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WAVE 2

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

Socio-economic inequality in the response to COVID-19 Pandemic

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Socio-economic inequality in the response to COVID-19 Pandemic

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Abstract

An understanding of individual health response behaviour is important in managing the pandemic risk in the country. Given the un-emphasizable economic and social divide that exists in South Africa, it is critical to acknowledge and manage the health response of its residents within the different socio-economic contexts that define the lived realities of individuals. The current policy paper therefore aims at assessing the socio-economic inequality in some of the major factors that drive individual health behaviour, viz, subjective risk perception, self-efficacy or the belief that good behaviour can yield desired health outcome, feasibility of adopting preventive measures as revealed by individual behaviour and lastly, the sources of information related to the pandemic. The study finds that there is significant income, education and age-related differences in the individual response to COVID-19. While there is significant increase in subjective risk perception between June and August 2020 across the board, the non-blacks have significantly higher subjective risk perception compared to the black African population. The optimism bias is observed to be more pronounced among the less affluent groups like black African, rural and young population groups. The use of facemasks has gained widespread popularity across socio-economic groups. It is however of concern that there is increasing complacency towards physical distancing especially among the low-income groups. The findings indicate the need for tailoring policies specific to the various socio-economic contexts in the country.

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Executive Summary

An understanding of individual health response behaviour is important in managing the pandemic risk in the country. Given the un-emphasizable economic and social divide that exists in South Africa, it is critical to acknowledge and manage the health response of its residents within the different socio-economic contexts that define the lived realities of individuals. The current policy paper therefore aims at assessing the socio-economic inequality in some of the major factors that drive individual health behaviour, viz, subjective risk perception, self-efficacy or the belief that good behaviour can yield desired health outcome, feasibility of adopting preventive measures as revealed by individual behaviour and lastly, the sources of information related to the pandemic. The following are the major study findings:

- There was a significant increase in subjective risk perception of COVID-19 infection over the months of April and June 2020 in South Africa. While 33% of respondents believed that they were at risk of infection in April, this increased to 50% in June.
- Significant socio-economic inequality in subjective risk perception exists. The subjective risk perception is significantly concentrated among the higher income groups, the educated and older respondents.
- There is an optimism bias among black Africans, lower income, less educated and younger age groups.
- Increased level of employment and increased coefficient effects have contributed significantly to increased subjective risk perception over the two periods of study.
- The optimism bias among the less affluent category, together with the higher subjective risk perception among the affluent section, point to the role of socio-economic status in subjective assessment of the risk of contracting the virus
- Enhanced behavioral responsiveness is visible with an increase from 92% to 99% of respondents reporting some form of change in behavior as a preventive measure against infection.
- Preventive behavior is evolving over time, the use of face masks has overtaken hand washing as the most utilised preventive measure.
- Face mask use in public is reported as high with an insignificant percentage reporting non-compliance with the regulation of wearing face mask while going out in public.
- While there is an increased use of hand sanitisers and home cleaning as preventive measures against infection in June as compared to April, other measures like social distancing, avoiding close contact, avoiding big groups and staying at home has declined between the two periods.
- It is clear that with the opening up of the economy and the return of individuals to employment; it has become harder for individuals especially in the lower income categories to observe physical distancing.
- There is significant income and education related inequality between the types of preventive measures adopted.
- Measures such as social distancing, avoiding close contact, use of sanitisers are practiced more by the rich and educated. The low-income respondents are not able to maintain physical distancing measures as the economy opens up.
- There is a pro-poor bias among the respondents who reported news (radio, TV, newspapers, internet etc.) as their primary source of reliable information. However, no education or age-related differences were found in this regard.
- The less educated and, older age groups reported health workers as the most trusted source of information on COVID-19.

Policy recommendations:

- The optimism bias among the less affluent economic groups needs to be addressed to prevent risky behavior.

- There is also a need to steer the affluent groups away from an over-assessment of risk. This is in the interest of controlling over-anxiety and mental health issues among these groups.
- With the increasing use of face masks across socio-economic groups, clear messaging on the appropriate use of masks like regular washing of re-usable masks need to be given so that the mask use remains effective.
- The growing complacency with regards to physical distancing is of concern. It is recommended that the emphasis on physical distancing be reinforced as a complementary measure to the use of face mask.
- Reintroduction of restricted capacity use of taxis will enable physical distancing for the less affluent who are the users of this mode of transport.
- To target the most-risky group of the elderly, less educated, low income individuals, it is important to utilise health workers and community leaders more.

1. Introduction

The impact of the Corona virus pandemic on the South African economy and the health of its residents is evolving in real time. South Africa went into hard lockdown (level 5) quite early in the pandemic (March 2020). During the hard lockdown, the residents were mostly confined to their homes, leaving very little need for pro-active decision-making by individuals. This however was untenable even with the fiscal relief measures put in place by the government (Jain et al. 2020). The economic implications of the nationwide shutdown made it unsustainable with increasing levels of hunger, poverty and unemployment among the vulnerable sections of society (Wills et al. 2020).

Since then, the government has reduced the level of lockdown in phases to permit the economy to function once again. The government declared the move to level 4 from 1 May, to level 3 from 1 June and, level 2 from 18 August. Behavioural restrictions have been lifted in a calibrated manner commensurate to the lockdown level, albeit with precautionary messages from the government. While regulations have been passed making the wearing of face masks essential and fines for non-compliance, the limited capacity for monitoring implies that it is largely left to the individuals to comply with the regulation and other precautionary measures to prevent COVID-19 infection. This means that the responsibility of managing the pandemic through restrained behaviour has essentially shifted to the residents of the country. With no immediate prospects of a vaccine being available to counter the pandemic, non-pharmaceutical interventions remain the most effective defence against the pandemic (Chowdhury et al., 2020).

Therefore, the control of the pandemic now depends on the behavioural response of individuals. Findings from the NIDS-CRAM wave 1, however, suggests that the high-impact behaviour changes are not happening fast enough in South Africa even though a large percentage of the population reported some form of change in behaviour (Burger et al 2020). In a country as economically and socially divided as South Africa (Kingdon & Knight, 2004; Leibbrandt & Woolard, 2010), it would be unrealistic to expect a uniform response from its residents. The purpose of this policy paper is to explore the role of socio-economic contexts in determining the health behaviour response of individuals. The findings of this study will enable effective policy making by taking into account the socio-economic inequality in behavioural responses. The purpose of this study is to provide this perspective to policy makers that will enable more nuanced policy formulation.

The paper is divided in five sections. The analytical framework and research objectives are outlined in section two, followed by a brief description of data in section three. Section four contains the main analysis with five sub-sections dedicated to each research question. Lastly, the study summary and the emanating policy recommendations bring up the fifth section.

2. Analytical framework and Research objectives

The study adopts the Health Belief Model (HBM) as its analytical framework. The Health Belief Model (Becker, 1974; Janz & Becker, 1984) highlights the role of people's awareness, perceived risk, self- efficacy (the confidence and belief that pro-health action can yield desirable outcome), and feasibility of precautionary/preventive action in explaining individual health response behavior. In a country like South Africa that is torn apart by dual realities, it is important not to assume a common behavioural response from all sections of society. The HBM model is therefore suited to understand the differential response from individuals in a country that is known as one of the most unequal in the world.

It is important to consider the individual motivation and impediment factors as additional drivers of behavioural response. The barriers against adopting a certain preventive measure by an individual is contingent on the living and livelihood circumstances of individuals. The awareness campaigns and policy recommendations therefore have to talk to the lived realities of individuals in different circumstances. The issue of feasibility aside, the optimism bias recorded in literature (Sharot 2012), can lead people to risky behaviour because they falsely believe that they are less at risk of negative events than other people. Identifying the category of individuals more prone to optimism bias can enable more targeted policy intervention. The purpose of the study is to ascertain the role of socio-economic contexts in the behavioural response to the pandemic. This will provide more information to policy makers which will assist them in providing meaningful support to public that is relevant and feasible within their respective contexts.

The study seeks answers to the following questions:

1. How has subjective risk perception evolved over the two NIDS-CRAM waves and what are the differences among socio-economic groups in this regard?
2. How has self-efficacy evolved and what are the differences among socio-economic groups in this regard?
3. What are the self-reported main sources of reliable information on the pandemic for the various socio-economic groups?
4. How has preventive behaviour evolved and what are the differences among socio-economic groups in this regard?
5. What are the key drivers behind the changing subjective risk perception?

The analysis is disaggregated to identify the role of sex, race, geographical location, age, education, and income in driving the individual health response behaviour. The study uses bivariate statistics to identify significant differences across binary variables like sex, race and geographical location. Concentration indices are used to estimate the income, education and age-related inequalities in behavioural response. Lastly, acknowledging that many of the inferences made through bivariate statistical analysis may be driven by a common underlying factor, we control for this through multivariate analysis. Multivariate logistic regression analysis is therefore used to assess the impact of variables while controlling for others. Further, an Oaxaca-Blinder decomposition is used to identify the drivers behind changing subjective risk perception between the two waves. More detailed description of estimation techniques is included in the relevant sections.

3. Data

The analysis utilises the first and second waves of the National Income Dynamics Survey (NIDS)-Coronavirus Rapid Mobile Survey (CRAM). The NIDS-CRAM survey is a special follow up with a subsample of adults from households in the Wave 5 of the National Income Dynamics Study (NIDS) run by SALDRU (Ingle 2020). The NIDS-CRAM has a smaller sample by comparison, covering complete questionnaire information for 7073 individuals in wave 1, and 5676 individuals in wave 2. Despite the smaller sample size, the survey is designed to be nationally representative and remains the best available source of quantitative information on a national scale to assess the socio-economic impact of the corona virus pandemic in South Africa. A limitation however remains that the data is not representative at sub-national levels and therefore the analysis cannot be conducted at provincial or municipal levels.

The first wave of the NIDS-CRAM survey was conducted over the months of May and June 2020, and the second wave was administered in July and August 2020. Therefore, about 25% of the first wave was under lockdown level 4 conditions, while 75% was under level 3 conditions. The second wave has been conducted in its entirety over lockdown level 3 conditions. Where possible, the analysis is structured to explore the evolving behaviour using both waves for comparison. However, this is limited by the availability of information in both survey waves. For example, certain variables like the sources of information was collected only in the first wave and therefore the analysis relies exclusively on the first wave for it.

A further limitation to be highlighted is the high proportion of missing information on household income. The analysis relating to household income therefore is restricted to 3,599 individuals in wave 1 and 3,569 individuals in wave 2. Despite these challenges NIDS-CRAM survey remains the best available source of data to analyse the nation's response to the pandemic. The descriptive statistics of the key socio-economic variables in the sample (Table 1) indicate resonance with national statistics.

Table 1: Descriptive Statistics of the key socio-economic variables

Variables	Wave 1			Wave 2		
	Mean/ %	**Lower conf interval**	**Upper conf interval**	**Mean/ %**	**Lower conf interval**	**Upper conf interval**
Male (%)	46. 9			46.8		
Female (%)	53.1			53.2		
Black (%)	78.7			78.7		
Non-Black (%)	21.3			21.3		
Urban (%)	81.9			75.8		
Rural (%)	18.1			24.2		
Education years	11.218	11.014	11.422	11.222	11.013	11.430
Age years	40.156	39.491	40.821	40.271	39.604	40.937
Income Quintiles (Rands)						
1	97.479	80.594	114.364	153.756	132.543	174.969
2	404.922	365.610	444.235	409.526	378.265	440.788
3	720.599	655.520	785.679	758.305	647.095	869.515
4	1431.516	1284.740	1578.292	1461.341	1300.360	1622.321
5	8626.576	7371.994	9881.158	8255.206	6831.270	9679.141

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted.

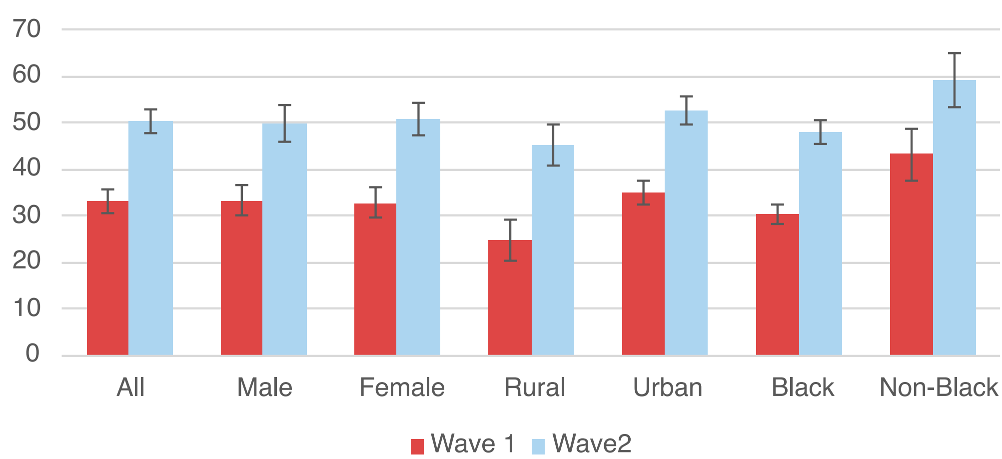
4. Analysis

4.1. Subjective risk perception

The process of subjective risk perception determination is seldom entirely rational. Both cognitive and emotional assessments contribute to the formulation of subjective risk perception. While cognitive skills through the logical weighing of evidence and reasoning contributes to subjective risk perception formulation; equally, emotional appraisals, through the use of intuition and imagination, plays an important role (Ropiek 2002). Literature has highlighted the role of optimism bias (the tendency to believe that one's own risk is less than that of others) in reducing the health-protective behavior or increasing risk-taking (Weinstein & Klein 1995). It is therefore important to identify the high-risk taking category for targeted policy making.

The subjective risk perception information in the study is obtained through the 'yes' or 'no' response to the question 'Do you think you are likely to get the Coronavirus?'. As indicated earlier, just over 75% of responses in wave 1 was captured under lockdown stage 3 and the rest under lockdown stage 4; and 100% of wave 2 responses were sought in lockdown 3 conditions. Despite this, the findings show that there is a significant increase in subjective risk perception in Wave 2 relative to Wave 1. While 33% of individuals reported a risk of infection, this increased to 50% in wave 2 (Fig 1).

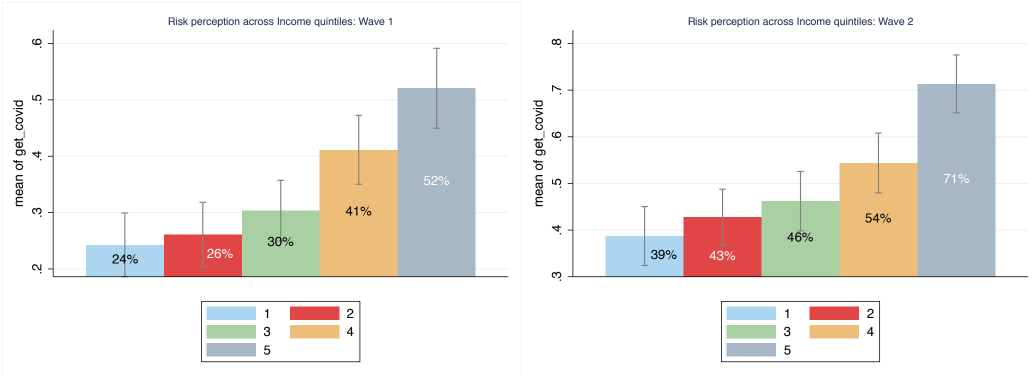
Fig 1: Subjective risk perception over wave 1 and wave 2



Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. The bars show the subjective risk perception in percentage. 95% confidence intervals are shown.

A comparison of the perceived risk of corona virus infection across the demographic categories indicate that there are no significant differences across sex but significant differences exist across race and geographical locations (Fig 1). Black Africans perceive a significantly lower risk (48% in wave 2) compared to non-blacks (60% in wave 2). Even though there is significant increase in the subjective risk perception of black Africans in the second wave, the non-black subjective risk perception has also increased and therefore the race gap remains significant in both waves. Similarly, the respondents based in rural locations reported significantly lower risk than those in urban areas. Both locations report increased subjective risk perceptions in the second wave and the difference in the subjective risk perceptions across the geographical divide remains significant. The lower subjective risk perception in rural areas can be attributed to a cognitive assessment based on the lower density of populations in relation to urban areas and, lesser interaction with the outside world that lowers the probability of acquiring this "imported" virus.

Fig 2: Subjective risk perception across Income Quintiles



Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. The bars show the subjective risk perception across income quintiles. 95% confidence intervals are shown.

An analysis of subjective risk perceptions levels across the income quintiles is further revealing (Fig 2). There are significant differences in subjective risk perceptions across income groups with higher income quantiles having significantly higher subjective risk perceptions compared to the lower income quantile. Explaining this rationally is difficult considering that higher income groups are in a better position to adopt protective measures. However, over exposure to information, especially from social media and informal sources can contribute to heightened subjective risk perceptions. Further, emotional response not entirely grounded in reality can contribute to higher subjective risk perceptions (Ropiek 2002). Counter to the above arguments, there is also evidence that at the initial stages of the outbreak of COVID-19, the affluent sections were the most affected. Further evidence show that private laboratories have more positivity rates compared to government facilities, which might justify the higher subjective risk perception of the affluent (NICD 2020). Perhaps, in line with this, there is distinct optimism bias among the lower income quantiles, although this has reduced from wave 1 to wave 2.

Further, we use the concentration index to quantify the level of concentration of subjective risk perception along key continuous variables like income, education and age. The concentration index is a measure of the socioeconomic inequality based on the ranking of individuals based on household per capita income (education or age) and the subjective risk perception levels of all individuals in the sample (Kollamparambil 2020). The concentration index CI(h), introduced by Kakwani (1980) and Wagstaff, Paci and Van Doorslaer (1991), is defined as follows:

$$\mathrm{CI(h)} = \frac{2}{n\mu}\sum_{i=1}^{n} h_i r_i - 1 \qquad (1)$$

where n is sample size, h the health subjective risk perception variable, μ its mean and r the rank of individual i by income (education or age) from poorest to richest.

Given that the subjective risk perception variable is binary, we estimate the Erreygers'-corrected concentration index (Erreygers 2009) as:

$$E(h) = \frac{4\mu}{b_h - a_h} CI(h) \qquad (2)$$

Where b_h and a_h are the maximum and minimum of the health risk variable (h) and μ its mean.

E(h) is expected to lie between +1 and -1, with a positive value of E(h) indicating that subjective risk perception is concentrated more among the higher end of the income (education or age) distribution, and a negative value indicating that it is concentrated more among the lower end of the income (education or age) distribution. Further, the absolute value of the index indicates the level of concentration.

The results in Table 2 indicates significant pro-rich, pro-education and pro-age concentration of subjective risk perception. This implies that subjective risk perception is concentrated more among the richer, more educated and older respondents.

Table2: Erreygers'-corrected Concentration Index of Subjective risk perception

Concentration index	Wave 1	lower bound CI	Upper bound CI	Wave 2	lower bound CI	Upper bound CI
Income related	0.231***	0.161	0.301	0.240***	0.179	0.299
Education related	0.134***	0.085	0.183	0.145***	0.093	0.196
Age related	0.071***	0.021	0.122	0.103***	0.048	0.158

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** p<0.01, ** p<0.05, * p<0.1

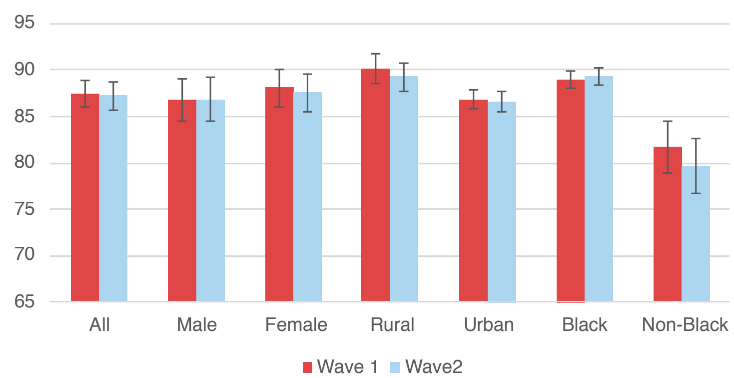
This could imply either that the rich suffer from an over-estimation of risk or that the poor have a high level of optimism bias, or both. Given the mental health implications of heightened risk perception (Oyenubi & Kollamparambl 2020), it is of concern that income, education and age-based concentration levels are high and is increasing across the waves. The highest concentration of subjective risk perception is along income lines, highlighting the social and health implications of the income divide of the country. Given that the black African and rural population in South Africa have lower average incomes (Kingdon & Knight, 2004; Leibbrandt & Woolard, 2010) the lower subjective risk perception identified earlier among the black African and rural population could be driven by income as the mediating factor. Isolating the impact of various variables therefore calls for a multivariate analysis, which is undertaken in section V.

4.2. Self-Efficacy

The belief that positive health outcomes can be achieved through personal action (self- efficacy) is an important motivation for individual good health behaviour (Hevey et al 1998). Self-efficacy is measured in NIDS-CRAM data through the 'yes' or 'no' response to the question 'Can you avoid getting the Coronavirus?'. Self-efficacy, unlike subjective risk perception, has remained unchanged over the two waves at 87% (Figure 3).

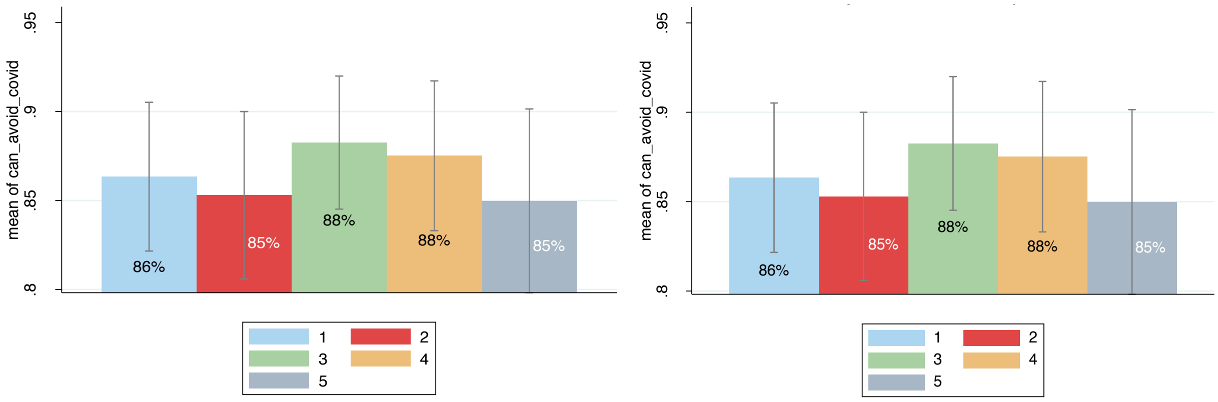
It is revealing to note that while there are no significant differences in self-efficacy across gender lines, urban respondents report significantly lower self-efficacy (86% in wave 2) than their rural counterparts (89% in wave 2). Similarly, non-black respondents report significantly lower self-efficacy (82% in wave 2) compared to black African population group (89% in wave 2). This further strengthens the argument made in the previous section of higher optimism bias among the black African population compared to the non-black population. The rate of self-efficacy has declined among the non-black race, even though this cannot be noted as being statistically significant (Fig 3).

Fig 3: Self-efficacy across wave 1 and wave 2



Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. The bars show the reported self-efficacy. 95% confidence intervals are shown.

Fig 4: Self-efficacy across Income Quintiles



Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. The bars show the reported self-efficacy. 95% confidence intervals are shown.

An analysis of self-efficacy across the income quantiles do not reveal any statistically significant patterns (Fig 4). The insignificant concentration index on income related inequality of self-efficacy (table 3) point to similar conclusions suggested by figure 4. There is no evidence of education related inequality in self-efficacy either, although the negative sign points to possibly higher self-efficacy and optimism among the less educated. This is much stronger and significant among the younger population group as highlighted by the negative and significant age-related concentration indices in both waves (Table 3).

Table 3: Erreygers'-corrected Concentration Index of Self-Efficacy

Concentration index	Wave 1	lower bound CI	Upper bound CI	Wave 2	lower bound CI	Upper bound CI
Income related	0.004	-0.042	0.051	-0.013	-0.057	0.032
Education related	0.03	-0.004	0.064	-0.001	-0.034	0.031
Age related	-0.0257*	-0.055	0.004	-0.046***	-0.079	-0.013

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** p<0.01, ** p<0.05, * p<0.1

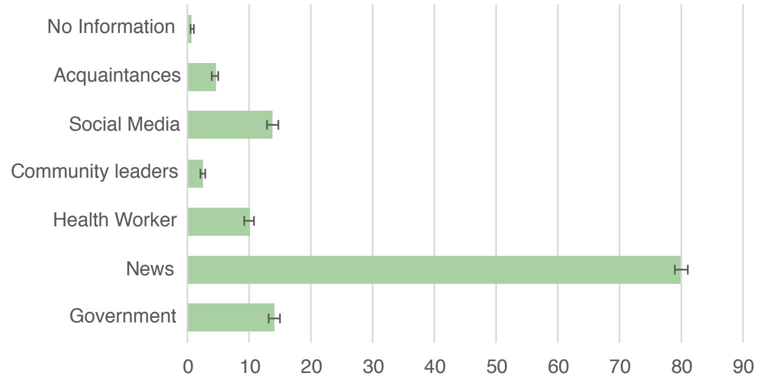
4.3. Source of Information

Awareness and access to information is a significant pillar determining individual health response behaviour. Access to reliable information is critical for countering any form of response bias. While lack of information can lead to an optimism bias, false and disproportionately alarming news can create over anxiety and mental health related problems (Oyenubi & Kollamparambil 2020).

Fig 5 shows that 80% of respondents reported news (through radio, TV, newspapers, internet etc.) as the most trusted source of information. Respondents report social media, government and health workers way below news as sources of reliable information. Similar findings have been highlighted by Burger et al (2020). Burger et al. (2020) also found that those relying on news had lower information on the three most common COVID-19 symptoms I relation to those who relied on health workers, social media and government.

While the respondents that reported a lack of reliable information source is negligible, it is nevertheless concerning to have individuals left behind in the fight against the pandemic. It needs to be noted here that the data presented in this section is exclusively from wave 1 as the second wave did not include questions relating to information source.

Fig 5: Sources of reliable information on Corona virus



Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. The bars show the reported source of reliable information in percentage. 95% confidence intervals are shown.

The income related concentration indices highlight the pro-rich bias of social media, acquaintances, government and, community leaders as self-reported sources of reliable information (Table 4). News on the other hand is found to be pro-poor source of trusted information. Given the reliance of the higher income groups on social media and social acquaintances; this may be construed as an additional explanation for their higher subjective risk perceptions. It is also not surprising that those reporting a lack of reliable information source is concentrated among the poor. Although statistically significant, the last result needs to be treated with caution due to the small number of respondents in this category.

Table 4: Erreygers'-corrected Concentration Index (income related) of Information Sources

Income related	Concentration Index Wave 1	lower bound CI	Upper bound CI
Government	0.072***	0.026	0.118
News	-0.059**	-0.106	-0.012
Health Worker	-0.017	-0.051	0.017
Community leaders	0.022*	-0.003	0.047
Social Media	0.091***	0.042	0.141
Acquaintances	0.087**	0.049	0.124
No Information	-0.005***	-0.011	0.000

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** p<0.01, ** p<0.05, * p<0.1

Education related inequality of information sources indicate government and social media to be concentrated among those with more years of education, while health worker as the source of information is concentrated among those with less education (Table 5). Age-related inequality of information sources indicates health workers and community leaders as concentrated among the older respondents, while social media concentration expectedly is pro-younger age (Table 6). No information is found to be concentrated along the older aged, uneducated and poor groups. Although statistically significant, the last result needs to be treated with caution due to the small number of respondents in this category.

Table 5: Erreygers'-corrected Concentration Index (education related) of Information Sources

Education related	Concentration Index Wave 1	lower bound CI	Upper bound CI
Government	0.091***	0.055	0.127
News	0.010	-0.025	0.046
Health Worker	-0.059***	-0.083	-0.035
Community leaders	-0.009	-0.022	0.004
Social Media	0.130***	0.097	0.163
Acquaintances	0.014	-0.009	0.036
No Information	-0.017***	-0.023	-0.010

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Erreygers'-corrected Concentration Index (age related) of Information Sources

Age related	Concentration Index Wave 1	lower bound CI	Upper bound CI
Government	-0.015	-0.049	0.019
News	0.027	-0.009	0.064
Health Worker	0.024**	0.002	0.046
Community leaders	0.015**	0.003	0.026
Social Media	-0.081***	-0.118	-0.045
Acquaintances	0.001	-0.020	0.023
No Information	0.012***	0.005	0.019

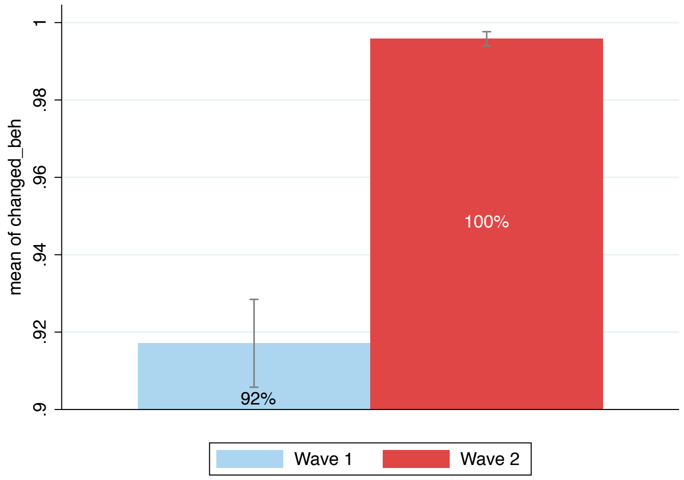
Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The findings on the socio-economic inequality in access to information provide direction on appropriate channels to target various groups in the population, and also provide cues on the differences in subjective risk perception and self-efficacy levels noted in earlier sections.

4.4. Preventive Measures

In the absence of a vaccine in the immediate future, the country relies on collective cooperative health behaviour in order to deal with the trade-off between the extent to which the economy can be open and the spread of the virus. The only way to manage the spread while keeping the economy functioning is for the population to adapt their response behaviour and follow preventive measures. It is therefore reassuring to see that there has been significant improvement in the percentage of individuals reporting adopting some form of behavioural change in response to the threat of corona virus. While 92% reported changing their behaviour in Wave 1, this rose to 99.7% in wave 2 (Fig 6). However, a note of caution needs to be highlighted given that the information garnered for the two waves is based on questions administered differently in the two questionnaires. In wave one, there was a dedicated question 'Have you changed your behavior since learning about the Coronavirus?', that required a 'yes' or 'no' response. In wave two, however, this was changed to 'Are you behaving differently to protect yourself from Coronavirus. If yes, what?'. The response to this question would be to choose from the list preventive measures with an additional response 'no, I am not doing anything'. The near 100% positive response to behavioural changes in wave 2 may be partially attributed to the construct of the question. Nevertheless, for want of a better tool, we make use of this for comparison.

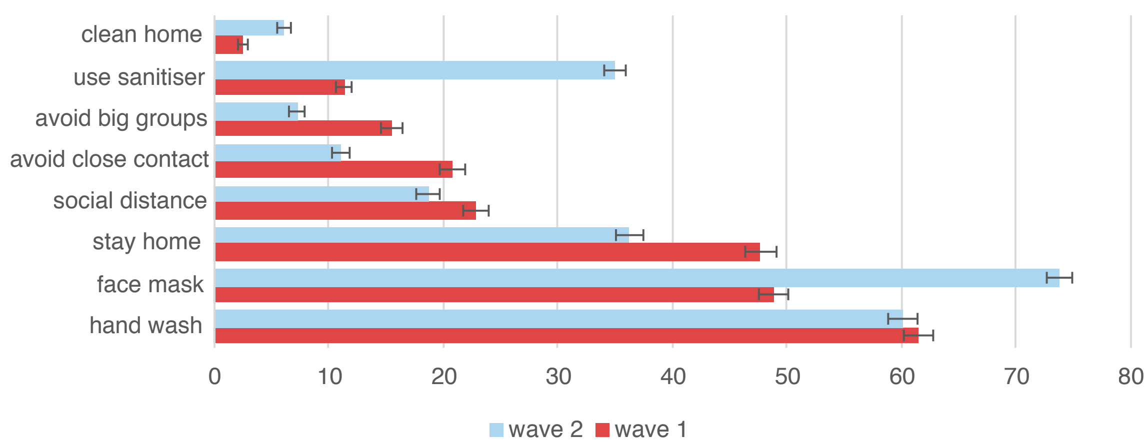
Fig 6: Behavioural change across wave 1 and wave 2



Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. The bars show the reported change in behaviour. 95% confidence intervals are shown.

There are significant changes in the preventive measures used between the two waves (Fig 7). While in wave 1, hand washing was the predominant measure, this has changed to the use of face mask in wave 2. It is clear that individuals are responding to public messaging, when in the initial phases hand washing was emphasized over face mask use. Subsequently, the expert views available to the public changed in favour of face mask and this is reflected in the surge of face mask use from under 50% to over 70%. While this gives an impression that a significant proportion is still not utilising face masks despite the regulation making it mandatory, this conclusion might be misleading. The response to a follow up question "In the last 7 days have you worn a face mask or covering when going out in public?" indicate much better compliance with the regulation, with only 1% reporting not using face mask while going out in public.

Fig 7: Types of Preventive Measures



Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. The bars show the use of different preventive measures in percentage. 95% confidence intervals are shown.

The other major shift observed in preventive behaviour is the reduction in the practice of physical distancing (Fig 7). With the opening up of the economy, it is noticeable that staying at home has reduced substantially from just under 50% to well below 40%. More concerning is that those reporting social distancing, avoiding close contact and, avoiding big groups have reduced significantly. While this seems to be compensated through the increase use of face masks and hand sanitisers, the reduction in physical distancing measures remains of concern. It is important for public messaging to emphasize the complementary nature of these measures given that any one measure in itself is not sufficient on its own.

The socio-economic inequality in the use of preventive measures is revealing. Awareness of the necessary measure is a necessary precondition, but the barriers to adopting it within an individual's living and livelihood conditions might make it infeasible. Therefore, socio-economic context is expected to play a key role in the nature of preventive measures adopted by individuals. While in wave 1 the use of face mask was concentrated among the economically affluent, the concentration index is not statistically significant in wave 2 (Table 7). This is an encouraging sign that face mask use has spread across income groups. However, physical distancing practices like social distancing and avoiding close contact remains pro-rich. Or in other words these practices are significantly more concentrated among the rich than the poor. This highlights the question of feasibility of these preventive measures for respondents who live in crowded households and neighbourhoods and have no alternative to public transport. The lifting of capacity restrictions in pubic taxis have particular bearing for individuals from the lower economic strata of society, exposing them to higher risks compared to those with private transport. Staying home as a preventive measure is seen to be concentrated among the poor, but is not significant in wave 2.

Table 7: Erreygers'-corrected Concentration Index (income related) of Preventive Measures

Income Related	Concentration Index Wave 1	lower bound	Upper bound	Concentration Index Wave 2	lower bound	Upper bound
Changed behaviour	0.005	-0.025	0.035	-0.003	-0.006	0.000
Hand wash	-0.033	-0.095	0.030	-0.039	-0.104	0.026
Avoid Close contact	0.095***	0.038	0.151	0.040**	0.002	0.079
Avoid Big groups	0.056	-0.002	0.115	-0.002	-0.037	0.034
Face mask	0.088***	0.024	0.152	0.019	-0.037	0.074
Stay home	-0.088***	-0.155	-0.021	-0.122	-0.183	-0.061
Use sanitiser	0.042	-0.006	0.090	0.105***	0.041	0.169
Clean home	-0.002	-0.025	0.020	0.040**	0.011	0.069
Social distance	0.106***	0.049	0.163	0.067**	0.011	0.123
Flu vaccine	0.004	-0.016	0.023	0.008	-0.001	0.017

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** p<0.01, ** p<0.05, * p<0.1

Education related inequality is visible along the lines of the income related inequality in the use of preventive measures (Table 8). The results indicate that social distancing, avoid close contact and the use of sanitisers are practiced more among the educated. The use of facemask was also pro-educated in wave 1 but has become insignificant in wave 2 indicating its popularity cutting across education lines.

Age related concentration indices indicate that the pro-young concentration in behavioural change has declined but still remains significant (Table 9). While the use of flu vaccine is revealed as a pro-older individual strategy, social distancing is evident as a pro-young measure.

Table 8: Erreygers'-corrected Concentration Index (education related) of Preventive Measures

Education related	Concentration Index Wave 1	lower bound CI	Upper bound CI	Concentration Index Wave 2	lower bound CI	Upper bound CI
Changed behaviour	0.005	-0.025	0.035	-0.003	-0.006	0.000
Hand wash	-0.033	-0.095	0.030	-0.039	-0.104	0.026
Avoid Close contact	0.095***	0.038	0.151	0.040**	0.002	0.079
Avoid Big groups	0.056	-0.002	0.115	-0.002	-0.037	0.034
Face mask	0.088***	0.024	0.152	0.019	-0.037	0.074
Stay home	-0.088***	-0.155	-0.021	-0.122	-0.183	-0.061
Use sanitiser	0.042	-0.006	0.090	0.105***	0.041	0.169
Clean home	-0.002	-0.025	0.020	0.040**	0.011	0.069
Social distance	0.106***	0.049	0.163	0.067**	0.011	0.123
Flu vaccine	0.004	-0.016	0.023	0.008	-0.001	0.017

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Erreygers'-corrected Concentration Index (age related) of Preventive Measures

Age related	**Concentration Index Wave 1**	**lower bound CI**	**Upper bound CI**	**Concentration Index Wave 2**	**lower bound CI**	**Upper bound CI**
Changed behaviour	-0.041***	-0.072	-0.010	-0.006**	-0.011	-0.001
Hand wash	-0.051*	-0.102	0.001	-0.023	-0.071	0.025
Avoid Close contact	-0.014	-0.050	0.022	0.002	-0.031	0.036
Avoid Big groups	-0.002	-0.038	0.034	-0.005	-0.027	0.018
Face mask	-0.002	-0.048	0.043	-0.020	-0.064	0.025
Stay home	0.000	-0.010	0.010	0.001	-0.004	0.006
Use sanitiser	0.006	-0.007	0.018	-0.010	-0.025	0.005
Clean home	-0.024	-0.080	0.032	0.027	-0.024	0.078
Social distance	-0.004	-0.033	0.024	-0.141***	-0.189	-0.093
Flu vaccine	0.002	-0.004	0.008	0.002**	0.000	0.005

Source: NIDS-CRAM, Wave 1 (2020) & NIDS-CRAM, Wave 2 (2020)
Notes: Data are weighted. CI is confidence interval. *** p<0.01, ** p<0.05, * p<0.1

4.5. Multivariate Analysis of Change in Subjective risk perception

The above four sections analysed the socio-economic inequality in individual response within the context of the health behaviour model using bivariate analysis. Race, income, education, location, age etc have been identified as important factors driving health response. The largest change was picked up in subjective risk perception and therefore this section looks at the phenomenon in a more in-depth manner using multivariate regression analysis. Multivariate analysis provides the advantage of isolating the impact of variables while simultaneously controlling for the effects of other variables.

As a first step, we undertake logit regression of subjective risk perception at the two time points to identify its correlates. Subsequently we decompose the means over the two time points using the Blinder-Oaxaca approach to highlight the drivers behind the increased subjective risk perception.

Logit Regression

Given the binary outcome variable on subjective risk perception, logit regression estimations are appropriate. The model is written as:

$$Y_i = \beta_i X_i + \varepsilon_i$$

Where:

1. Y_i is 1 if the respondent indicates the possibility of getting infected and 0 otherwise
2. $\beta_i X_i$ is a vector of control variables regressions
3. ε_i represents the error term.

We present the estimation results for the logit model at two time points to observe changes in coefficient estimates over time (Table 10). The results indicate that the employed, higher income and those relying on information from social acquaintances have a significantly higher subjective risk perception in wave 2. Additional factors that increased subjective risk perception in wave 1 were age and urban informal location. These factors however cease to be significant in the second wave.

Race ceases to be significant in the logit regression, indicating that the race effect highlighted in the earlier sections were driven fundamentally by the mediating effects of income and education.

Table 10: Logit Regression Estimates, dependent variable: Subjective risk perception

VARIABLES	Wave 1	Wave 2
Age	0.0478*	0.0386
	(0.0267)	(0.0323)
Male	-0.219	-0.0235
	(0.139)	(0.141)
Black African	-0.281	0.0155
	(0.228)	(0.258)
Employed	0.645***	0.399***
	(0.146)	(0.146)
Years of Schooling	0.0470**	0.0568**
	(0.0217)	(0.0231)
Per capita household Income	0.200***	0.241***
	(0.0583)	(0.0568)
Urban	0.151	0.131
	(0.183)	(0.155)
Urban informal	0.488**	-0.000367
	(0.212)	(0.232)
Government info	-0.161	-0.269
	(0.194)	(0.208)
News info	0.0626	-0.0623
	(0.173)	(0.179)
Health worker info	-0.0137	-0.204
	(0.206)	(0.199)
Community leader info	-0.0775	-0.191
	(0.410)	(0.417)
Social media info	0.0718	0.263
	(0.221)	(0.220)
Acquaintance info	0.727**	0.779*
	(0.346)	(0.399)
No information source	-1.391	-0.765
	(0.922)	(0.881)
Province dummies	yes	yes
Constant	-2.526***	-1.817***
	(0.547)	(0.570)
Observations	2,890	2,530

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Oaxaca-Blinder Decomposition of changes in Subjective risk perception

Oaxaca (1973) and Blinder (1973) introduced a decomposition procedure that enabled the attribution of the SWB gap of two time periods to composition effect and coefficient effect (Kollamparambil & Razak, 2016).

$$y_i^{w1} = \alpha^{w1} + \beta^{w1} x_i^{w1} + \varepsilon_i^{w1} \quad (1)$$

$$y_i^{w2} = \alpha^{w2} + \beta^{w2} x_i^{w2} + \varepsilon_i^{w2} \quad (2)$$

Where y is the subjective risk perception variable and x is a vector of regressors.

The decomposition is calculated by subtracting the two equations which yields:

$$Y^{w2} - Y^{w1} = \beta^{w2}(X^{w2} - X^{w1}) + (\alpha^{w2} - \alpha^{w1}) + (\beta^{w2} - \beta^{w1})X^{w1} \quad (3)$$

Where Y is the mean of subjective risk perception and X is the mean of regressors. From equation 3, $\beta^{w2}(X^{w2} - X^{w1})$ is the "explained" portion of the gap. It is the subjective risk perception-gap attributable to the differences in mean observable characteristics between wave 1 and wave 2. $(\alpha^{w2} - \alpha^{w1}) + (\beta^{w2} - \beta^{w1})X^{w1}$ is the "unexplained" portion i.e. the differences in constant and coefficient estimates. This is the subjective risk perception disparity that would still remain if wave 2 had the average characteristics of wave 1 persons. The total gap at means between wave 2 and wave 1 is the sum of the observable characteristics (or endowment) portion and returns (or coefficient) portion.

The results of the decomposition points to the significant increase in subjective risk perception from 35.3 in wave 1 to 52.5 in wave 2 (table 11). The estimates of the average slightly differ from that noted in fig (1) because the sample size is lower given the missing values in the household income variable included in the analysis. Nevertheless, the substantive conclusion about increasing subjective risk perceptions remain unchanged. The coefficient or unexplained component, driven mainly by the constant, has contributed to the increase in subjective risk perception between the waves entirely. This can be interpreted as the increased intensity of response rather than a change in the level of any of the factors contributing to subjective risk perception. With increased numbers of infection and deaths reported in July and August (in relation to May and June), the increased fear and subjective risk perception is to be expected. The number of reported infections at the end of June was under 150,000, but July witnessed a sharp hike and, by the end of August the number of infections had risen to over 600,000. The reported daily new infections peaked in July with 14000 cases, while the highest reported new infection in May and June was substantially lower at 1643 and 6945 respectively (Worldometer, 2020). The increased fear across all sections of society is commensurate with the increased infection numbers.

The increase in the people returning to work between the waves has significantly contributed to the increase in subjective risk perception. Returning to employment exposes individuals to closer interaction to others during the course of commute and in the work place environment. It is therefore, not surprising that the endowment effect of employment has positively contributed to increased subjective risk perception in wave 2.

Table 11: Oaxaca-Blinder decomposition of changing Subjective risk perception

VARIABLES	overall	endowments	coefficients	interaction
Age		-0.00533*	-0.00644	0.000728
		(0.00323)	(0.0441)	(0.00498)
Male		5.15e-05	0.0171	-4.43e-05
		(0.000955)	(0.0197)	(0.000822)
Black African		-0.00188	0.0525	0.00196
		(0.00199)	(0.0592)	(0.00261)
Employed		0.0111***	-0.0191	-0.00341
		(0.00394)	(0.0214)	(0.00392)
Years of Schooling		0.00154	0.0348	0.000482
		(0.00161)	(0.0778)	(0.00117)
Per capita household Income		-0.00110	0.0426	-0.000372
		(0.00284)	(0.0539)	(0.00106)
Urban		-0.00191	0.00169	-0.000137
		(0.00233)	(0.0408)	(0.00331)
Urban informal		-0.000716	-0.0126	0.000712
		(0.00156)	(0.00906)	(0.00159)
Government info		-7.75e-05	-0.00377	-5.74e-05
		(0.000556)	(0.00936)	(0.000431)
News info		-0.000209	-0.0218	0.000410
		(0.000607)	(0.0437)	(0.000943)
Health worker info		3.38e-05	-0.00443	0.000395
		(0.000388)	(0.00637)	(0.000740)
Community leader info		9.98e-06	-0.000584	1.20e-05
		(0.000131)	(0.00329)	(0.000162)
Social media info		-5.44e-05	0.00635	-0.000139
		(0.000325)	(0.0100)	(0.000763)
Acquaintance info		-0.00166	-0.000424	8.76e-05
		(0.00193)	(0.00506)	(0.00105)
No information source		8.15e-05	0.000121	-1.01e-05
		(0.000417)	(0.00107)	(0.000103)
Province Dummies		yes	yes	yes
Wave 2	0.525***			
	(0.0161)			

Wave 1	0.353***			
	(0.0145)			
difference	0.171***			
	(0.0216)			
endowments	0.000515			
	(0.00827)			
coefficients	0.172***			
	(0.0217)			
interaction	-0.000830			
	(0.00781)			
Constant			0.108	
			(0.167)	
Observations	5,420	5,420	5,420	5,420

Robust standard errors in parentheses
******* p<0.01, ** p<0.05, * p<0.1

5. Summary and Conclusion

This study undertakes an in-depth look into the socio-economic inequality of behavioural response towards Coronavirus pandemic. The key findings are listed as follows:

- There is a significant increase in subjective risk perception of COVID-19 infection over the months of April and June 2020 in South Africa. While 33% of respondents believed that they were at risk of infection in April, this increased to 50% in June.
- Significant socio-economic inequality in subjective risk perception exists. The subjective risk perception is significantly concentrated among the higher income groups, the educated and older respondents.
- There is an optimism bias among the black Africans, lower income, less educated and younger age groups.
- Increase in people returning to work and increased coefficient effect of income have contributed significantly to increased subjective risk perception over the two periods of study.
- There appears to be an optimism bias among the less affluent categories. This points to the role of socio-economic status in the self-assessed risk of individuals to COVID-19 infection.
- The self-efficacy rate has remained unchanged with 87% of respondents reporting that COVID-19 can be avoided in both survey periods.
- Enhanced behavioral responsiveness is visible with an increase from 92% to 99% of respondents reporting some form of change in behavior as a preventive measure against infection.
- Preventive behavior is evolving over time, the use of face mask has overtaken hand washing as the most utilised preventive measure. Hand washing featured as the second most popular measure in June.
- While there is an increased use of hand sanitisers, and home cleaning as preventive measures against infection in June as compared to April, other measures like social distancing, avoiding close contact, avoiding big groups and staying at home has declined subsequently between the two periods.
- It is clear that with the opening up of the economy and the return of individuals to employment; it has become harder for individuals especially in the lower income categories to observe physical distancing.
- There is significant income and education related inequality between the types of preventive measures adopted.
- Measures such as social distancing, avoiding close contact, use of sanitisers are practiced more by the rich and educated. The low-income respondents are not able to maintain physical distancing measures as the economy opens up.
- There is a pro-poor bias among the respondents who reported news (Radio, TV, newspapers, internet etc.) as their primary source of reliable information. However, no education or age-related differences were found in this regard.
- Respondents reporting no reliable information sources are concentrated among the poor, less educated, older groups.
- Social media as a source of information on COVID-19 is concentrated among the rich, educated and, younger age groups.

- Health workers as a source of information on COVID-19 is concentrated among the less educated and, older age groups.

The above findings of the study have key policy implications in managing the pandemic risk in the country. The study finds that there is significant income, education and age-related differences in the individual response to COVID-19. The findings of the study indicate the need for a targeted policy response to the pandemic. Some key policy response are as follows:

- The optimism bias among the black Africans, young and the less affluent economic groups needs to be addressed to prevent risky behavior.

- Awareness is desirable, but subjective risk perceptions need to be grounded in reality. There is a need to steer the affluent groups away from an over-assessment of risk influenced by social media and social interaction. This is in the interest of maintaining mental health and controlling over-anxiety among these groups.

- The use of face mask has gained popularity across socio-economic groups. Clear messaging on the appropriate use of masks like regular washing of re-usable masks need to be given so that mask use remains effective.

- The use of other complementary preventive measures has waned and need to be re-emphasized. It is recommended that the emphasis on physical distancing be taken up as a complementary measure to the use of face mask.

- Reintroduction of restricted capacity use of taxis will enable physical distancing for the less affluent who are the users of this mode of transport.

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