unemployment rate, and so a focus on employment status in this context may be misleading (since a large fraction of people are unemployed anyway). Therefore, examining employment transition is more important because it focuses attention on the experience of job losers and gainers. Furthermore, the initial analysis is univariate in nature so that while mitigating factors might have lowered the burden, the employment channel is still important even after adjusting for the relationship with other mitigating factors.

Income and job losses between February and March are large and disproportionately affect vulnerable workers. It is, therefore, unlikely that the effect of mitigating factors will be sufficient to negate the impact of labour market disengagement. This is especially since most of the households that benefit from social grants also depend on income from the labour market (Wills et al, 2020). Our result shows that net of the mitigating effects, job loss in February/March is related to higher depressive symptoms (although the relationship is not statistically significant). Furthermore, depending on the specification, acquiring a job in the said period is associated with a significant reduction in depressive symptoms, especially for male workers. This confirms the fact that the labour market is an important channel through which COVID-19 related job losses have contributed to the depressive symptoms of workers, especially vulnerable workers.

The implication of this finding is that slow economic recovery will have significant costs in terms of mental health. As noted earlier, even if the virus no longer presents a threat, this may only ease the mental health burden on the rich. For the less affluent, economic recovery is key for recovery in terms of mental health. This is important because poor mental health has economic costs. As noted by de Quidt and Haushofer (2017), depressed individuals reduce their labour supply, consumption and investment while they increase temptation spending and have altered eating and sleeping patterns.

Therefore, policies that are geared towards a speedy recovery of the economy are even more important now than they were before the pandemic. For example, policies such as the public works programme that are being contemplated by the government can, if executed properly, provide an immediate counter-shock that may help recover some of the jobs lost as a result of the pandemic. Furthermore, providing incentives for employers to pull employment back to their pre-COVID-19 levels can also assist in this effort. Such a policy can be implemented in the same way the Employment Tax Incentive (ETI) that focuses on the youth is being implemented.

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Appendix

Figure A1: Proportion of respondent that screened positive for depressive symptoms by employment status and Gender across 2017 and 2020

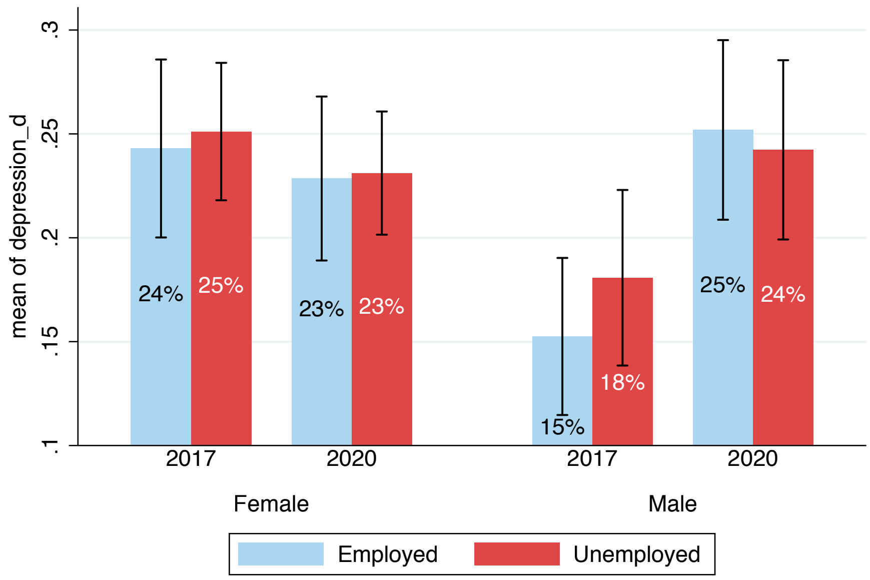

Figure A2 Proportion of respondent that screened positive for depressive symptoms by Geo-location

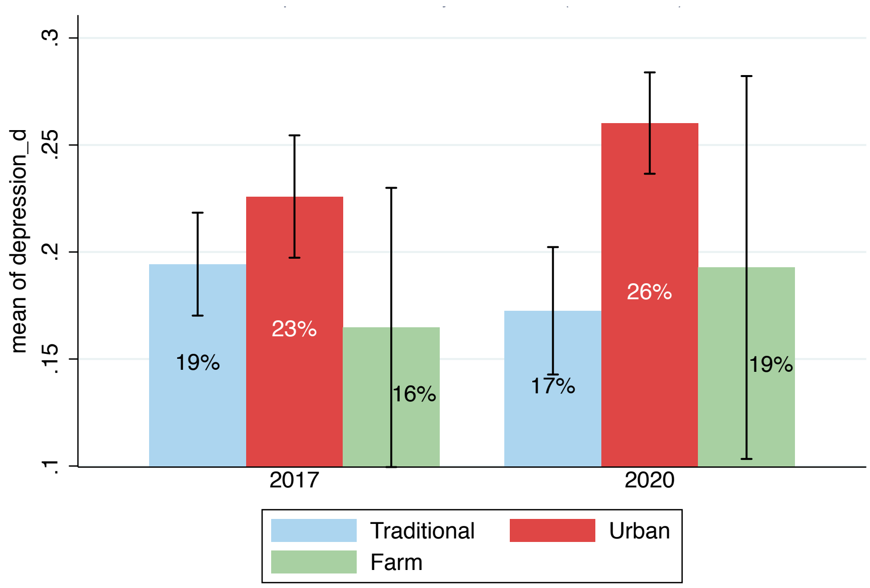

Figure A3 Proportion of respondent that screened positive for depressive symptoms by number of grants received (Households in the bottom 2 quintiles)

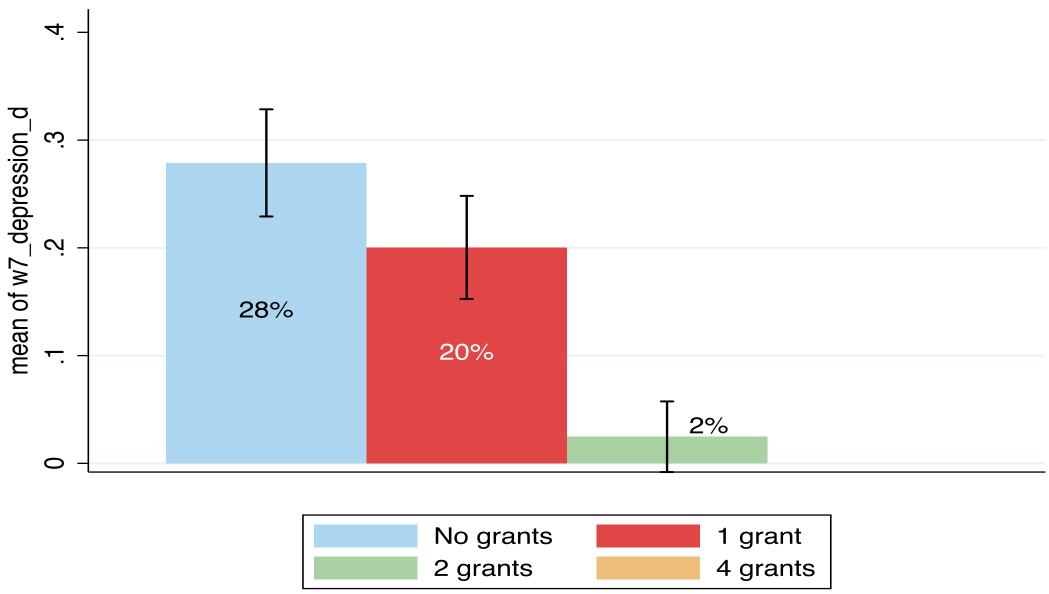

Figure A4: Proportion of respondent that screened positive for depressive symptoms by number of CSG received

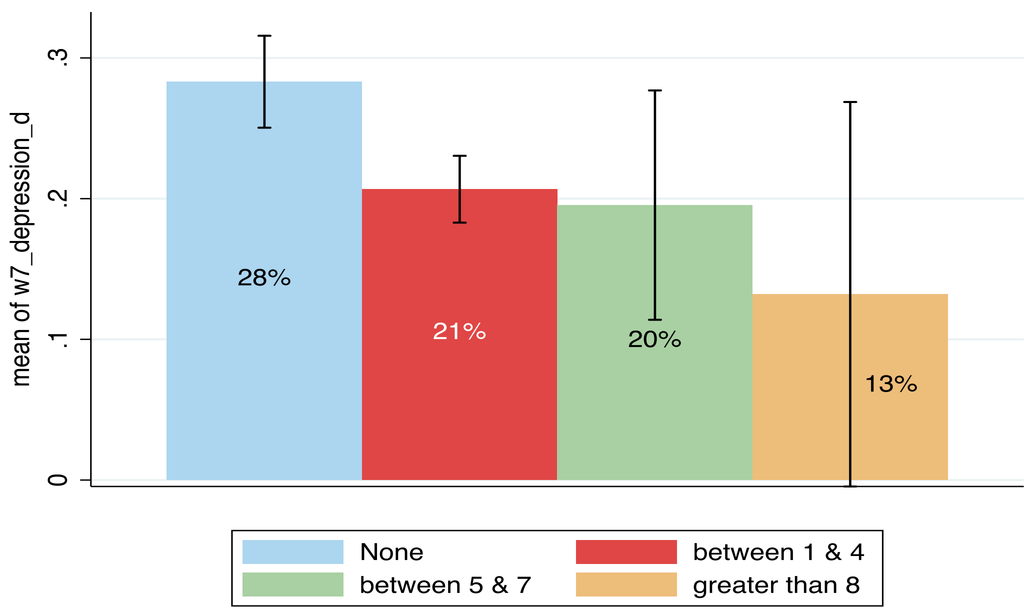

Figure A5: Household size by per capita income quintiles

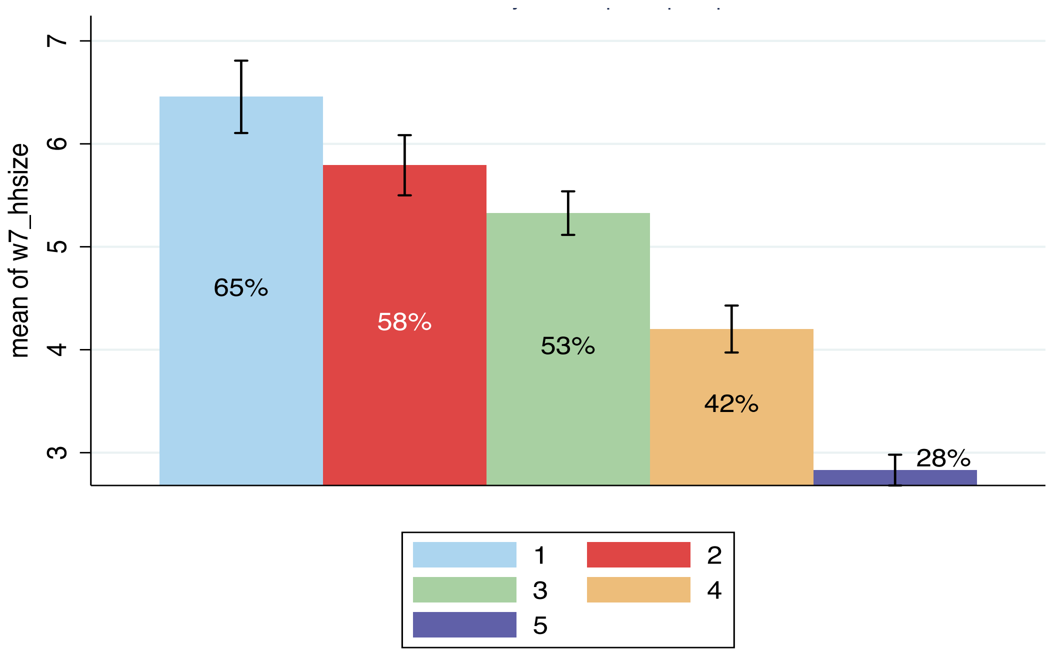

Figure A6: Proportion of respondent that screened positive for depressive symptoms by severity of hunger

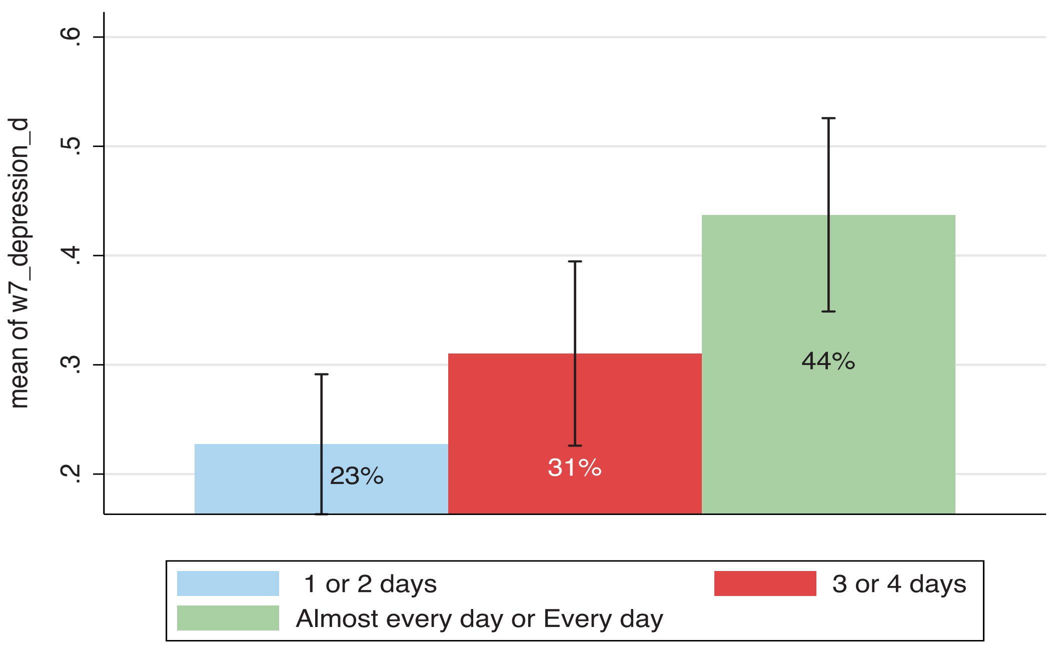

Figure A7: Proportion of respondent that screened positive for depressive symptoms by Employment type

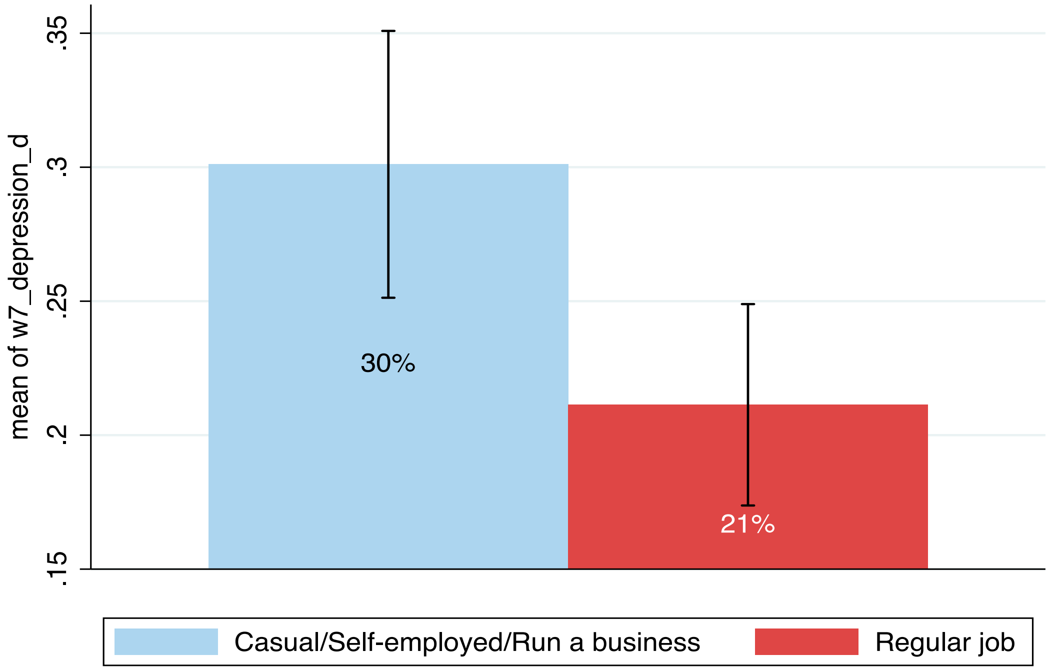

Table A2: Multivariate analysis of correlates of depressive symptoms in the COVID era

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Depression scores (PHQ-2)					
Base category (no change)											
job loss (Feb/March)	0.31**	0.32**	0.34**	0.30*	0.31**	0.31**	0.31**	0.31*	0.26	0.27	0.29*
job gain (Feb/March)	-0.10	-0.11	-0.10	-0.10	-0.09	-0.10	-0.10	-0.07	-0.17	-0.16	-0.10
Social Grants											
w7_no_oap		-0.18***									
w7_no_csg			-0.06***								
Tertiary Education				0.20**							
Water					-0.17**						
Electricity					-0.12						
Household size						-0.02**					
Chronic illness							0.13				
Risk of Corona								0.27***			
Hunger Severity									0.30***		
Base Category (no change)											
Lost income (Decreased)										0.31***	
Lost income (Unchanged)										0.08	
HH Income source (Employment)											
HH source (business)											0.68***
HH source (Government grants)											-0.08
HH source (friends or family)											-0.03
HH source (Other)											0.23
HH source (no income in June)											-0.31
HH source (Pension)											0.41**
Constant	1.31***	1.40***	1.39***	1.28***	1.63***	1.41***	1.28***	1.16***	0.82***	1.17***	1.26***
Observations	5,351	4,955	5,012	4,073	5,351	5,324	5,332	4,448	1,004	4,797	5,049
R-squared	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.03	0.01	0.02

Robust standard errors are used to determine the p-values (*** p<0.01, ** p<0.05, * p<0.1)

For further information please see **cramsurvey.org**