Investigating the relationship between computer literacy and job vulnerability during the coronavirus pandemic in 2020: Evidence from South Africa

A Research Report submitted in partial fulfilment of the Degree of Master of Commerce (Economic Science) in the School of Economics and Finance,
University of the Witwatersrand

by

Leila Raffee

Student number: 1519705

Supervised by: Professor Volker Schöer

28 June 2022

Research Paper Code: ECON7008A

Word Count: 10760

Abstract

Despite the acceleration of digital adoption in the workplace with the coronavirus pandemic, there have been few studies on how and which workers have adapted to this in South Africa. This study investigates the relationship between computer literacy levels, ICT ownership, and the probability of employment during the coronavirus pandemic in 2020. Using data from Wave 5 of the National Income Dynamics Study and Wave 1 and Wave 2 of the National Income Dynamics Study – Coronavirus Rapid Mobile Survey, this paper compares computer literacy against employment outcomes during the month of April 2020, when South Africa was in a stringent lockdown, and June 2020, when the economy began to open up. This paper restricts its estimations to those employed in February 2020, to observe whether computer literacy and ICT hardware ownership protected their employment during April 2020 and June 2020. The results show that there is considerable variation in computer literacy levels increasing the likelihood of employment in April 2020 and June 2020. Owning a computer and having a post-matric education increased probabilities in April, while computer literacy was not shown to protect employment much during the hard lockdown. As the economy opened up in June and firms began to digitally adopt, computer literacy played a positive, significant role in increasing the likelihood of employment. However, when observing by subgroup analysis, we see that those with a post-matric education did not actually benefit as much as expected from being highly computer literate. Furthermore, while female employment probabilities were generally negative overall, females with a matric benefit most from computer literacy in June, which is in line with Casale and Shepherd (2020) who showed that women saw slightly larger employment improvements compared to men from April to June. In addition, Ranchhod and Daniels (2020b) observed that from April to June, there was an increase in the percentage of individuals with a matric employed, and suggested that less-skilled workers who were employed in February and lost their jobs in April were able to recover in June. This suggests that, in addition to sectors reopening, the adoption of task-based work shifted in this period to being conducted remotely and digitally, and digital platforms being associated with employment creation, which may require less-skilled workers to have some computer literacy skill.

Keywords: employment, computer literacy, ICT, matric, lockdown, South Africa

Contents

List of tables

1. Introduction

The South African government implemented a national lockdown on 26 March 2020 in response to the Covid-19 outbreak which consisted of five lockdown levels. Non-essential industries were closed during this time, while essential industries were allowed to remain operational for the provision of medicine, food items, and necessary services (Department of Co-operative Governance and Traditional Affairs "COGTA", 2020). Individual mobility was also restricted to essential travel only. These measures brought a large share of the already recessionary South African economy to a standstill. From 1 May 2020, South Africa then moved to lockdown level 4 where strict protocols were in place with regards to working conditions (COGTA, 2020b). Economic activity had begun to resume, and firms or employers had to instil remote working where possible, or social distance and minimise face-to-face contact. Lockdown level 3 then began from June to mid-August 2020 (COGTA, 2020c). Here, firms had begun adapting to Covid-19 safety protocols and government regulations. Moderate restrictions were still in place including social distancing, facemasks, sanitisation, temperature checks, and working from home where possible (ibid).

Workers were heavily impacted by these measures with many facing job losses (Spaull et al, 2020). The nature of the pandemic and lockdown measures must be considered when assessing effects on individuals. Due to physical interactions increasing the coronavirus transmission risk, health protocols call for restrictions on mobility and non-essential goods and services. Depending on the circumstances, some were able to adapt to the restrictions and had the technological access and literacy to do so. Digital adoptions have become increasingly important prior to the pandemic to access employment opportunities, skills, and work tasks and this has accelerated with lockdown restrictions across countries (Kudyba, 2020; Naidoo, 2020).

One of the starting points to enter into the digital labour market is computer literacy (Heeks, 2020) Computer literacy allows an individual to access anything from job tasks to creating a resume. In South Africa, there is unequal distribution in who can digitally adopt. A large proportion of the population are not computer literate (Govindasamy, 2013) and are thus closed off to the digital labour market and its opportunities (Matli and Ngoepe, 2020)

There has been much literature on the dire state of unemployment in South Africa in general and during the pandemic (Daniels et al, 2021; De Lannoy, 2020; Bhorat et al, 2016; Bhorat, 2014;). Unemployment in South Africa has been at persistently high levels, with youth unemployment being at 49% in 2019, and worse off are individuals who have not completed high school, are African, and/or women (Naidoo, 2020). While there have been studies on earnings and computer literacy, there have been few on employment outcomes and computer literacy, and much less so in South Africa (Govindasamy, 2013). This makes it crucial to study whether variables such as computer literacy and digital access improve employment outcomes, as the increased demand shift towards digital technologies and its services thereof, may affect employment positively (Naidoo, 2020). It is reasonable to expect that such technology shifts would have also affected employment outcomes during the pandemic. It is important then, to consider whether computer literacy was associated with the likelihood of employment during the lockdown shock in 2020. This paper aims to investigate the relationships between computer literacy and access to information and communication technologies ("ICT") capital (ownership of a cell phone or computer) with reported employment outcomes during the coronavirus pandemic. For workers who were employed in February 2020, this paper estimates employment outcomes reported in April 2020 and June 2020 in the National Income Dynamics Study – Coronavirus Rapid Mobile Survey ("NIDS-CRAM") against reported computer literacy levels and ICT ownership in the 2017 National Income Dynamics Study ("NIDS"). Through subgroup analysis, it will break down which workers were associated with increased employment probabilities from computer literacy, by gender, education, and youth.

The paper is structured as follows: section 2 describes the questions of interest to the study, section 3 presents a literature review, section 4 describes the data and methodology used for analysis, stating limitations, discussing variables, and providing some descriptive statistics, section 5 presents results and discussion of the estimations, and section 6 concludes. Section 7 provides an appendix with regression tables of the subgroup analysis.

2. Research questions

In the context of the coronavirus pandemic and a stringent lockdown in place, this paper estimates whether workers employed during February 2020 benefitted from having computer literacy and access to ICT assets through having higher probabilities of employment during April and June 2020.

(i) Conditional on being employed in February 2020, is there a relationship between computer literacy level and the likelihood of employment during April 2020 and June 2020?

(ii) Is there a relationship between ownership of ICT hardware – either owning a cell phone and/or a computer – with the probability of employment?

(iii) Does the association of computer literacy play a role in the likelihood of employment across individual characteristics of education, gender, and age?

3. Literature review

Computer literacy and labour market outcomes

As Govindasamy (2013) uses the same NIDS variable of computer literacy (from Wave One), this paper adopts his definition. Drawing from Claro et al (2012), Cole and Kelsey (2004), and De le Fuente and Ciccone (2002), Govindasamy defines computer literacy as "the minimum knowledge and skill required to operate a computer to carry out routine tasks and functions in the workplace or in everyday life" (Govindasamy, 2013:9)

International literature, particularly in the Global North, has generally focused on the relationship between computer literacy and earnings (Falck et al 2020, Lane and Conlon 2016, Olsen et al, 2011; Peng and Eunni, 2011; Dolton and Makepeace, 2004; Pabilonia, 2007; Morissette and Drolet, 1998; Kreuger, 1993). Kreuger (1993) uses American Current Population Survey data from 1984 and 1989. Kreuger investigates the relation between job-related computer use and earnings and finds that employees who utilize computers in their work earn a 10 to 15 percent premium. While there has been an establishment of returns to computer use in developed countries, there is limited empirical evidence based on developing countries (Govindasamy, 2013; Oosterbeek and Ponce, 2011; Ng, 2006). In a South African context, Govindasamy (2013) builds on Kreuger (1993) using 2008 NIDS Wave 1 data. With OLS regressions on earnings, computer literacy has a positive relation to higher earnings – working-age adults earn around 30% more per hour if they are computer literate and employed in regular work (not self-employed). Similarly, Yu (2016) uses the first three waves of NIDS data from 2008 to 2012 and finds being computer literate has a significant, positive effect on earnings.

However, there have been even fewer studies on employment outcomes and computer literacy (Non et al, 2021; Lane and Conlon, 2016) and much less so in South Africa (Govindasamy, 2013). Although literature attributes digital skills leading to better employment outcomes (Mbaye et al 2021, Naidoo 2020, Rao 2005), there has been minimal empirical analysis examining the link between employment and computer literacy in South Africa and developing countries. Empirical studies establishing the role of computer literacy in the probability of employment include Non et al (2021) which is based on the Dutch population and Govindasamy (2013) who studies the South African population. Non et al (2021) use a 2012 OECD Survey of Adult Skills which reports digital skills levels and combines this with register data on labour market outcomes from 2012 to 2019 for the Dutch population. The authors find that individuals with basic digital skills at minimum have around a ten percentage points higher employment rate than those who failed a basic digital skill test in 2012 (ibid). In South Africa, Govindasamy (2013) finds that having computer literacy increased the likelihood of employment among the working-age sample of 18 – 65-year-olds. With working-age youth (18 – 25-year-olds), high computer literacy skills increase the chance of employment. While most literature finds the relationship between computer literacy and earnings, given the coronavirus pandemic, the precarious nature of work, and the emphasis to adapt digitally to survive, this paper, drawing from Govindasamy (2013) and Non et al (2021), intends to focus on whether computer literacy was correlated with workers employment during April 2020 and June 2020 for those employed in February 2020.

Another aspect in which computer literacy influences labour market outcomes is aiding in finding a job. In a qualitative study, Matli and Ngoepe (2020) find that people who are not in education, employment, or training (NEET) face barriers to finding work on digital platforms as they are not digitally literate. They find that when people are digitally literate, they are able to search for employment opportunities online – although there are data constraints that setback looking for work online. A consensus was found among participants that with digital skill competency, one can find a job faster, and that there was a shift from the traditional hand delivery towards submitting and accepting job applications online. However, while some are aware of employment opportunities on Google, they do not have the competency or know-how to search for employment. Thinyane et al (2006) found in case studies that when introducing computers to marginalised and semi-marginalised South African communities, interventions that helped individuals learn basic computer skills were used to search for jobs online or improve their CVs. This adds to the importance of computer literacy not only having a relationship to increasing wage earnings and employment but also helping in the steps to finding employment and earnings, with searching for a job.

Computer literacy and ICT hardware ownership

The ownership of ICT assets such as a computer or cell phone has been shown to influence income generation (Diga, 2020; Zoghi and Pabilonia, 2007). Using two panels of the Canadian Workplace and Employee Survey from 1999-2000 and 2001-2002, Zoghi and Pabilonia (2007) find that the average worker who adopts a computer attains a significant immediate return compared to those who did not. Diga (2020) investigates the relationship between information and communication technologies (ICTs) and poverty reduction in South Africa by making a "digital basket" (ibid) from the household's access to ICT. Diga finds that the likelihood of living in a poor household decreased with each additional unit of the digital basket, and tertiary education completed by at least one household member significantly influenced this outcome as well. Diga accounts for a physical basket of ICTs in the household and explains through the 'asset approach' where people have the option to use these assets as resources for work or to generate an income. Diga qualifies ICT devices cell phones and computers under physical capital which can be used for work or income generation.

Lessons for South Africa and findings from the coronavirus pandemic

During the pandemic, differences in workers' education and employment have been highlighted by NIDS-CRAM studies. For the probability of losing a job between February and April 2020, having a tertiary education offered these workers some level of protection, with the likelihood of losing a job being lowest at 28.7%, compared to 42.8% for those with just a matric education and 45.5% with less than a matric education (Ranchhod and Daniels, 2020a). Casale and Posel (2020) also find that with job losses occurring between February and April, African workers, females, and workers with matric education or less than a matric education suffered most. In June, those with a matric were able to regain employment, showing that semi-skilled workers who had lost employment between February and April, were able to recover (Ranchhod and Daniels, 2020b). With this in mind, this paper seeks to assess whether computer literacy and ICT ownership further enhanced employment probabilities during these precarious months.

Davies et al (2021) present how the Covid-19 pandemic has affected firms in sub-Saharan African countries. South Africa was reported to have the highest adoption of digital platform technologies, with formal firms having a higher likelihood of adopting or increasing the use of digital platform technologies than informal firms, and thus they report that digital advancement in developing countries is likely to increase with firm size. In addition to the increased adoption of digital platforms among businesses since the pandemic; the tertiary sector has steadily risen to make up 72% of employment in 2019 from making up 60% of employment in 1994 (Naidoo, 2020). The share of skills in the labour market is changing. A pattern of "skills-biased labour demand" (ibid) is reflected, with the share of high-skilled occupations increasing in primary and secondary sectors. This demand for skills may be translated into the demand for computer literacy. For example, Rao (2005) asserts that people who are computer literate have better chances of getting secretarial or administrative jobs than those who cannot operate computers. With the adoption of firms adopting new technologies, this requires workers' skills to adapt as well and Mabanza (2020) infers that a way of assisting the adult population in South Africa is by providing computer literacy training for them to contribute to the workforce.

With the relationship between computer literacy and employment being established, it is important to consider the lag South Africa faces in its population being able to digitally adopt. In South Africa, and much of low- and middle-income countries, there exists a digital divide within access, use, and competency of digital technologies (Ziphorah, 2011). In its Digital Economy Report, UNCTAD found that in 2013 and 2014 the ICT sector value-added just 2.1 percentage points each respectively, as a share of GDP in South Africa *(*UNCTAD, 2019). While this is significant, it still lags behind the world average ICT sector value-added GDP of 4.5 percentage points (ibid). However, while the ICT sector is concentrated in the use of digital technologies and is generally associated with an advanced level of computer skill, many jobs unrelated to this sector have begun to digitally adopt, for example through digital-platform labour (Naidoo, 2020). Digital-platform labour makes use of platforms based online to outsource work by crowd work, which involves advertising work tasks online to workers on a first-come-first-serve basis (Naidoo, 2020). These work tasks have a wide range, including administrative support, software development, and filling out questionnaires (Naidoo, 2020; Heeks, 2017). Another form of digital-platform labour is through location-based apps which involve transport, delivery services, and household cleaning services (Naidoo, 2020). The digital-platform labour market is estimated to be around 1% of the employed in South Africa (ibid), and this is expected to grow with increased demand for services being offered on digital platforms like food delivery and transportation. This suggests some growth in task-based work shifting towards being conducted remotely and digitally, and digital platforms being associated with employment creation, which may require workers to have some computer literacy. Elvis (2020) concurs with this, suggesting that opportunities can be opened by providing basic, task-based digital literacy for lower-skilled workers in Africa.

Considering the above, the literature suggests that computer literacy may benefit the probability of employment amongst lower-skilled or semi-skilled workers, However, education is still the starting point to accessing these jobs, with computer literacy enhancing labour outcomes. For example, Zoghi and Pabilonia (2007) find that there are differences in benefits of adopting a computer between different types of workers – less-educated and lower-skilled workers do not earn wage premiums while higher educated and higher-skilled workers earn high premiums for computer adoption. This is important as one must consider the heterogeneity in workers' education, and whether computer literacy will be of benefit across these differences. Unskilled and uneducated workers may not necessarily have increased employment probabilities as the task content of jobs available to them may not require a high level of know-how when it comes to computers and digital platforms; with Govindasamy (2013) showing, when controlling for education with computer literacy, that individuals with no secondary education completed have no significance in their increased likelihood of employment. On the other hand, the author finds that those with a matric education or post-matric education have significant positive correlations with employment (ibid). Non et al (2021) found that individuals with low digital skills generally have lower literacy and numeracy scores and may not necessarily have a lower likelihood of employment. For those who have little to no skills then, a marginal increase in digital literacy skills may not lead to better job outcomes, however, those acquiring digital skills to those with some skill level may yield better employment outcomes (ibid). Gattiker (1995) explains that computer skills will benefit semi-skilled employee returns when added to the individual's already existing skills base. Traditional human capital in the form of school qualifications is still the starting point to increasing job prospects with the returns to schooling well established (Mincer,1970). Educated workers, who do not necessarily have to be highly educated, may have enhanced employment prospects with the addition of computer literacy.

This digital divide and lag in the ICT sector are postulated in the majority of South Africans whose job characteristics do not afford them to work remotely. Ranchod and Daniels (2020b) found that only 15% of South African workers employed in June 2020 could work from home, and this was skewed to those with some form of tertiary education, whites, and older individuals. Similarly, Benhura and Magejo (2021) show that the demographics of workers such as their age, race, gender, geographic location, marital status, dwelling type, and geographic location as well as the type of work and occupation significantly influence whether a worker can work from home or not. They find the probability that a South African worker cannot work from home is higher among men than women, and higher in black Africans, Coloureds, and Indians/Asians than in whites showing the persistent racial and spatial disparities in South Africa (ibid). The authors also note that controlling for access to ICT at home as well as employment tasks performed at home are important factors when considering who can work from home or not. In light of this, this paper intends to be a building block in determining who can work from home or not, by examining relationships into whether being computer literate increases the likelihood of employment which may play a role in determining who can work from home or not.

The literature has described the returns to computer literacy, ICT hardware, education, and demographics influencing labour market returns. It has also discussed the acceleration of digital adoption amidst the coronavirus pandemic, and subsequent job outcome findings in South Africa. Based on this, and considering covid-19, this paper explores the relationships between computer literacy and job vulnerability during the 2020 lockdown.

4. Data and Methodology

To explore whether computer literacy and ICT ownership had any association with workers who were employed in February 2020 and their probability of employment in April 2020 and March 2020, this study uses data from wave 1 and wave 2 of the National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM) against as well as wave 5 (2017) of the National Income Dynamics Study (NIDS). NIDS and NIDS-CRAM are conducted by the Southern Africa Labour and Development Research Unit (SALDRU) situated at the University of Cape Town's School of Economics.

This research involved an empirical cross-sectional study that sought to measure, describe, and analyse patterns of education, computer literacy, ICT ownership, and the likelihood of employment during the coronavirus pandemic. This paper follows Govindasamy (2013) who estimated probit regressions on computer literacy and employment probabilities using NIDS Wave 1 (2008) data. For this study, the adult data collected in NIDS Wave 5 was merged with Wave 1 and Wave 2 of NIDS-CRAM data. Individuals from NIDS-CRAM can be matched with their responses from NIDS Wave 5 through their unique identifier (pid). The sample is restricted to those who reported computer literacy levels as well as computer and cell phone ownership in 2017. It was then restricted to those who were employed in February 2020, over the age of 18, and subsequent covariates.

To estimate whether the likelihood of employment has any association with an individual's computer literacy and access to ICT hardware, this study restricts its sample to those only employed in February 2020. This is done as the stringent lockdown level 1 was deployed from March to April, and this lockdown acts as an exogenous shock to those who were employed in February. Those who were employed in February and then unemployed in April, were likely to lose their jobs due to the exogenous shock of lockdown, and less likely by other factors than those who were unemployed in February. By restricting the sample then to those only employed in February, it allows analysis of whether computer literacy and access to ICT hardware had any correlation with increasing the probability of employment, in the face of an exogenous shock of the Covid-19 lockdown. Of course, there are limitations to this, for example, the analysis does not extend to those unemployed in February, and whether their computer literacy levels had any correlations with increasing their probabilities of a job search or employment probabilities during the lockdown.

To observe whether computer literacy had any correlation with the probability of employment before the National State of Disaster, a probit regression is run with the same variables for the subsequent regressions for April and June. A weakly significant association is shown between basic computer literacy and the probability of employment in February. This paper attempts to dissect this association further by restricting the sample to those only employed in February and observing their subsequent correlations with computer literacy and employment likelihood in the event of the exogenous shock of lockdown.

Table 1 – Probit regression of employment probabilities in February, prior to lockdown

	Employment in February 2020
High computer literacy	0.0479
	(0.0353)
Basic computer literacy	0.0474*
	(0.0257)
Ownership of a computer	0.0149
	(0.0377)
Ownership of a cellphone	0.0963***
	(0.0288)
Has a matric education	0.0868***
	(0.0261)
Has a post-matric education	0.174***
	(0.0308)
Aged 18 to 24	0.0333
	(0.0381)
Aged 25 to 34	0.256***

	(0.0328)
Aged 35 to 44	0.348***
	(0.0306)
Aged 45 to 54	0.354***
	(0.0327)
Female	-0.130***
	(0.0203)
African	-0.0434
	(0.0478)
Coloured	0.00373
	(0.0610)
Indian	-0.141
	(0.0948)
Observations	5,139

Source: NIDS-CRAM Wave 1 and NIDS Wave 5 (2017); own calculations; marginal effects reported
Note: Data is weighted, Standard errors in parentheses
Omitted variables: No computer literacy, Less than matric, Aged 55 and over, Male, White
**** p<0.01, ** p<0.05, * p<0.1*

It is important to keep in mind that employment outcome variables during the pandemic were available for February 2020, April 2020, and June 2020. However, the NIDS-CRAM survey is a shorter survey with questions centred around the national lockdown and covid-19, and as such, the survey did not capture questions to the full NIDS extent (Ingle et al, 2021). This paper therefore makes use of computer literacy levels reported in 2017 as well as responses to computer and cell phone ownership in 2017. This paper admits that this is limiting, as computer literacy levels are subject to increasing (or decreasing) in quality; and furthermore, if individuals still had access to their ICT assets reported in 2017 in 2020 (or possibly did not, and attained them since 2017). However, these reported outcomes in 2017 do give an indication of whether an individual has been exposed to computer literacy and ICT assets. While this is not perfect, it is a useful starting point in determining if computer literacy and ICT hardware influence employment probabilities. Non et al (2021) faced similar limitations where their digital skills and background variables for the Dutch population were only available for 2012, a single point in time (as in this paper) and as such are not time-variant. They cannot estimate a fixed-effects panel model and a random-effects panel model could not be estimated as the standard errors need correction for skills are measured in plausible values. Thus, they estimate separate logit regressions for each year (2012-2018), to give unbiased standard errors. Given the scarcity of data on computer literacy levels for South Africans, this paper is a building block to see how computer literacy went in hand with the digital acceleration experienced during the covid-19 pandemic in 2020 through investigating correlations between computer literacy and the probability of employment.

This study predicted that there would be a higher likelihood of employment over the lockdown months for individuals with higher computer literacy and ICT ownership, however, taking into account the findings of Govindasamy (2013) and NIDS-CRAM findings from Ranchhod and Daniels (2020a) and Casale and Posel (2020), this would be restricted to those with a matric or post-matric education. The study predicts that those with less than a matric education would be unlikely to benefit from computer literacy and would not result in higher employment probabilities for these individuals.

In section 5, probit regressions are used to establish whether there is a positive association between computer literacy and employment. Following a similar model presented by Govindasamy (2013), these regressions are begun by overall computer literacy and then disaggregated by high computer literacy and basic computer literacy. Socio-economic factors are then controlled for which include education, age, gender, and race. Drawing from Diga (2020), ownership of ICT hardware including ownership of a computer and ownership of a cell phone is then included. These covariates are added to observe how the relationship between computer literacy and the likelihood of employment changes. Furthermore, subgroup analysis is then done, disaggregating by education (less than matric, matric, post-matric), gender (female, male), and youth (18 to 35-year-olds, and older than 35 years); as well as education within gender, and education within youth.

To estimate the relation between computer literacy and employment outcomes, a probit model will be used drawing from the approach of Govindasamy (2013), with employment (holding a job) as the dichotomous dependent variable; conditional on being employed in February 2020. Following Govindasamy (2013), Katchova, (2020), and Gujarati and Porter (2009), the probit model is specified as:

$$\Pr(y_i = 1) = x_i\beta + u_i \qquad (1)$$

Where y_i is a binary categorical variable, taking the value of 1 if the individual *i* is employed, and 0 otherwise. The model follows a standard cumulative normal distribution Φ. X_i is a vector of observed characteristics for individual i which includes education, race, gender, age, computer ownership and cell phone ownership as well as a dummy variable representing individual i's overall computer literacy taking the value of 1 if the individual is computer literate and 0 otherwise. This is further disaggregated in additional models and subgroup analysis by a high computer literacy variable and basic computer literacy variable. We estimate equation (1) separately for each month an employment outcome was reported (April 2020 and June 2020) for all individuals employed in February 2020. Regression estimations are weighted using new-scaled person weights. As only the signs, and not magnitudes of the coefficients of a probit model are interpreted (Katchova, 2020; Gujarati and Porter, 2009), we report the marginal effects of the covariates to evaluate the extent to which our covariates influence a worker's likelihood of employment in April 2020 and June 2020 whereby:

$$\frac{\Delta P\ (y=1)}{\Delta X_i} = \ \phi(X\beta) * \beta_i \qquad (2)$$

Where ϕ is the probability density function of the normal distribution. This estimation is limiting in that it does not account for the unobserved heterogeneity of worker's who reported employment in February 2020, which may further influence their likelihood of employment. This paper emphasises that these estimations do not seek to claim causality on the observed patterns but provide indications of what characteristics are associated with likelihood of employment during the pandemic and where these associations may be in line with other findings in the literature.

4.1. Limitations

This paper is not without limitations. First, as Govindasamy (2013) highlights, the NIDS data on computer literacy levels is self-reported by individuals, and one cannot determine if individuals have provided accurate levels and as such is prone to measurement error. Govindasamy (2013) encounters the same problem, and notes from (Bunz et al, 2007) that self-reported data can result in individuals overestimating their skills due to social desirability. This results in the effect of computer literacy estimations having an upward bias, while the relationship between computer literacy and employment has a downward bias (ibid).

Second, as mentioned earlier, this paper makes use of computer literacy levels reported in 2017 as well as responses to computer and cell phone ownership in 2017. Due to the nature of the NIDS-CRAM survey having to be captured quickly and under constrained circumstances during the coronavirus pandemic, the survey did not capture questions to the full NIDS extent. Thus, the last reported computer literacy levels and ownership of ICT hardware we have for individuals are reported in 2017 in Wave 5 of NIDS. Computer literacy levels are subject to increasing (or decreasing) in quality; furthermore, if individuals still had access to their ICT assets reported in 2017 in 2020 (or possibly did not and attained them since 2017).

Third, because the computer literacy levels were available for 2017 and not during the time of interest (2020), it is not time-variant, and cannot observe changes over time with a fixed-effects panel model (unless using previous waves of NIDS data only).

Fourth, the estimations do not control for unobservable factors, for example, innate ability (Govindasamy, 2013) – where, for example, individuals could learn computer skills easily and adapt to the changing nature of employment during the pandemic. Importantly many factors make up the probability of employment which cannot be captured in this paper. The paper does not provide occupations, employment sectors, or formal and informal workers in its estimations. While Non et al (2021) and Govindasamy (2013) do not specify occupation or sector in their estimations of employment, these are relevant variables to consider as the importance placed on computer literacy varies across occupations and sectors. Indeed, Non et al (2021) propose their research be extended in the future to observe how the value of digital skills fluctuates dependent on the sector and its level of digitalisation, and it would be interesting to do this in the context of South Africa as well. However, sector codes were unavailable for the Wave 1 of NIDS-CRAM data and were only captured from Wave 2 onwards. Including occupations reduced the paper's sample substantially, due to high levels of missing occupations on an already restricted sample. However, given the importance of occupations going hand in hand with computer literacy, the paper provides occupation transitions for results of interest within the subgroup estimations.

Fifth, this paper estimates probabilities conditional that individuals were employed in February 2020. This leads to sample selection bias as those employed in February 2020 may not be a random sample of those in employment, and those in employment may not be randomised individuals' part of the labour force (Govindasamy, 2013).

Sixth, very importantly, there is the problem of endogeneity, it cannot determine whether workers acquired their skills on the job (Govindasamy, 2013) – thus making computer skills an outcome of employment, and not employment an outcome of computer literacy skill. This is further exacerbated as computer literacy levels used in this paper were captured in 2017. Probit models do not account for endogeneity, and endogeneity may come about from the factors mentioned above, including measurement error and omitted variable bias (Gujarati and Porter, 2009).

4.2. Discussion of variables

The key individual characteristics of the estimations were dummy variables for computer literacy, which included overall computer literacy, and then high computer literacy and basic computer literacy. This was derived from the following question in the NIDS Wave 5 (2017) survey:

H29 *edlitcomp*	Are you computer literate?	Yes highly literate	1		
		Yes basic use	2		
		No	3		

Source: SALDRU, 2017. "National Income Dynamics Study Wave 5 2017 Adult (15+) Questionnaire". Question H29, p39.

As noted in the limitations, this computer literacy level was self-reported, and as such is prone to measurement error. Govindasamy (2013), following Casale and Posel (2011) attempts to address this by having a strict definition of computer literacy which requires individuals to be highly computer literate, and a weaker definition of basic use. This paper follows this, first by employing the broad definition which encompasses highly literate and basic use responses into an "overall computer literacy" dummy variable and thereafter in subgroup analysis, employs the strict separations between a highly computer literate dummy variable and a basic computer literacy dummy variable.

Adopting part of Govindasamy's (2013) probit regression model, a series of binary variables were included to capture workers' education status, gender, age category, and race. Ownership of ICT hardware was also included in the model drawing from Diga (2020) as digital technology was emphasised during the hard lockdown period. Education was captured in three categories, namely less than matric, matric, and post-matric. An individual's education was categorised as less than matric if they had no matric completed (this was omitted), matric (South African Grade 12), and post-matric education which includes any diplomas, degrees, or certificates obtained after a matric qualification.

Gender was a dummy variable, capturing 1 as female, and 0 as male. Race dummy variables were created for African, Coloured, Indian, and White population groups respectively, with White as the omitted race category. Age categories were created as binary variables for where categories entailed: 18 to 24-year-olds; 25 to 34-year-olds; 35 to 44-year-olds; and 55-year-olds and above. Following the National Youth Commission Act (1996) which categorises youth as 14 to 35 years old; as our data was restricted to 18 years and above, this paper categorised youth as 18 to 35-year-olds. A youth binary variable was created for sub-group analysis, where youth were categorised as being aged 18 to 35-year-olds holding a value of 1 while older workers (non-youth) were over 35-years-old and hold a value of 0.

Access to ICT hardware was captured through reported answers from the NIDS Wave 5 questionnaire. Computer ownership was captured as 1 if the individual owned a computer and 0 if not; similarly, for cell phone ownership, the dummy variable was recorded as 1 if the individual owned a cell phone and 0 otherwise.

Lastly, the outcome variable, employed in April and employed in June was made dichotomous and given a value of 1 if employed and 0 if unemployed. Employment status for April and June were derived by SALDRU and NIDS-CRAM, where individuals are classified as *employed*, or *unemployed-strict/searching*, or *unemployed- discouraged/non-searching*, or *not economically active*. The employment status for February was derived from various questions in the labour market section of the NIDS-CRAM questionnaire. This included labour market questions such as: "*In month x, did you have any kind of job?*"; "*In month x, did you work for any profit or pay, even if just for an hour or a small amount?*"; and "*In month x, did you do any kind of business such as selling things - big or small - even if only for one hour?*" The employment status for February was used to restrict the sample to those employed in February so that the analysis could observe whether workers who were employed in February showed a relationship between their computer literacy level and employment likelihood in April and June.

4.3. Descriptive statistics

The following section presents descriptive statistics for the dependent variables of interest (April employment; June employment) alongside the independent variables of the study. A descriptive relationship between reported levels of computer literacy and education is reported for April and June respectively. These are conditional on workers being employed in February 2020. The summary statistics are then presented by each education level for the respective months.

Table 2 describes the relationship between computer literacy levels and employment in April and June by education level respectively. For April, there seems to be a relationship between computer literacy and employment according to the worker's educational level. Dissecting workers with a post-matric education who remained employed in April shows that 60% of those employed in April had a high level of computer literacy and this remains steady through to June. Only 10.7% who had a post-matric qualification and no computer literacy remained employed in April. This suggests that computer literacy was associated with some level of employment probability in the hardest lockdown stage. However, the effects were still detrimental even with a post-matric qualification and high computer literacy. Among the workers with a post-matric in April who lost their jobs, 43.7 had high computer literacy and 47.1 had basic computer literacy. Interestingly, unemployment from April to June for those with a post-matric and no computer literacy increased from 9% to 14%. Of workers with a matric qualification who had lost their jobs in April, 40% comprised those with no computer literacy, compared to 28% with high computer literacy. For those with less than a matric, as mentioned in the literature, computer literacy does not seem to offer much benefit. Those who had lost their job with no computer literacy made up 64.1%, however similarly those who remained employed in April made up 66.2%. In June, we see some interesting fluctuations among workers with matric. While those with less than matric do not tend to fluctuate, those with matric seem to show the significance of computer literacy in job recovery. Among those not employed in June, for those with a matric, we see around 45% have no computer literacy, increasing by 5% from April. The proportion of those not employed with matric and high computer literacy has decreased from 28% in April to 22% in June, around 6%. Among those employed in June with a matric, we see that those with no computer literacy have decreased to 28%, and those with a high computer literacy level have increased to 35%. However, the paper notes that given the relatively small sample size and corresponding large standard errors, caution should be exercised about drawing inferences from relatively small changes.

Table 2: Computer literacy variations in employment in April and June, by education level.

	No computer literacy	Basic computer literacy	High computer literacy		No computer literacy	Basic computer literacy	High computer literacy
Less than matric				*Less than matric*			
Not employed in April	64.15 (4.83)	32.75 (4.87)	3.091 (0.98)	Not employed in June	64.79 (4.99)	32.74 (5.06)	2.479 (0.75)
Employed in April	66.2 (2.96)	27.77 (2.89)	6.03 (1.40)	Employed in June	65.67 (2.97)	27.41 (2.74)	6.92 (1.57)
Matric				*Matric*			
Not employed in April	40.00 (5.21)	32.03 (5.16)	27.97 (4.78)	Not employed in June	44.57 (5.22)	33.63 (6.11)	21.8 (4.88)
Employed in April	30.35 (3.82)	37.55 (3.52)	32.1 (3.72)	Employed in June	28.31 (3.74)	36.29 (3.27)	35.4 (3.66)

Post-matric				*Post-matric*			
Not employed in April	9.146 (2.78)	47.13 (5.88)	43.72 (5.84)	Not employed in June	13.95 (3.69)	39.76 (5.93)	46.29 (6.30)
Employed in April	10.66 (1.81)	29.37 (3.21)	59.97 (3.363)	Employed in June	9.41 (1.69)	30.39 (3.30)	60.2 (3.33)

Source: own calculations using NIDS Wave 5 and NIDS-CRAM Wave 1 and Wave 2 data. Notes: First row as row percentages for each respective month, second row has linearised standard errors in brackets. Data is weighted to represent population estimates.

Table 3 reports the weighted means, standard errors, and confidence intervals at the 95% level for the entire sample, by education category and conditional that individuals were employed in February 2020. Most variables will reflect similar values over April and June as they are time-invariant, however for completeness the summary statistics for each variable in each month are reported in Table 23 in the Appendix. There are considerable differences in employment by education level, with post-matric workers having the highest mean of over 80% for both April and June. For workers with matric, this decreases by approximately 10%, fluctuating around 70% for April and June. For workers without a matric, employment in June was the lowest out of the groups at 63%. This reflects Casale and Shepherd's (2020) findings that those without a matric education were most affected by job losses over this period.

Those with less than a matric also have the highest means of no computer literacy, at 65%, and the least access to computers at 6%. Interestingly, all groups have high levels of cell phone ownership, at around 90%. 15% of those with a matric have had computer ownership showing a huge jump to 46% when it comes to those with post-matric education. Those with a post-matric education also report the highest computer literacy rates at 54% for high computer literacy and 32% for basic computer literacy. Computer literacy is evenly dispersed among those with a matric education: 31% have high computer literacy, 36% have basic computer literacy and 33% have no computer literacy. The highest average white population are those with a post-matric, while the highest African population are those with no matric at 84% reflecting the inequalities that are still within South Africa. The youth (18 to 35-year-olds) population has the highest mean within the matric category. These descriptive statistics highlight the differences among workers employed in February 2020 by education, illustrating how the exogenous shock of lockdown has affected workers' employment by computer literacy and education. The differences in education have reflected computer literacy and computer ownership characteristics, as well as demographic characteristics reflective of South Africa. Considering this, the paper then investigates the relations of computer literacy and employment probabilities further using probit regressions and subsequent subgroup analysis.

Table 3 - Summary statistics by worker's education

Variable	Mean	Std. Err.	[95% Conf	. Interval]
Less than matric n = 1200				
Employed in April	.6989426	.0132476	.6729516	.7249336
Employed in June	.6357632	.0138973	.6084975	.6630289
High computer literacy	.0515441	.0063854	.0390163	.0640719
Basic computer literacy	.2970384	.0131966	.2711474	.3229294
No computer literacy*	.6514175	.0137617	.6244177	.6784172
Computer ownership	.0614522	.0069357	.0478449	.0750596
Cell phone ownership	.8919875	.0089641	.8744005	.9095746
African	.840256	.0105806	.8194976	.8610145
Coloured	.1293812	.0096926	.1103649	.1483975
Indian	.009621	.002819	.0040902	.0151517
White*	.0207418	.0041159	.0126667	.0288169
Youth (18 to 35-year-olds)	.3267548	.0135453	.3001797	.3533299
Aged 18 to 24	.0860495	.0080989	.0701599	.1019391
Aged 25 to 34	.2407053	.0123463	.2164824	.2649281
Aged 35 to 44	.3188493	.0134588	.292444	.3452546
Aged 45 to 54	.2089235	.0117407	.1858889	.231958
Aged 55 and over	.1454724*	.0101823	.1254954	.1654494
Female	.4679863	.0144101	.4397144	.4962582
Matric n=613				
Employed in April	.6907861	.0186669	.6541274	.7274449
Employed in June	.7059796	.0184166	.6698123	.742147
High computer literacy	.3132825	.0187491	.276462	.350103
Basic computer literacy	.3571137	.0193684	.319077	.3951503
No computer literacy*	.3296038	.0190014	.2922879	.3669197
Computer ownership	.1544243	.0146069	.1257386	.1831101
Cell phone ownership	.913747	.0113481	.891461	.936033
African	.817889	.0156005	.7872519	.8485261
Coloured	.0990973	.012078	.075378	.1228166
Indian	.0280089	.0066697	.0149107	.0411071
White*	.0550048	.0092159	.0369061	.0731035
Youth (18 to 35-year-olds)	.4873377	.0202048	.4476585	.5270169
Aged 18 to 24	.1520228	.0145135	.1235205	.180525
Aged 25 to 34	.335315	.0190835	.2978378	.3727921
Aged 35 to 44	.2730604	.0180095	.2376924	.3084284
Aged 45 to 54	.1902632	.0158662	.1591044	.2214221
Aged 55 and over*	.0493387	.0087545	.0321462	.0665312
Female	.4214928	.0199606	.3822932	.4606924
Post-matric n=685				

Employed in April	.8365466	.0141492	.8087654	.8643277
Employed in June	.8153805	.0148351	.7862527	.8445083
High computer literacy	.5749399	.018902	.5378269	.6120528
Basic computer literacy	.323147	.0178821	.2880366	.3582575
No computer literacy*	.1019131	.0115677	.0792007	.1246255
Computer ownership	.4620736	.0190629	.4246448	.4995024
Cell phone ownership	.9419586	.0089404	.9244046	.9595125
African	.6929823	.0176366	.658354	.7276107
Coloured	.052299	.0085124	.0355854	.0690127
Indian	.0299215	.0065143	.0171311	.0427119
White*	.2247972	.0159615	.1934576	.2561367
Youth (18 to 35-year-olds)	.4570222	.0190472	.4196241	.4944202
Aged 18 to 24	.0942295	.0111705	.0722968	.1161622
Aged 25 to 34	.3627926	.0183841	.3266966	.3988886
Aged 35 to 44	.2509996	.0165787	.2184484	.2835508
Aged 45 to 54	.1757089	.0145515	.1471379	.20428
Aged 55 and over*	.1162693	.0122564	.0922045	.1403341
Female	.5134765	.019111	.4759531	.5509998

*Source: own calculations using NIDS Wave 5 and NIDS-CRAM Wave 1 and Wave 2 data. Data is weighted to represent population estimates. *Omitted variables in the regressions.*

5. Results and discussion

Table 4 shows the results for the probit regression estimates for employment in April 2020 and employment in June 2020 conditional on those employed in February 2020, with marginal effects reported to interpret magnitudes. Five regressions are run for each month. Regression I show the association between overall computer literacy and employment in April 2020, and June 2020 respectively, without controlling for other variables. Regression II considers the changes in overall computer literacy and employment once education is added. Education is categorised by those with a post-matric qualification, those with a matric qualification only, and those with less than a matric (omitted). Regression III includes demographic variables age, race, and gender. Regression IV includes ICT assets of owning a computer and/or owning a cell phone. Regression V includes the same variables as regression IV but differentiates computer literacy by high computer literacy and basic computer literacy.

In the first regression of Table 4 for April 2020, we see a significant positive association between overall computer literacy and the probability of employment. However, as covariates are added in further regressions, computer literacy becomes insignificant even when it is at a high level. Interestingly, ownership of a computer had a significantly positive correlation with employment likelihood, suggesting that during the hard lockdown, it was not computer literacy associated as much as access to digital capital, when keeping a positive employment probability in April, from being employed in February. Unsurprisingly, having a post-matric qualification was consistently significantly positive in the probability of being employed in April, compared to those with just a matric or no matric. Gender also significantly affected the likelihood of being employed in April, with females having a lower probability of employment around 9% in April.

Turning to regression results for June, where lockdown began easing and firms began opening up as well as implementing digital platform adoptions such as Zoom meetings on a higher level, we see that high computer literacy becomes significantly correlated with the likelihood of employment by 10% for June, while just having basic computer literacy remained insignificant. Post-matric education remained positively significant on the likelihood of employment in June. Post-matric education going hand-in-hand with computer literacy in increasing the likelihood of employment in June correlates with formal firms in South Africa being 53% more likely to start or expand the use of digital platforms when adjusting to Covid-19 business conditions Davies et al (2021). The authors found that in contrast, informal firms adapting to digital technologies amid the pandemic were less widespread, with the likelihood probability of starting or expanding digital platforms being 38% in South Africa (ibid). Workers with a post-matric education are more likely to work in a formal firm; compared to those with less than a matric and Amra et al (2013) find that in the informal sector, 70% of workers employed have less than a matric education while only 4% have a post-matric education. Furthermore, Benhura and Magejo (2020) find that from April to June, informal workers suffered higher rates of job loss compared with formal workers. However, age played the most significant role in increasing the probability of employment with 35 to 44-year-olds saw a 13% increase in their probability of employment and 45 to 54-year-olds being associated with a near 16% increase in their likelihood of employment. On the other hand, youth in the 18 to 24-year-old category saw a significantly negative association with employment. Race had a strong negative correlation to the likelihood of employment in June, with Africans experiencing a 19% decrease in their employment probabilities. There remains a negative association between females and their employment probability, as Govindasamy (2013) found using NIDS Wave 1 data. However, in June, females' negative relation is of a less magnitude than compared with April, suggesting some recovery. In a gendered employment analysis, Casale and Shepherd (2020) show with NIDS-CRAM data that women did see a slight increase in employment between April and June 2020.

Table 4 - Probit regression analysis of the probability of being employed in April 2020 and the probability of being employed in June 2020, conditional on workers being employed in February 2020.

	(I) April 2020	(II) April 2020	(III) April 2020	(IV) April 2020	(V) April 2020	(I) June 2020	(II) June 2020	(III) June 2020	(IV) June 2020	(V) June 2020
Computer literacy variables										
Overall computer literacy	0.0633**	0.0138	0.00945	-0.0113		0.113***	0.0516	0.0372	0.0294	
	(0.0265)	(0.0307)	(0.0298)	(0.0300)		(0.0278)	(0.0330)	(0.0307)	(0.0314)	
High computer literacy					0.0347					0.0973**
					(0.0417)					(0.0422)
Basic computer literacy					-0.0262					0.00846
					(0.0310)					(0.0327)
ICT hardware variables										
Ownership of a computer				0.156***	0.141***				0.0534	0.0305
				(0.0389)	(0.0398)				(0.0437)	(0.0447)
Ownership of a cell phone				0.00303	0.00156				0.00374	0.000787
				(0.0394)	(0.0395)				(0.0394)	(0.0392)
Education variables										
Has a matric education		-0.0117	-0.00290	-0.00869	-0.0177		0.0488	0.0591*	0.0578*	0.0449
		(0.0349)	(0.0339)	(0.0334)	(0.0329)		(0.0375)	(0.0351)	(0.0351)	(0.0346)
Has a post-matric education		0.138***	0.143***	0.112***	0.0973***		0.155***	0.141***	0.130***	0.107***
		(0.0356)	(0.0344)	(0.0345)	(0.0353)		(0.0387)	(0.0356)	(0.0360)	(0.0364)
Demographic variables										
Aged 18 to 24			-0.0811	-0.0642	-0.0643			-0.141**	-0.135**	-0.137**
			(0.0584)	(0.0581)	(0.0579)			(0.0598)	(0.0605)	(0.0601)
			0.165	0.270	0.267			0.0183	0.0262	0.0226
Aged 25 to 34			-0.00792	0.00220	-0.00425			0.0538	0.0575	0.0465
			(0.0482)	(0.0481)	(0.0480)			(0.0496)	(0.0496)	(0.0484)
			0.869	0.964	0.930			0.278	0.246	0.337
Aged 35 to 44			0.0593	0.0520	0.0500			0.137***	0.135***	0.131***
			(0.0474)	(0.0469)	(0.0467)			(0.0483)	(0.0481)	(0.0470)
			0.211	0.268	0.284			0.00445	0.00486	0.00547
Aged 45 to 54			0.0321	0.0284	0.0273			0.162***	0.161***	0.158***
			(0.0519)	(0.0516)	(0.0514)			(0.0517)	(0.0515)	(0.0505)
			0.536	0.581	0.595			0.00166	0.00179	0.00179
Female			-0.0988***	-0.0899***	-0.0917***			-0.0662**	-0.0633**	-0.0654**
			(0.0252)	(0.0251)	(0.0251)			(0.0264)	(0.0266)	(0.0265)
African			-0.0693	-6.18e-05	0.00435			-0.216***	-0.193***	-0.191***
			(0.0562)	(0.0590)	(0.0586)			(0.0586)	(0.0623)	(0.0614)
Coloured			-0.0163	0.0556	0.0594			-0.114	-0.0902	-0.0892
			(0.0766)	(0.0778)	(0.0775)			(0.0780)	(0.0799)	(0.0793)
Indian			-0.125	-0.0880	-0.0913			0.00699	0.0191	0.0114
			(0.111)	(0.107)	(0.105)			(0.112)	(0.114)	(0.115)
Observations	2,498	2,498	2,498	2,498	2,498	2,498	2,498	2,498	2,498	2,498

Source: NIDS-CRAM Wave 1 and NIDS Wave 5 (2017); own calculations
Note: Data is weighted, Standard errors in parentheses
Omitted variables: No computer literacy, Less than matric, Aged 55 and over, Male, White
**** p<0.01, ** p<0.05, * p<0.1*

These regressions point to some interesting associations during the months of lockdown, and this paper breaks these associations down through subgroup analysis where regressions are restricted by education, gender, and youth categories. These are then further distinguished by gender within education and youth within education, to see where exactly computer literacy and ownership of ICT assets correlated with the probability of employment during the pandemic within these sub-populations. Found in the Appendix, Table 5 shows a probit regression analysis of the probability of being employed in April 2020, and Table 6 shows the probability of being employed in June 2020 by education (less than matric, matric, no matric); Table 7 and Table 8 shows the probability of being employed in these April and June respectively by gender (female, male); Table 9 and Table 10 shows the probability of being employed in April and in June respectively, by youth (18 to 35-year-olds) and non-youth (over 35-year-olds). Tables 11-16 show the probabilities of being employed in April by gender and matric categories. Lastly, Tables 17-22 show the probabilities of being employed during these months by youth and non-youth and their respective education.

Education levels

Taking a closer look at April's employment probabilities by education in Table 5, it is clear that computer literacy was not significantly correlated for those with less than matric and those with matric during the hard lockdown. Those with a post-matric and just basic computer literacy decreased their probabilities of employment significantly in April. This is postulated again in June (Table 6), where high computer literacy among the post-matric population shows a positive relationship but is insignificant. In Table 13 and Table 14's analysis, we see that computer literacy remains insignificant among the post-matric population with males and females, for April and June.

Computer literacy did not seem to help those with less than a matric in April, but in June (Table 8), those with less than a matric education with high computer literacy are significantly correlated with increasing their likelihood of employment by around 19.7%. However, Africans with less than a matric have a significantly lower chance of employment compared to their white counterparts. Africans with less than matric are nearly 40% less likely to be employed in June, showing that racial disparities still loom over South African employment (Ranchhod and Daniels, 2020a; Govindasamy, 2013; Lekena, 2006).

For those with a matric, computer literacy was positive but insignificant in April (Table 7). However, in June (Table 8), basic computer literacy and high computer literacy both show significant positive associations with the probability of employment. Those with high computer literacy are more likely to be employed by 15.7% while those with basic computer literacy by 12.4%. While females were generally shown to have significant negative employment probabilities during the lockdown and in previous regressions shown, of interest is that females with a matric, as shown in Table 17, benefit the most from computer literacy at both levels in June. High computer literacy is weakly significant with the probability of employment with females with matric, however, those with basic computer literacy show a consistently strong positive association with their employment likelihood increasing by 26%. This association is interesting within the context of NIDS-CRAM studies conducted over this period, with Casale and Shepherd (2020) showing that women saw a slightly larger increase in employment gains compared to men from April to June. In addition to this, Ranchhod and Daniels (2020b) observed that from April to June 2020, there was an increase in the percentage of matriculants employed and suggested that less-skilled workers who were employed in February and lost their jobs in April were able to recover in June. Furthermore, this may suggest the growth and acceleration of the digital-platform labour market which Naidoo (2020) suggests is expected to grow with increased demand for services being offered on digital platforms like food delivery and transportation. This suggests some growth in task-based work shifting towards being conducted remotely and digitally, and digital platforms being associated with employment creation, which may require workers to have some computer literacy. Elvis (2020) concurs with this suggesting that opportunities can be opened by providing basic, task-based digital literacy for less-skilled workers in Africa.

To further explore this outlying association, the paper analyses occupation transitions for females with matric. It is limited, as mentioned previously, occupation variables had a high amount of missing data, and February did not record current occupations or previous occupations for individuals who were employed and unemployed. Nonetheless, some assumptions are made to observe the occupation churn within this subgroup. As the sample is restricted to those in February, the assumption is made that if the individual was still employed in April, their occupation remained the same for February. If the individual reported unemployment in April, their previous occupation is recorded as the occupation which they held in February. We then observe which occupations held from February to April, and which moved into unemployment. From April to June, occupations that moved from unemployment to employment into other occupations are observed. This paper bears in mind that these are extremely large assumptions to make, nonetheless, it is a potentially useful exercise to observe where recovery happened according to occupation for females with matric. The paper disaggregates the occupation transitions by computer literacy level.

For females with a matric education, from February to April (Table 24), occupations that remained employed were higher among those with overall computer literacy compared to those with no computer literacy. No managers or professionals were reported as occupations for females with matric with no computer literacy. Technicians with no computer literacy shifted into unemployment in April by 35.8% compared to technicians with computer literacy, shifting into unemployment by 23%. However, turning to June (Table 25), 11% of females with matric and computer literacy shifted from unemployment in April to clerk occupations in June; and 10.7% shifted from unemployment in April to technician occupations in June. Females with craft occupations and computer literacy and a matric were also able to shift to clerk and service occupations. These transitions to administrative intensive jobs, which are likely to require some basic literacies are observed and suggest that computer literacy played a role in this transition to these jobs. Unemployment for both April and June remained dire at 53%, however, females with matric and no computer literacy had reported unemployment of 69.6%. Females with matric and no computer literacy (Table 26) who were unemployed in April, mainly shifted to elementary occupations and did not have as much occupational shift variance as those with computer literacy. Casale and Shepherd (2020) analyse activity in sectors in June and show that June, being in lockdown level 3 had more activity in the retail, restaurant and elementary (domestic work) sectors. They find that these sectors were where women experienced the largest job gains (ibid).

Age

Age also showed to play a significant role in employment probabilities in June, with 18 to 24-year-olds correlating negatively with employment while 45 to 54-year-olds showing positive correlations with employment. Previous work experience may be more important for increasing employment probabilities with older populations being favoured for a higher likelihood of employment. Older populations (over 35-year-olds) with less than matric also may have learned their computer literacy skills learning on the job as while youth (18 to 35-year-olds) may not have had employment spells long enough to develop these skills and experience to influence their job retention (Govindasamy 2013).

Youth were significantly worse off in employment during April and June. Observing Table 9 and Table 10, in April and June, youth with a post-matric qualification showed a strong significant positive relationship to employment. However, African and Coloured youth all showed strong negative correlations with the probability of employment compared to white counterparts both for April and June in Tables 9 and 10. (note, in Table 19, African youth show a significant positive relationship to employment in April. In June, it is significantly negative again) On the other hand, older Africans showed a weak positive significant relationship to employment in April. Computer literacy and/or owning a computer did not make a difference for youth with less than a matric in April or for those with a matric. Youth with a post-matric did not have a significant relation to high computer literacy and April employment, however, interestingly, youth having a post-matric education with only basic computer literacy were significantly less likely to be employed by around 18.6%. Non-youth with post-matric initially show computer literacy as a positive significant relation to employment in June, however, this loses significance when ICT hardware variables are added, and it is rather ownership of a computer that significantly increases their likelihood of employment by around 11%. Non-youth with less than matric or a matric benefits the most from having high computer literacy, with a 30.4% and 20.9% increase respectively in their probability of employment in June. However, older Africans with less than a matric have lower employment probabilities, with a weakly significant negative correlation of 27.5%. Youth do not seem to benefit from computer literacy even with a post-matric education while non-youth with a matric or even less benefitting from high computer literacy suggests there are other factors to consider. Lekena (2006) suggests that work experience may play a larger role in predicting the likelihood of employment more so that adult household employment, household income, or even the quality of education the individual has.

ICT hardware ownership

Of interest is the difference in the associations' computer literacy and owning a computer played between April and June. What seems to significantly persist in April is the correlations between owning digital capital – specifically owning a computer – and the likelihood of employment. Even though owning a computer was recorded in NIDS Wave 5, it still provides a decent indication of whether the person has or had access to digital hardware and connectivity. Looking at April in Table 4, owning a computer was associated with a strong significant positive relation to employment, while computer literacy did not show much significance in April. This persists in education – even those with less than a matric may not have significantly benefitted from being computer literate in April, however being connected in a hard lockdown significantly increased employment probability by 23%. This reflects the literature which suggests that ownership of ICT assets such as a computer can influence income generation (Diga, 2020; Zoghi and Pabilonia, 2007). Those with post-matric also strongly benefitted from owning a computer, however, their magnitudes were lesser than those with less than matric, increasing their likelihood of employment by 13.6%. In Table 13, both males and females with a post-matric education showed a significant positive relationship to owning a computer in April. Table 19 indicates that both youth and non-youth who had a post-matric education had significant positive probabilities of employment in April when owning a computer. However, in June, only non-youth with post-matric seemed to continue to benefit from computer ownership (Table 22). Owning a cell phone was consistent in not showing significant correlations with the probability of employment. The difference between the roles that ICT play are interesting – computers seem to be significant and can be broadly used and are generally not replaced very quickly. Cell phones differ in their quality – some smartphones could perform most functions similar to a computer and be used to connect to work, or even create work. On the other hand, there are cell phones which can only perform basic functions, like making a call or sending a text. This heterogeneity in function may contribute to cell phones not showing significance in increasing the likelihood of employment.

6. Conclusion and further research

This paper aimed to investigate whether, in the exogenous face of a strict lockdown, computer literacy and access to ICT hardware in the form of owning a computer or cell phone were associated with the likelihood of employment during the early stages of the coronavirus pandemic in April 2020, when the government had imposed stringent physical restrictions, as well as in June 2020, when the South African economy began to open up again. Using the NIDS Wave 5 2017 adult dataset to derive computer literacy and ICT variables, the paper then estimated the probability of employment in April and June respectively, conditional on those employed in February 2020 with Wave 1 and Wave 2 of NIDS-CRAM data. A probit estimation is first run for the employed and unemployed in February, and a weak association is found between basic computer literacy and employment in February 2020, before the pandemic. The paper then excludes those unemployed in February, to assess whether the employed in February – in the face of an exogenous shock that led to unemployment effects – had any increased likelihood of employment which was associated with computer literacy levels and access to ICT hardware.

From the descriptive statistics, it is observed that the labour market still uses education as a key criterion and signal for employment. There were considerable differences in employment by education level found, with those at a post-matric level attaining the highest employment means, followed by those with matric for both April and June. For individuals without a matric education, employment further decreased in June. While these descriptives are limited and provide only a starting point, they were in line with the literature (Casale and Shepherd, 2020) which found that individuals with less than a matric were most affected by job losses over the 2020 April and June period. These education lines illustrated further disparities, with those with a post-matric education reporting much higher computer ownership and computer literacy rates on average compared to those with a matric or less. Computer literacy levels highlighted some interesting differences in employment for individuals with a matric. The proportion of those unemployed with a matric education and a high computer literacy level decreased substantially from April to June. Individuals with matric and a basic computer literacy level were among the highest proportion of matric individuals employed in April and in June. Similarly, the highest proportion of individuals with matric education who were not employed was among those with no computer literacy, and this proportion increased from April to June.

However, results from the estimations suggest that during April 2020, the most restrictive lockdown level, computer literacy did not significantly improve the likelihood of employment among workers employed in February.

Rather, during April, it was access to digital capital – the ownership of a computer being associated with increasing the likelihood of employment. This persists in education subgroups –those with a post-matric, and even those with less than a matric may not have significantly benefitted from being computer literate in April, however, having reported access to a computer was associated with significantly positive employment probabilities. This reflects the literature which suggests that ownership of ICT assets such as a computer can influence income generation (Diga, 2020; Zoghi and Pabilonia, 2007). In addition, high computer literacy seemed to benefit older workers (over 35-year-olds) more than younger workers (18 to 35-year-olds). Youth were significantly worse off in employment during April and June and were observed to have stronger correlations with post-matric education overall rather than computer literacy. Furthermore, the regression estimates confirm what was reflected in the descriptives, with educational attainment remaining to be a strong and consistent association with the likelihood of employment, with those with a post-matric qualification being correlated with having a higher probability of employment in April. As the economy opened in June, and firms began to digitally adopt, computer literacy played a positive, significant role in increasing the likelihood of employment, particularly in those with a matric education, which was also described in the descriptives.

With the various limitations in mind, this paper does not seek to make causal claims or strong policy recommendations. It has observed various associations between computer literacy and employment probability outcomes during the coronavirus lockdown in South Africa, and in particular to females with a matric education and computer literacy. While the probability of employment for females was generally negative overall, females with a matric benefit the most from computer literacy at both levels in June. This correlation is within the context of Casale and Shepherd's (2020) findings which indicate that women saw a slightly larger increase in employment gains compared to men from April to June, as well as Ranchhod and Daniels (2020b) observed that from June to April 2020, there was an increase in the percentage of matriculants employed. The authors suggested that less-skilled workers who were employed in February and lost their jobs in April were able to recover in June indicating some likelihood of computer literacy contributing to increased employment probabilities.

This suggests the adoption of task-based work shifted in this time to being conducted remotely and digitally, and digital platforms are associated with employment creation (Naidoo, 2020; Elvis, 2020), which may require less-skilled workers to have some computer literacy. To explore this further, the paper observed (making strong assumptions) occupation transitions for females with matric by overall computer literacy. Results indicated that occupations that remained employed in April were higher among those with overall computer literacy compared to those with no computer literacy. Furthermore, in June, there were transitions among those who had computer literacy, from unemployment and other occupations such as craft workers into administrative intensive jobs. These transitions to administrative-type occupations, which are likely to require some computer use, are observed and suggest that computer literacy played a role in this transition to these jobs.

Given South Africa's persistent unemployment problem and the acceleration of digital adoption with the pandemic, one might be tempted to push for digital intensive programs to be implemented in order to improve employment outcomes. As these associations presented are not causal, and further, following Non et al (2021), digital skills training may not result in significant outcomes. A randomised controlled experiment could be conducted to causal effects of computer literacy training on employment outcomes in South Africa. However, this paper is cautious in suggesting a blanket approach to digital training. For example, there has been a push toward highly intensive computer training in developing countries, like coding boot camps, which Meng (2013) describes as training programs, where participants learn programming skills in a short space of time to make them immediately employable. Mulas et al (2013) find from an impact evaluation in Colombia that coding boot camps do not have significant effects on attaining generic employment access even when controlling for education level and may only have an impact on accessing high-quality technology-intensive 'IT' jobs. Further research is needed in South Africa is needed on computer literacy training, and this paper would suggest at a more accessible level – where it has found associations to the administrative-type clerk and service occupations requiring some computer use and literacy, and not necessarily advanced coding. Given other findings (Casale and Posel, 2020 and Ranchhod and Daniels 2020b), and a strong association found among those with a matric education and particularly females with matric further research could be done with a focus on semi or lower-skilled occupations and whether computer literacy does, in fact, enhance, together with a matric education, employment probabilities. In addition, an update to the NIDS questionnaire level could offer observations over time during a post-pandemic period where digital adoption has accelerated. A more robust data collection of computer literacy levels in South Africa could be adopted with computer literacy test scores of the labour force population compared to self-reported computer literacy skills to curb measurement error and further dissect the role computer literacy may play in the likelihood of employment.

7. Appendix

The following tables are by subgroup analysis using probit regressions.

- *Note that for all regressions first row is marginal coefficients, second row is standard errors in parentheses, and third row is p-values.*
- **** p<0.01, ** p<0.05, * p<0.1*
- *Source: NIDS-CRAM Wave 1 and Wave 2 and NIDS Wave 5 (2017); own calculations*
- *Note: Data is weighted, Standard errors in parentheses*

By education (T5 and T6)

Table 5 - April, by education

APRIL VARIABLES	Less than matric (1) y1	Less than matric (2) y1	Less than matric(3) y1	Matric (1) y1	Matric (2) y1	Matric (3) y1	Post-matric (1) y1	Post-matric (2) y1	Post matric(3) y1
High computer Literacy	0.129	0.134	0.0773	0.0880	0.0811	0.0807	0.0212	0.0110	-0.0492
	(0.0807)	(0.0838)	(0.0818)	(0.0765)	(0.0712)	(0.0724)	(0.0539)	(0.0538)	(0.0558)
	0.110	0.110	0.345	0.250	0.255	0.265	0.694	0.838	0.378
Basic computer literacy	-0.0414	-0.0380	-0.0564	0.0926	0.0994*	0.0968	-0.0854	-0.0859	-0.110**
	(0.0493)	(0.0467)	(0.0459)	(0.0661)	(0.0601)	(0.0599)	(0.0565)	(0.0550)	(0.0545)
	0.402	0.416	0.219	0.161	0.0982	0.106	0.131	0.118	0.0440
Ownership of a Computer			0.230**			0.0477			0.136***
			(0.0900)			(0.0829)			(0.0400)
			0.0107			0.565			0.000693
Ownership of a Cell phone			0.0803			-0.146*			-0.0376
			(0.0576)			(0.0799)			(0.0620)
			0.163			0.0677			0.544
Aged 18 to 24		-0.166*	-0.150*		-0.108	-0.116		0.0909	0.108
		(0.0903)	(0.0890)		(0.133)	(0.132)		(0.0825)	(0.0829)
		0.0665	0.0921		0.416	0.380		0.270	0.192
Aged 25 to 34		-0.0485	-0.0428		-0.00884	-0.0134		0.0495	0.0780
		(0.0698)	(0.0693)		(0.120)	(0.119)		(0.0704)	(0.0698)
		0.487	0.536		0.941	0.910		0.482	0.263
Aged 35 to 44		-0.00678	-0.0180		0.152	0.137		0.0759	0.0890
		(0.0652)	(0.0641)		(0.120)	(0.118)		(0.0713)	(0.0705)
		0.917	0.779		0.205	0.246		0.287	0.207
Aged 45 to 54		-0.00451	-0.00536		0.0511	0.0319		0.0842	0.0891
		(0.0674)	(0.0670)		(0.135)	(0.133)		(0.0852)	(0.0848)
		0.947	0.936		0.705	0.811		0.323	0.294
o.Aged 55 and		-	-		-	-		-	-
		-	-		-	-		-	-
Female		-0.0985**	-0.0991**		-0.112**	-0.102*		-0.0882**	-0.0653*
		(0.0402)	(0.0395)		(0.0516)	(0.0525)		(0.0363)	(0.0361)
		0.0143	0.0121		0.0298	0.0531		0.0150	0.0706
African		-0.0371	0.0209		-0.0358	-0.0225		-0.0525	-0.00164
		(0.174)	(0.183)		(0.114)	(0.121)		(0.0528)	(0.0537)
		0.831	0.909		0.754	0.853		0.320	0.976
Coloured		0.000954	0.0598		0.119	0.141		-0.0486	-0.0138
		(0.188)	(0.196)		(0.162)	(0.166)		(0.0945)	(0.0913)
		0.996	0.761		0.462	0.394		0.607	0.880
Indian		-0.279	-0.279		0.272	0.289		-0.219**	-0.193**
		(0.270)	(0.284)		(0.204)	(0.206)		(0.107)	(0.0981)
		0.301	0.327		0.183	0.161		0.0408	0.0497
o.White		-	-		-	-		-	-
Observations	1,200	1,200	1,200	614	614	614	684	684	684

Table 6 - June, by education

JUNE	NM (1)	NM (2)	NM (3)	M (1)	M (2)	M (3)	PM (1)	PM (2)	PM (3)
VARIABLES	y1	y1	y1	y1	y1	y1	y1	y1	y1
High computer literacy	0.218***	0.191**	0.197**	0.186**	0.174***	0.157**	0.0965	0.0492	0.0281
	(0.0817)	(0.0798)	(0.0887)	(0.0751)	(0.0669)	(0.0672)	(0.0603)	(0.0578)	(0.0599)
	0.00765	0.0169	0.0267	0.0135	0.00912	0.0194	0.110	0.395	0.639
Basic computer literacy	-0.0460	-0.0495	-0.0462	0.119*	0.134**	0.124**	0.0211	-0.00697	-0.0154
	(0.0539)	(0.0499)	(0.0510)	(0.0641)	(0.0595)	(0.0588)	(0.0623)	(0.0574)	(0.0576)
	0.393	0.321	0.365	0.0637	0.0245	0.0350	0.735	0.903	0.790
Ownership of a computer			-0.0476			0.122			0.0428
			(0.114)			(0.0870)			(0.0469)
			0.676			0.160			0.361
Ownership of a cell phone			0.0264			-0.0388			-0.00108
			(0.0592)			(0.0743)			(0.0776)
			0.655			0.602			0.989
Aged 18 to 24		-0.275	-0.259***		-0.0926	-0.0842		-0.0283	-0.0210
		(0.306)	(0.0968)		(0.120)	(0.119)		(0.0906)	(0.0917)
		0.369	0.00735		0.438	0.478		0.755	0.819
Aged 25 to 34		0.00812	0.0189		0.0986	0.105		0.0967	0.106
		(0.316)	(0.0731)		(0.110)	(0.108)		(0.0722)	(0.0719)
		0.979	0.796		0.370	0.334		0.180	0.139
Aged 35 to 44		0.0783	0.0949		0.173	0.159		0.203***	0.209***
		(0.319)	(0.0682)		(0.108)	(0.106)		(0.0749)	(0.0734)
		0.806	0.164		0.107	0.133		0.00677	0.00432
Aged 45 to 54		0.134	0.151**		0.184	0.166		0.211***	0.214***
		(0.321)	(0.0711)		(0.121)	(0.120)		(0.0803)	(0.0787)
		0.675	0.0332		0.127	0.166		0.00864	0.00659
o.Aged 55 and over			-		-	-		-	-
			-		-	-		-	-
female2		-0.0689	-0.0706*		-0.0972*	-0.0896*		-0.0515	-0.0448
		(0.0426)	(0.0426)		(0.0518)	(0.0531)		(0.0382)	(0.0380)
		0.106	0.0970		0.0606	0.0916		0.177	0.238
African		-0.388***	-0.398***		-0.0381	0.0182		-0.211***	-0.195***
		(0.149)	(0.151)		(0.110)	(0.121)		(0.0614)	(0.0638)
		0.00940	0.00838		0.728	0.880		0.000594	0.00223
Coloured		-0.311*	-0.322*		0.129	0.194		-0.0771	-0.0675
		(0.167)	(0.168)		(0.165)	(0.171)		(0.0952)	(0.0960)
		0.0623	0.0545		0.433	0.257		0.418	0.482
Indian		-0.260	-0.258		0.214	0.259		-0.0214	-0.00883
		(0.255)	(0.248)		(0.199)	(0.201)		(0.132)	(0.132)
		0.309	0.298		0.283	0.198		0.871	0.947
o.White		-	-		-	-		-	-
Observations	1,200	1,200	1,200	613	613	613	685	685	685

By gender (T7 and T8)

Table 7 - April, by gender

APRIL BY GENDER VARIABLES	F (1) y1	F (2) y1	F (3) y1	F (4) y1	M (1) y1	M (2) y1	M (3) y1	M (4) y1
High computer literacy	0.127***	0.0660	0.0691	0.0272	0.137***	0.0803	0.0786	0.0474
	(0.0480)	(0.0566)	(0.0580)	(0.0589)	(0.0474)	(0.0560)	(0.0540)	(0.0570)
	0.00826	0.244	0.234	0.644	0.00376	0.152	0.145	0.406
Basic computer literacy	-0.0128	-0.0482	-0.0484	-0.0622	0.0218	0.00478	0.0122	0.00261
	(0.0444)	(0.0484)	(0.0466)	(0.0461)	(0.0411)	(0.0424)	(0.0414)	(0.0413)
	0.774	0.319	0.299	0.177	0.596	0.910	0.768	0.950
Ownership of a computer				0.160**				0.119**
				(0.0625)				(0.0513)
				0.0106				0.0208
Ownership of a cell phone				-0.0237				0.0205
				(0.0544)				(0.0529)
				0.663				0.698
Matric		-0.0399	-0.0246	-0.0203		-0.0213	-0.00969	-0.0149
		(0.0483)	(0.0471)	(0.0466)		(0.0459)	(0.0452)	(0.0446)
		0.409	0.601	0.663		0.643	0.830	0.738
Post-matric		0.123**	0.130**	0.118**		0.111**	0.105**	0.0799*
		(0.0532)	(0.0523)	(0.0516)		(0.0505)	(0.0478)	(0.0480)
		0.0209	0.0127	0.0223		0.0272	0.0283	0.0959
o.No matric		-	-	-		-	-	-
		-	-	-		-	-	-
Aged 18 to 24			-0.0524	-0.0464			-0.0832	-0.0656
			(0.0875)	(0.0874)			(0.0749)	(0.0748)
			0.549	0.595			0.267	0.380
Aged 25 to 34			-0.0223	-0.0123			-0.00517	0.00573
			(0.0719)	(0.0721)			(0.0620)	(0.0622)
			0.756	0.865			0.934	0.927
Aged 35 to 44			0.0485	0.0382			0.0662	0.0641
			(0.0689)	(0.0686)			(0.0633)	(0.0629)
			0.481	0.577			0.296	0.309
Aged 45 to 54			0.00138	-0.00192			0.0617	0.0584
			(0.0738)	(0.0738)			(0.0711)	(0.0710)
			0.985	0.979			0.385	0.411
o.Aged 55 and over			-	-			-	-
			-	-			-	-
African			-0.0367	0.0249			-0.0661	-0.0119
			(0.0895)	(0.0938)			(0.0679)	(0.0693)
			0.682	0.791			0.330	0.863
Coloured			0.0206	0.0845			-0.0212	0.0374
			(0.113)	(0.116)			(0.100)	(0.0994)
			0.856	0.468			0.833	0.707
Indian			-0.264	-0.228			0.0299	0.0532
			(0.178)	(0.167)			(0.136)	(0.147)
			0.138	0.172			0.827	0.718
o.White			-	-			-	-
			-	-			-	-
Observations	1,410	1,410	1,410	1,410	1,088	1,088	1,088	1,088

Table 8 - June, by gender

JUNE BY GENDER	(1)	(2)	(3)	(4)	M (1)	M (2)	M (3)	M (4)
VARIABLES	y1	y1	y1	y1	y1	y1	y1	y1
High computer literacy	0.190***	0.124**	0.0918	0.0868	0.210***	0.145**	0.123**	0.106*
	(0.0486)	(0.0579)	(0.0576)	(0.0593)	(0.0535)	(0.0631)	(0.0564)	(0.0586)
	8.92e-05	0.0328	0.111	0.143	8.30e-05	0.0215	0.0286	0.0702
Basic computer literacy	0.0674	0.0306	0.0288	0.0288	0.0229	-0.000757	-0.00490	-0.00911
	(0.0457)	(0.0506)	(0.0462)	(0.0463)	(0.0452)	(0.0478)	(0.0445)	(0.0451)
	0.141	0.545	0.532	0.534	0.612	0.987	0.912	0.840
Ownership of a computer				0.00410				0.0535
				(0.0641)				(0.0626)
				0.949				0.393
Ownership of a cell phone				0.0700				-0.0482
				(0.0563)				(0.0553)
				0.214				0.383
Matric		0.00899	0.0244	0.0211		0.0433	0.0681	0.0681
		(0.0500)	(0.0472)	(0.0475)		(0.0516)	(0.0489)	(0.0485)
		0.857	0.606	0.657		0.401	0.164	0.160
Post-matric		0.122**	0.115**	0.112**		0.111**	0.0953*	0.0868*
		(0.0551)	(0.0513)	(0.0519)		(0.0556)	(0.0489)	(0.0492)
		0.0269	0.0250	0.0304		0.0463	0.0514	0.0774
o.No matric		-	-	-		-	-	-
		-	-	-		-	-	-
Aged 18 to 24			-0.0881	-0.0795			-0.188**	-0.185**
			(0.0934)	(0.0938)			(0.0760)	(0.0765)
			0.345	0.397			0.0134	0.0156
Aged 25 to 34			0.0352	0.0391			0.0515	0.0550
			(0.0692)	(0.0691)			(0.0647)	(0.0651)
			0.611	0.571			0.426	0.398
Aged 35 to 44			0.122*	0.123*			0.135**	0.134**
			(0.0662)	(0.0664)			(0.0654)	(0.0653)
			0.0655	0.0634			0.0385	0.0398
Aged 45 to 54			0.178***	0.183***			0.134*	0.128*
			(0.0669)	(0.0669)			(0.0740)	(0.0740)
			0.00790	0.00623			0.0713	0.0836
o.Aged 55 and over			-	-			-	-
			-	-			-	-
African			-0.258***	-0.256***			-0.156**	-0.133
			(0.0886)	(0.0897)			(0.0759)	(0.0815)
			0.00354	0.00434			0.0402	0.103
Coloured			-0.184*	-0.187*			-0.0246	0.00132
			(0.110)	(0.109)			(0.111)	(0.113)
			0.0926	0.0856			0.824	0.991
Indian			-0.0569	-0.0612			0.0539	0.0632
			(0.157)	(0.154)			(0.157)	(0.162)
			0.717	0.691			0.732	0.696
o.White			-	-			-	-
			-	-			-	-
Observations	1,410	1,410	1,410	1,410	1,088	1,088	1,088	1,088

By youth (T9 and T10)

Table 9 - April, by youth

APRIL BY YOUTH VARIABLES	YOUTH (1) y1	YOUTH (2) y1	YOUTH (3) y1	YOUTH (4) y1	NON-Y(1) y1	NON-Y(2) y1	NON-Y(3) y1	NON-Y(4) y1
High computer literacy	0.126**	0.0563	0.0372	0.0191	0.157***	0.123**	0.123**	0.0569
	(0.0541)	(0.0603)	(0.0581)	(0.0608)	(0.0436)	(0.0514)	(0.0518)	(0.0532)
	0.0202	0.350	0.522	0.754	0.000319	0.0165	0.0172	0.285
Basic computer literacy	-0.0249	-0.0454	-0.0576	-0.0610	0.0550	0.0384	0.0352	0.0152
	(0.0519)	(0.0522)	(0.0493)	(0.0493)	(0.0367)	(0.0394)	(0.0393)	(0.0384)
	0.631	0.384	0.242	0.216	0.134	0.330	0.370	0.692
Ownership of a computer				0.116*				0.172***
				(0.0663)				(0.0494)
				0.0793				0.000486
Ownership of a cell phone				-0.00424				0.00817
				(0.0561)				(0.0532)
				0.940				0.878
Matric		-0.0434	-0.0343	-0.0304		0.00560	0.00177	-0.00453
		(0.0538)	(0.0521)	(0.0522)		(0.0444)	(0.0440)	(0.0430)
		0.420	0.510	0.560		0.900	0.968	0.916
Post-matric		0.158***	0.164***	0.145***		0.0562	0.0755*	0.0600
		(0.0583)	(0.0546)	(0.0551)		(0.0457)	(0.0448)	(0.0437)
		0.00658	0.00270	0.00871		0.218	0.0921	0.170
o.No matric		-	-	-		-	-	-
		-	-	-		-	-	-
African			-0.316***	-0.284***			0.0424	0.123*
			(0.102)	(0.104)			(0.0622)	(0.0656)
			0.00198	0.00641			0.495	0.0597
Coloured			-0.272**	-0.238*			0.105	0.190**
			(0.138)	(0.139)			(0.0854)	(0.0867)
			0.0492	0.0856			0.221	0.0282
Indian			-0.685***	-0.672***			0.0359	0.0815
			(0.218)	(0.206)			(0.116)	(0.118)
			0.00167	0.00111			0.758	0.490
o.White			-	-			-	-
			-	-			-	-
Female			-0.0893**	-0.0849**			-0.106***	-0.0957***
			(0.0417)	(0.0417)			(0.0312)	(0.0307)
			0.0321	0.0418			0.000703	0.00186
Observations	1,005	1,005	1,005	1,005	1,493	1,493	1,493	1,493

Table 10 – June, by youth

JUNE BY YOUTH VARIABLES	YOUTH (1) y1	YOUTH (2) y1	YOUTH (3) y1	YOUTH (4) y1	NON-Y (1) y1	NON-Y (2) y1	NON-Y (3) y1	NON-Y (4) y1
	0.183***	0.0903	0.0674	0.0699	0.282***	0.236***	0.209***	0.185***
High computer literacy	(0.0587)	(0.0679)	(0.0670)	(0.0676)	(0.0397)	(0.0481)	(0.0495)	(0.0544)
	0.00187	0.183	0.315	0.301	0	9.10e-07	2.39e-05	0.000686
	0.0582	0.0271	0.0109	0.0146	0.0678*	0.0452	0.0321	0.0251
Basic computer literacy	(0.0564)	(0.0579)	(0.0556)	(0.0559)	(0.0367)	(0.0396)	(0.0396)	(0.0398)
	0.302	0.640	0.844	0.794	0.0647	0.254	0.419	0.529
				-0.0139				0.0655
Ownership of a computer				(0.0809)				(0.0540)

				0.863				0.225
Ownership of a cell phone				0.0534				-0.0217
				(0.0630)				(0.0512)
				0.397				0.671
Matric		0.0893	0.0939	0.0903		0.0134	0.0115	0.00885
		(0.0600)	(0.0587)	(0.0587)		(0.0436)	(0.0426)	(0.0422)
		0.137	0.110	0.124		0.759	0.788	0.834
Post-matric		0.174***	0.159***	0.159***		0.0773*	0.0781*	0.0730*
		(0.0632)	(0.0605)	(0.0603)		(0.0453)	(0.0438)	(0.0442)
		0.00595	0.00843	0.00836		0.0878	0.0748	0.0989
o.No matric		-	-	-		-	-	-
		-	-	-		-	-	-
African			-0.306***	-0.310***			-0.0836	-0.0515
			(0.118)	(0.117)			(0.0639)	(0.0665)
			0.00965	0.00817			0.191	0.439
Coloured			-0.270*	-0.279*			0.0622	0.0960
			(0.153)	(0.150)			(0.0835)	(0.0846)
			0.0780	0.0629			0.456	0.256
Indian			-0.234	-0.244			0.135	0.152
			(0.236)	(0.232)			(0.134)	(0.139)
			0.320	0.294			0.313	0.276
o.White			-	-			-	-
			-	-			-	-
Female			-0.0607	-0.0615			-0.0641**	-0.0603**
			(0.0476)	(0.0478)			(0.0306)	(0.0307)
			0.202	0.198			0.0362	0.0494
Observations	996	996	996	996	1,502	1,502	1,502	1,502

By gender and education (T11a, T12a, T13a, T14j, T15j, T16j)

Table 11 - April, by gender and less than matric

APRIL, GENDER WITH LESS THAN MATRIC	F (1)	F (2)	F (3)	M (1)	M (2)	M (3)
VARIABLES	y1	y1	y1	y1	y1	y1
High computer literacy	0.144	0.179	0.119	0.112	0.0834	0.0704
	(0.121)	(0.116)	(0.119)	(0.107)	(0.115)	(0.115)
	0.237	0.122	0.319	0.293	0.469	0.540
Basic computer literacy	-0.128*	-0.104	-0.127*	0.0165	0.0189	0.00654
	(0.0749)	(0.0690)	(0.0663)	(0.0616)	(0.0641)	(0.0621)
	0.0887	0.131	0.0547	0.789	0.768	0.916
Ownership of a computer			0.187			0.259**
			(0.138)			(0.114)
			0.176			0.0236
Ownership of a cell phone			-0.0113			0.159*
			(0.0707)			(0.0834)
			0.873			0.0563
Aged 18 to 24		-0.179	-0.171		-0.135	-0.0932
		(0.136)	(0.134)		(0.121)	(0.116)
		0.187	0.204		0.267	0.424
Aged 25 to 34		-0.0495	-0.0477		-0.0383	-0.0296
		(0.0948)	(0.0942)		(0.0995)	(0.0969)
		0.602	0.613		0.701	0.760
Aged 35 to 44		0.00607	-0.00736		-0.0149	-0.0126
		(0.0846)	(0.0838)		(0.0981)	(0.0945)
		0.943	0.930		0.879	0.894
Aged 45 to 54		0.0178	0.0173		-0.00941	-0.0126
		(0.0826)	(0.0824)		(0.107)	(0.106)
		0.830	0.834		0.930	0.905
o.Aged 55 and over		-	-		-	-
		-	-		-	-

African		0.0833	0.0776		0.0793	0.184
		(0.268)	(0.270)		(0.276)	(0.308)
		0.756	0.774		0.774	0.551
Coloured		0.122	0.123		0.134	0.247
		(0.288)	(0.291)		(0.290)	(0.319)
		0.672	0.672		0.645	0.438
Indian		-0.453	-0.500		-	-
		(0.374)	(0.361)			
		0.226	0.166		-	-
o.White		-	-		-	-
		-	-		-	-
Observations	703	703	703	497	490	490

Table 12 - April, by gender and matric

APRIL, GENDER WITH MATRIC	F (1)	F (2)	F (3)	M (1)	M (2)	M (3)
VARIABLES	y1	y1	y1	y1	y1	y1
High computer literacy	0.150	0.108	0.0928	0.112	0.0834	0.0704
	(0.102)	(0.108)	(0.111)	(0.107)	(0.115)	(0.115)
	0.142	0.317	0.403	0.293	0.469	0.540
Basic computer literacy	0.138	0.157*	0.150*	0.0165	0.0189	0.00654
	(0.0843)	(0.0809)	(0.0814)	(0.0616)	(0.0641)	(0.0621)
	0.101	0.0518	0.0660	0.789	0.768	0.916
Ownership of a computer			0.0922			0.259**
			(0.139)			(0.114)
			0.506			0.0236
Ownership of a cell phone			0.0177			0.159*
			(0.139)			(0.0834)
			0.899			0.0563
Aged 18 to 24		-0.129	-0.121		-0.135	-0.0932
		(0.186)	(0.185)		(0.121)	(0.116)
		0.489	0.511		0.267	0.424
Aged 25 to 34		-0.0920	-0.0856		-0.0383	-0.0296
		(0.167)	(0.167)		(0.0995)	(0.0969)
		0.582	0.607		0.701	0.760
Aged 35 to 44		0.0578	0.0505		-0.0149	-0.0126
		(0.165)	(0.165)		(0.0981)	(0.0945)
		0.725	0.759		0.879	0.894
Aged 45 to 54		-0.0688	-0.0746		-0.00941	-0.0126
		(0.176)	(0.175)		(0.107)	(0.106)
		0.695	0.671		0.930	0.905
o.Aged 55 and over		-	-		-	-
		-	-		-	-
African		-0.150	-0.113		0.0793	0.184
		(0.179)	(0.186)		(0.276)	(0.308)
		0.404	0.546		0.774	0.551
Coloured		0.195	0.235		0.134	0.247
		(0.199)	(0.207)		(0.290)	(0.319)
		0.327	0.255		0.645	0.438
Indian		0.0745	0.0713		-	-
		(0.288)	(0.277)			
		0.796	0.797		-	-
o.White		-	-		-	-
		-	-		-	-
Observations	308	308	308	497	490	490

Table 13 - April, by gender and post-matric

APRIL, BY GENDER AND POST MATRIC VARIABLES	F (1) y1	F (2) y1	F (3) y1	M (1) y1	M (2) y1	M (3) y1
High computer literacy	0.00257	-0.0191	-0.0639	0.0266	0.0155	-0.0522
	(0.0809)	(0.0806)	(0.0828)	(0.0698)	(0.0702)	(0.0731)
	0.975	0.813	0.440	0.704	0.826	0.475
Basic computer literacy	-0.0871	-0.0929	-0.104	-0.0824	-0.0915	-0.126*
	(0.0832)	(0.0787)	(0.0781)	(0.0745)	(0.0717)	(0.0704)
	0.295	0.238	0.183	0.268	0.202	0.0745
Ownership of a computer			0.136**			0.116**
			(0.0607)			(0.0490)
			0.0248			0.0176
Ownership of a cell phone			0.00715			-0.0638
			(0.0920)			(0.0696)
			0.938			0.359
Aged 18 to 24		0.135	0.148		0.0313	0.0508
		(0.135)	(0.136)		(0.0885)	(0.0880)
		0.317	0.275		0.723	0.564
Aged 25 to 34		0.0434	0.0628		0.0431	0.0807
		(0.125)	(0.124)		(0.0697)	(0.0655)
		0.729	0.614		0.536	0.218
Aged 35 to 44		0.0632	0.0741		0.0733	0.0870
		(0.125)	(0.123)		(0.0723)	(0.0688)
		0.612	0.546		0.310	0.206
Aged 45 to 54		0.0115	0.0169		0.161*	0.174**
		(0.142)	(0.141)		(0.0833)	(0.0822)
		0.935	0.905		0.0539	0.0346
o.Aged 55 and over		-	-		-	-
		-	-		-	-
African		-0.0525	0.00896		-0.0562	-0.0204
		(0.0824)	(0.0871)		(0.0580)	(0.0535)
		0.524	0.918		0.332	0.704
Coloured		-0.0850	-0.0361		0.0380	0.0468
		(0.126)	(0.126)		(0.101)	(0.0994)
		0.500	0.774		0.706	0.637
Indian		-0.450***	-0.375**		-0.0247	-0.0592
		(0.163)	(0.164)		(0.108)	(0.105)
		0.00575	0.0222		0.819	0.574
o.White		-	-		-	-
		-	-		-	-
Observations	399	399	399	285	285	285

Table 14 - June, by gender and less than matric

JUNE, BY GENDER AND LESS THAN MATRIC VARIABLES	F (1) y1	F (2) y1	F (3) y1	M (1) y1	M (2) y1	M (3) y1
High computer literacy	0.202	0.190	0.173	0.234**	0.162	0.212*
	(0.123)	(0.116)	(0.121)	(0.110)	(0.109)	(0.118)
	0.101	0.103	0.154	0.0343	0.137	0.0737
Basic computer literacy	-0.0863	-0.0759	-0.0833	-0.0213	-0.0371	-0.0276
	(0.0796)	(0.0674)	(0.0654)	(0.0725)	(0.0712)	(0.0728)
	0.278	0.261	0.203	0.769	0.603	0.705
Ownership of a computer			0.0532			-0.151
			(0.141)			(0.155)

			0.707			0.329
Ownership of a cell phone			0.0545			-0.00480
			(0.0702)			(0.0976)
			0.437			0.961
Aged 18 to 24		-0.133	-0.130		-0.330***	-0.333***
		(0.148)	(0.147)		(0.121)	(0.120)
		0.368	0.375		0.00644	0.00536
Aged 25 to 34		-0.0209	-0.0155		0.0523	0.0503
		(0.0915)	(0.0914)		(0.108)	(0.108)
		0.819	0.865		0.628	0.642
Aged 35 to 44		0.154*	0.149*		0.0419	0.0446
		(0.0859)	(0.0859)		(0.105)	(0.104)
		0.0725	0.0822		0.690	0.668
Aged 45 to 54		0.175**	0.179**		0.118	0.129
		(0.0850)	(0.0852)		(0.115)	(0.117)
		0.0400	0.0356		0.305	0.270
o.Aged 55 and over		-	-		-	-
		-	-		-	-
African		-0.353*	-0.345		-0.0208	-0.0746
		(0.212)	(0.214)		(0.272)	(0.253)
		0.0954	0.107		0.939	0.768
Coloured		-0.354	-0.350		0.140	0.0795
		(0.229)	(0.231)		(0.288)	(0.270)
		0.123	0.130		0.628	0.768
Indian		0.0978	0.0920		-	-
		(0.300)	(0.302)			
		0.744	0.761		-	-
o.White		-	-		-	-
		-	-		-	-
Observations	703	703	703	497	490	490

Table 15 - June, by gender and matric

JUNE, BY GENDER AND MATRIC VARIABLES	F (1) y1	F (2) y1	F (3) y1	M (1) y1	M (2) y1	M (3) y1
High computer literacy	0.256***	0.183*	0.188*	0.134	0.146	0.212*
	(0.0902)	(0.0996)	(0.0994)	(0.115)	(0.0920)	(0.118)
	0.00463	0.0658	0.0586	0.247	0.112	0.0737
Basic computer literacy	0.223***	0.247***	0.262***	0.0364	0.0603	-0.0276
	(0.0750)	(0.0704)	(0.0688)	(0.0947)	(0.0842)	(0.0728)
	0.00289	0.000438	0.000141	0.700	0.474	0.705
Ownership of a computer			-0.0848			-0.151
			(0.132)			(0.155)
			0.520			0.329
Ownership of a cell phone			0.209*			-0.00480
			(0.108)			(0.0976)

			0.0531			0.961
Aged 18 to 24		-0.233	-0.197		0.0198	-0.333***
		(0.182)	(0.180)		(0.142)	(0.120)
		0.201	0.275		0.889	0.00536
Aged 25 to 34		-0.0663	-0.0626		0.173	0.0503
		(0.166)	(0.165)		(0.136)	(0.108)
		0.689	0.704		0.203	0.642
Aged 35 to 44		-0.121	-0.0956		0.354***	0.0446
		(0.161)	(0.161)		(0.133)	(0.104)
		0.452	0.553		0.00779	0.668
Aged 45 to 54		0.00464	0.0229		0.247	0.129
		(0.170)	(0.169)		(0.157)	(0.117)
		0.978	0.892		0.115	0.270
o.Aged 55 and over		-	-		-	-
		-	-		-	-
African		-0.00278	-0.0262		-0.112	-0.0746
		(0.168)	(0.180)		(0.148)	(0.253)
		0.987	0.884		0.448	0.768
Coloured		0.398**	0.377*		-0.0574	0.0795
		(0.185)	(0.195)		(0.226)	(0.270)
		0.0314	0.0539		0.800	0.768
Indian		0.244	0.255		-	-
		(0.287)	(0.294)			
		0.395	0.385		-	-
o.White		-	-		-	-
		-	-		-	-
Observations	307	307	307	306	303	490

Table 16 - June, by gender and post-matric

JUNE BY GENDER AND POST MATRIC VARIABLES	F (1) y1	F (2) y1	F (3) y1	M (1) y1	M (2) y1	M (3) y1
High computer literacy	0.0738	0.0250	0.0162	0.111	0.0406	0.0119
	(0.0825)	(0.0832)	(0.0851)	(0.0890)	(0.0783)	(0.0813)
	0.371	0.764	0.849	0.214	0.605	0.884
Basic computer literacy	0.0484	0.0303	0.0352	-0.00838	-0.0681	-0.0830
	(0.0847)	(0.0805)	(0.0790)	(0.0915)	(0.0794)	(0.0809)
	0.567	0.707	0.656	0.927	0.391	0.305
Ownership of a computer			0.0248			0.0389
			(0.0652)			(0.0676)
			0.704			0.565
Ownership of a cell phone			0.0829			-0.0735
			(0.122)			(0.0733)
			0.495			0.316
Aged 18 to 24		0.0621	0.0813		-0.180*	-0.178*

		(0.142)	(0.139)		(0.0964)	(0.100)
		0.662	0.558		0.0611	0.0766
Aged 25 to 34		0.150	0.160		0.0487	0.0589
		(0.114)	(0.112)		(0.0836)	(0.0875)
		0.189	0.156		0.560	0.500
Aged 35 to 44		0.232**	0.238**		0.191**	0.195**
		(0.115)	(0.114)		(0.0918)	(0.0894)
		0.0440	0.0359		0.0376	0.0293
Aged 45 to 54		0.282**	0.290**		0.128	0.132
		(0.121)	(0.118)		(0.0991)	(0.0958)
		0.0202	0.0145		0.197	0.167
o.Aged 55 and over		-	-		-	-
		-	-		-	-
African		-0.306***	-0.298***		-0.139**	-0.126*
		(0.109)	(0.108)		(0.0704)	(0.0747)
		0.00481	0.00606		0.0477	0.0924
Coloured		-0.181	-0.177		0.0467	0.0545
		(0.142)	(0.137)		(0.108)	(0.108)
		0.202	0.196		0.666	0.613
Indian		-0.166	-0.167		-	-
		(0.180)	(0.165)			
		0.357	0.310		-	-
o.White		-	-		-	-
		-	-		-	-
Observations	400	400	400	285	279	279

By youth and education (T17a, T18a, T19a, T20j, T21j, T22j)

Table 17 - April, by youth and less than matric

April by youth and less than matric VARIABLES	Youth (1) y1	Youth (2) y1	Youth (3) y1	Non-Y (1) y1	Non-Y (2) y1	Non-Y (3) y1
High computer literacy	0.0967	0.0929	0.0648	0.166	0.174	0.0972
	(0.124)	(0.121)	(0.123)	(0.111)	(0.118)	(0.112)
	0.435	0.442	0.600	0.134	0.142	0.386
Basic computer literacy	-0.0888	-0.121	-0.124	0.0155	0.0150	-0.0162
	(0.0858)	(0.0792)	(0.0783)	(0.0581)	(0.0565)	(0.0550)
	0.301	0.127	0.112	0.790	0.790	0.768
Ownership of a computer			0.176			0.241**
			(0.146)			(0.109)
			0.228			0.0274

Ownership of a cell phone			0.0649			0.0972
			(0.0920)			(0.0733)
			0.481			0.185
Female		-0.156**	-0.158**		-0.0796*	-0.0783*
		(0.0732)	(0.0730)		(0.0464)	(0.0453)
		0.0326	0.0305		0.0861	0.0836
African		-0.441	-0.402		0.0607	0.140
		(0.291)	(0.302)		(0.177)	(0.171)
		0.129	0.184		0.732	0.413
Coloured		-0.362	-0.329		0.107	0.190
		(0.318)	(0.327)		(0.193)	(0.186)
		0.254	0.314		0.579	0.308
o.Indian		-	-		-0.176	-0.156
					(0.269)	(0.273)
		-	-		0.514	0.568
o.White		-	-		-	-
		-	-		-	-
Observations	367	367	367	833	833	833

Table 18 - April, by youth and matric

April, by youth with matric	Youth (1)	Youth (2)	Youth (3)	Non-Youth (1)	Non-Youth (2)	Non-Youth (3)
VARIABLES	y1	y1	y1	y1	y1	y1
High computer literacy	0.0688	0.0656	0.0666	0.165*	0.121	0.117
	(0.111)	(0.109)	(0.109)	(0.0946)	(0.101)	(0.100)
	0.536	0.548	0.540	0.0804	0.232	0.242
Basic computer literacy	0.0850	0.0788	0.0792	0.141*	0.127	0.144*
	(0.0988)	(0.0979)	(0.0983)	(0.0793)	(0.0827)	(0.0800)
	0.390	0.421	0.420	0.0759	0.124	0.0708
Ownership of a computer			-0.0971			0.0725
			(0.152)			(0.0919)
			0.522			0.430
Ownership of a cell phone			0.00813			-0.342***
			(0.118)			(0.114)
			0.945			0.00269
Female		-0.0588	-0.0612		-0.146**	-0.113*
		(0.0858)	(0.0864)		(0.0672)	(0.0673)
		0.493	0.479		0.0299	0.0925
African		0.0272	-0.0104		-0.00444	0.0141
		(0.222)	(0.222)		(0.124)	(0.131)
		0.902	0.963		0.971	0.914
Coloured		0.133	0.0918		0.222	0.257
		(0.297)	(0.298)		(0.149)	(0.156)
		0.653	0.758		0.135	0.100
o.Indian		-	-		-	-
		-	-		-	-
o.White		-	-		-	-

		-	-		-	-
Observations	329	328	328	285	280	280

Table 19 - April, by youth and post-matric

April, youth and post-matric VARIABLES	Youth(1) y1	Youth (2) y1	Youth (3) y1	Non - Youth (1) y1	Non - Youth (2) y1	Non - Youth (3) y1
High computer literacy	0.0188	-0.0108	-0.0817	0.0221	0.0251	-0.0500
	(0.0824)	(0.0905)	(0.0929)	(0.0710)	(0.0700)	(0.0700)
	0.820	0.905	0.379	0.756	0.720	0.475
Basic computer literacy	-0.122	-0.152	-0.186**	-0.0564	-0.0506	-0.0732
	(0.0876)	(0.0953)	(0.0937)	(0.0734)	(0.0721)	(0.0685)
	0.165	0.112	0.0471	0.442	0.483	0.285
Ownership of a computer			0.165**			0.169***
			(0.0678)			(0.0560)
			0.0148			0.00250
Ownership of a cell phone			-0.142			0.00473
			(0.0962)			(0.0971)
			0.138			0.961
Female		-0.0523	-0.0408		-0.118**	-0.0882*
		(0.0586)	(0.0566)		(0.0512)	(0.0499)
		0.372	0.471		0.0206	0.0770
African		0.275	0.283**		0.0456	0.129*
		(0.169)	(0.143)		(0.0639)	(0.0694)
		0.104	0.0471		0.476	0.0624
Coloured		0.264	0.245		0.0564	0.126
		(0.199)	(0.180)		(0.130)	(0.126)
		0.184	0.173		0.665	0.315
Indian		-	-		-0.0446	-0.0117
					(0.123)	(0.118)
		-	-		0.717	0.922
o.White		-	-		-	-
		-	-		-	-
Observations	309	287	287	375	375	375

Table 20 - June, by youth and less than matric

June, youth with less than matric VARIABLES	Youth (1) y1	Youth (2) y1	Youth (3) y1	Non - Youth (1) y1	Non - Youth (2) y1	Non- Youth (3) y1
High computer literacy	0.210	0.207	0.191	0.282***	0.267**	0.304**
	(0.129)	(0.129)	(0.132)	(0.108)	(0.111)	(0.126)
	0.103	0.107	0.150	0.00922	0.0165	0.0162

Basic computer literacy	-0.0349	-0.0696	-0.0735	0.00462	-0.00840	0.00144
	(0.0927)	(0.0866)	(0.0877)	(0.0627)	(0.0629)	(0.0648)
	0.706	0.421	0.402	0.941	0.894	0.982
Ownership of a computer			0.124			-0.0791
			(0.160)			(0.136)
			0.437			0.562
Ownership of a cell phone			0.0739			0.00500
			(0.0977)			(0.0746)
			0.450			0.947
Female		-0.142*	-0.142*		-0.0349	-0.0347
		(0.0819)	(0.0820)		(0.0495)	(0.0497)
		0.0832	0.0831		0.481	0.486
African		-0.0503	-0.0447		-0.251*	-0.275*
		(0.147)	(0.146)		(0.146)	(0.155)
		0.733	0.760		0.0843	0.0763
Coloured		-	-		-0.127	-0.153
					(0.166)	(0.172)
		-	-		0.443	0.375
o.Indian		-	-		-0.133	-0.136
					(0.268)	(0.259)
		-	-		0.620	0.600
o.White		-	-		-	-
		-	-		-	-
Observations	366	364	364	834	834	834

Table 21 - June, by youth and matric

June, youth and matric VARIABLES	youth (1) y1	youth (2) y1	youth (3) y1	Non-youth (1) y1	Non-youth (2) y1	Non-youth (3) y1
High computer literacy	0.151	0.150	0.148	0.284***	0.234***	0.209**
	(0.111)	(0.108)	(0.108)	(0.0837)	(0.0887)	(0.0845)
	0.173	0.162	0.170	0.000697	0.00838	0.0136
Basic computer literacy	0.125	0.123	0.127	0.139*	0.121	0.120
	(0.0963)	(0.0956)	(0.0958)	(0.0772)	(0.0810)	(0.0802)
	0.194	0.199	0.185	0.0721	0.134	0.134
Ownership of a computer			0.105			0.102
			(0.178)			(0.0931)
			0.555			0.273
Ownership of a cell phone			0.0529			-0.113
			(0.112)			(0.106)
			0.637			0.287
Female		0.00963	0.00928		-0.153**	-0.135**
		(0.0860)	(0.0865)		(0.0633)	(0.0670)
		0.911	0.915		0.0154	0.0444
African		0.155	0.195		-0.0430	-0.000667
		(0.209)	(0.223)		(0.122)	(0.134)
		0.459	0.382		0.724	0.996
Coloured		0.246	0.288		0.234	0.289*
		(0.287)	(0.296)		(0.152)	(0.162)
		0.391	0.331		0.124	0.0739
o.Indian		-	-		-	-

		-	-			
o.White		-	-		-	-
					-	-
		-	-			
					-	-
Observations	325	324	324	288	283	283

Table 22 - June, by youth and post-matric

June, youth and post matric VARIABLES	Youth (1) y1	Youth (2) y1	Youth (3) y1	Non-youth (1) y1	Non-youth (2) y1	Non-youth (3) y1
High computer literacy	0.0428	1.54e-05	0.0172	0.148**	0.134**	0.0854
	(0.116)	(0.113)	(0.114)	(0.0580)	(0.0589)	(0.0639)
	0.713	1.000	0.880	0.0107	0.0226	0.182
Basic computer literacy	0.0139	-0.0156	-0.00202	0.0211	0.0121	-0.00598
	(0.119)	(0.114)	(0.115)	(0.0616)	(0.0590)	(0.0585)
	0.907	0.892	0.986	0.733	0.838	0.919
Ownership of a computer			-0.0311			0.110**
			(0.0854)			(0.0465)
			0.716			0.0178
Ownership of a cell phone			0.0499			-0.0333
			(0.123)			(0.0914)
			0.686			0.715
Female		-0.0563	-0.0579		-0.0545	-0.0354
		(0.0697)	(0.0697)		(0.0430)	(0.0426)
		0.419	0.406		0.205	0.405
African		-0.341**	-0.355***		-0.0436	0.0175
		(0.141)	(0.131)		(0.0563)	(0.0535)
		0.0152	0.00650		0.439	0.743
Coloured		-0.288	-0.297*		0.192*	0.246**
		(0.184)	(0.175)		(0.105)	(0.108)
		0.118	0.0903		0.0683	0.0233
o.Indian		-0.187	-0.207		0.104	0.121
		(0.243)	(0.229)		(0.122)	(0.121)
		0.441	0.367		0.393	0.318
o.White		-	-		-	-
		-	-		-	-
Observations	305	305	305	380	380	380

Table 23 - Summary statistics for April and June, by education

1. No matric April n= 1200					1. No matric June n=1200				
Variable	Mean	Std. Err.	[95% Conf	. Interval]	Variable |	Mean	Std. Err.	[95% Conf.	Interval]
Employed in April	.6989426	.0132476	.6729516	.7249336	Employed in June	.6357632	.0138973	.6084975	.6630289
High computer literacy	.0514643	.0063807	.0389456	.0639829	High computer literacy	.0515441	.0063854	.0390163	.0640719
Basic computer literacy	.2926882	.0131401	.2669081	.3184683	Basic computer literacy	.2970384	.0131966	.2711474	.3229294
No computer literacy*	.6558475	.0137204	.6289288	.6827662	No computer literacy*	.6514175	.0137617	.6244177	.6784172

Computer ownership	.0607584	.0068989	.0472231	.0742938	Computer ownership	.0614522	.0069357	.0478449	.0750596
Cell phone ownership	.8914139	.008985	.8737859	.909042	Cell phone ownership	.8919875	.0089641	.8744005	.9095746
African	.8466026	.0104073	.826184	.8670212	African	.840256	.0105806	.8194976	.8610145
Coloured	.124914	.0095482	.106181	.1436471	Coloured	.1293812	.0096926	.1103649	.1483975
Indian	.0079254	.0025608	.0029013	.0129495	Indian	.009621	.002819	.0040902	.0151517
White*	.020558	.004098	.012518	.028598	White*	.0207418	.0041159	.0126667	.0288169
Youth (18 to 35-year-olds)	.3281921	.0135605	.301587	.3547971	Youth (18 to 35-year-olds)	.3267548	.0135453	.3001797	.3533299
Aged 18 to 24	.0902983	.0082771	.074059	.1065375	Aged 18 to 24	.0860495	.0080989	.0701599	.1019391
Aged 25 to 34	.2378938	.0122967	.2137683	.2620193	Aged 25 to 34	.2407053	.0123463	.2164824	.2649281
Aged 35 to 44	.3191523	.0134621	.2927403	.3455642	Aged 35 to 44	.3188493	.0134588	.292444	.3452546
Aged 45 to 54	.2067001	.0116944	.1837563	.229644	Aged 45 to 54	.2089235	.0117407	.1858889	.231958
Aged 55 and over*	.1459556	.0101963	.1259511	.1659601	Aged 55 and over	.1454724*	.0101823	.1254954	.1654494
Female	.4686407	.0144113	.4403664	.4969149	Female	.4679863	.0144101	.4397144	.4962582
2. Matric April n=614					2. Matric June n = 613				
Variable |	Mean	Std. Err.	[95% Conf.	Interval]	Variable |	Mean	Std. Err.	[95% Conf.	Interval]
Employed in April	.6907861	.0186669	.6541274	.7274449	Employed in June	.7059796	.0184166	.6698123	.742147
High computer literacy	.3082238	.0186503	.2715976	.34485	High computer literacy	.3132825	.0187491	.276462	.350103
Basic computer literacy	.3584445	.0193686	.3204077	.3964813	Basic computer literacy	.3571137	.0193684	.319077	.3951503
No computer literacy*	.3333317	.0190398	.2959405	.3707229	No computer literacy*	.3296038	.0190014	.2922879	.3669197
Computer ownership	.1509316	.0144588	.1225369	.1793263	Computer ownership	.1544243	.0146069	.1257386	.1831101
Cell phone ownership	.912797	.0113952	.8904186	.9351754	Cell phone ownership	.913747	.0113481	.891461	.936033
African	.8275835	.0152569	.7976215	.8575456	African	.817889	.0156005	.7872519	.8485261
Coloured	.0960521	.0119013	.0726798	.1194244	Coloured	.0990973	.012078	.075378	.1228166
Indian	.0227682	.0060247	.0109367	.0345997	Indian	.0280089	.0066697	.0149107	.0411071
White*	.0535962	.0090965	.0357321	.0714603	White*	.0550048	.0092159	.0369061	.0731035
Youth (18 to 35-year-olds)	.4949179	.0201938	.4552605	.5345752	Youth (18 to 35-year-olds)	.4873377	.0202048	.4476585	.5270169
Aged 18 to 24	.1685711	.0151208	.1388763	.1982659	Aged 18 to 24	.1520228	.0145135	.1235205	.180525
Aged 25 to 34	.3263468	.0189377	.2891562	.3635375	Aged 25 to 34	.335315	.0190835	.2978378	.3727921
Aged 35 to 44	.2816928	.0181682	.2460133	.3173724	Aged 35 to 44	.2730604	.0180095	.2376924	.3084284
Aged 45 to 54	.1734032	.0152913	.1433734	.2034329	Aged 45 to 54	.1902632	.0158662	.1591044	.2214221
Aged 55 and over*	.0499861	.0088016	.0327013	.067271	Aged 55 and over*	.0493387	.0087545	.0321462	.0665312
Female	.4230755	.0199544	.3838882	.4622627	Female	.4214928	.0199606	.3822932	.4606924
3. Post matric April n=684					3. Post matric June n=685				
Variable |	Mean	Std. Err.	[95% Conf.	Interval]	Variable |	Mean	Std. Err.	[95% Conf.	Interval]
Employed in April	.8365466	.0141492	.8087654	.8643277	Employed in June	.8153805	.0148351	.7862527	.8445083
High computer literacy	.5731822	.0189259	.5360222	.6103422	High computer literacy	.5749399	.018902	.5378269	.6120528
Basic computer literacy	.3227223	.0178891	.2875981	.3578465	Basic computer literacy	.323147	.0178821	.2880366	.3582575
No computer literacy*	.1040955	.0116852	.0811523	.1270388	No computer literacy*	.1019131	.0115677	.0792007	.1246255
Computer ownership	.457051	.0190613	.4196253	.4944767	Computer ownership	.4620736	.0190629	.4246448	.4995024
Cell phone ownership	.9405666	.0090469	.9228036	.9583297	Cell phone ownership	.9419586	.0089404	.9244046	.9595125
African	.7004136	.0175278	.6659987	.7348285	African	.6929823	.0176366	.658354	.7276107
Coloured	.0507064	.008395	.0342233	.0671896	Coloured	.052299	.0085124	.0355854	.0690127

Indian	.0238271	.0058356	.0123692	.0352851	Indian	.0299215	.0065143	.0171311	.0427119
White*	.2250529	.0159797	.1936777	.2564281	White*	.2247972	.0159615	.1934576	.2561367
Youth (18 to 35-year-olds)	.4627219	.0190787	.4252619	.5001819	Youth (18 to 35-year-olds)	.4570222	.0190472	.4196241	.4944202
Aged 18 to 24	.0952492	.0112327	.0731944	.1173041	Aged 18 to 24	.0942295	.0111705	.0722968	.1161622
Aged 25 to 34	.3674727	.0184477	.3312517	.4036937	Aged 25 to 34	.3627926	.0183841	.3266966	.3988886
Aged 35 to 44	.2486591	.016539	.2161856	.2811326	Aged 35 to 44	.2509996	.0165787	.2184484	.2835508
Aged 45 to 54	.1756931	.0145617	.1471021	.2042841	Aged 45 to 54	.1757089	.0145515	.1471379	.20428
Aged 55 and over*	.1129259	.0121106	.0891474	.1367044	Aged 55 and over*	.1162693	.0122564	.0922045	.1403341
Female	.5144987	.0191239	.47695	.5520475	Female	.5134765	.019111	.4759531	.5509998

*Source: own calculations using NIDS Wave 5 and NIDS-CRAM Wave 1 and Wave 2 data. Data is weighted to represent population estimates. *Omitted variables in the regressions.*

Table 24 - Occupation transitions from February to April for females with matric, by computer literacy

Occupation in February, computer literate	Occupation in April if employed in April, computer literate	Unemployed, computer literate	Total	Occupation in April if employed in April, not computer literate	Unemployed, not computer literate	Total
1. Managers	99.1	0.9	100.0	0.0	100.0	100.0
	(1.1)	(1.1)		(0.0)	(0.0)	
2. Professionals	78.0	22.0	100.0	0.0	100.0	100.0
	(12.2)	(12.2)		(0.0)	(0.0)	
3. Technicians	76.5	23.5	100.0	64.2	35.8	100.0
	(16.8)	(16.8)		(28.3)	(28.3)	
4. Clerical support work	72.9	27.1	100.0	79.7	20.3	100.0
	(11.3)	(11.3)		(11.9)	(11.9)	
5. Services and sales	64.6	35.4	100.0	61.1	38.9	100.0
	(11.4)	(11.4)		(14.2)	(14.2)	
6. Skilled agriculture	7.0	93.0	100.0	0.0	100.0	100.0
	(8.2)	(8.2)		(0.0)	(0.0)	
7. Craft and related trades	95.1	4.9	100.0	68.7	31.3	100.0
	(4.2)	(4.2)		30.4	(30.4)	
8. Plant	71.6	28.4	100.0	100.0	0.0	100.0

operators						
	(28.7)	(28.7)		(0.0)	(0.0)	
9. Elementary occupations	46.6	53.4	100.0	45.6	54.4	100.0
	(15.0)	(15.0)		(9.7)	(9.7)	
10. Self-employed	41.7	58.3	100.0	29.0	71.0	100.0
	(28.6)	(28.6)		(29.1)	(29.1)	

Source: NIDS Wave 5, NIDS-CRAM Wave 1 and 2, own calculations, data is weighted, standard errors in parentheses

Table 25 - Occupation transitions from April to June for computer literate females with matric

Computer literate	June occupation											
April Occupation	1. Managers	2. Professionals	3. Technicians	4. Clerical support work	5. Service and sales work	6.Skilled agriculture	7. Craft and related trades	8. Plant and machine operators	9. Elementary occupation	10. Self-employed	11 Unemployed	Total
1.	31.8	5.5	0.0	57.8	0.0	0.0	0.0	0.0	4.8	0.0	0.0	100.0
	(22.3)	(6.2)	(0.0)	(26.9)	(0.0)	(0.0)	(0.0)	(0.0)	(5.4)	(0.0)	(0.0)	
2.	32.6	57.2	0.0	6.3	0.0	0.0	0.0	0.0	0.0	0.0	3.9	100.0
	(23.6)	(22.1)	(0.0)	(6.5)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(4.0)	
3.	17.0	1.2	53.0	19.3	4.3	0.0	0.0	0.0	5.1	0.0	0.0	100.0
	(6.9)	(1.5)	(15.6)	(17.2)	(4.9)	(0.0)	(0.0)	(0.0)	(5.9)	(0.0)	(0.0)	
4.	0.0	9.6	0.0	77.5	0.0	0.0	0.0	0.0	5.7	0.0	7.3	100.0
	(0.0)	(9.2)	(0.0)	(11.2)	(0.0)	(0.0)	(0.0)	(0.0)	(3.6)	(0.0)	(5.7)	
5.	3.2	0.0	2.2	0.5	77.7	0.0	6.2	1.9	4.4	0.0	3.8	100.0
	(3.3)	(0.0)	(2.3)	(0.5)	(9.8)	(0.0)	(6.1)	(2.0)	(4.4)	(0.0)	(3.0)	
6.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	100.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
7.	0.0	3.9	0.0	26.6	11.7	0.0	40.3	17.5	0.0	0.0	0.0	100.0
	(0.0)	(4.1)	(0.0)	(21.1)	(11.5)	(0.0)	(23.0)	(13.7)	(0.0)	(0.0)	(0.0)	
8.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	100.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
9.	0.0	0.0	0.0	9.9	0.0	0.0	0.0	16.8	41.7	0.0	31.5	100.0

	(0.0)	(0.0)	(0.0)	(9.5)	(0.0)	(0.0)	(0.0)	(14.7)	(14.8)	(0.0)	(16.6)	
10.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	100.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
11.	3.1	9.0	10.7	11.2	4.9	1.1	0.0	1.0	5.9	0.0	53.2	100.0
	(3.1)	(6.7)	(9.5)	(8.7)	(3.1)	(1.1)	0.0	(1.0)	(3.7)	(0.0)	(12.7)	
Total	8.1	8.2	8.7	18.7	18.9	0.3	6.1	4.8	7.8	0.0	18.5	100.0
	(3.2)	(2.7)	(5.0)	(5.7)	(5.5)	(0.3)	3.8	(2.2)	(2.2)	(0.0)	(5.2)	

Source: NIDS Wave 5, NIDS-CRAM Wave 1 and 2, own calculations, data is weighted, standard errors in parentheses

Table 26 - Occupation transitions from April to June for non-computer literate females with matric

Not computer literate	June occupation											
April occupation	1. Manager	2. Professsional	3. Technicians	4. Clerical support	5. Service and sale	6. Skilled agriculture	7. Craft and related trades	8. Plant operators	9. Elementary occupations	10. Self-employed	11 Unemployed	Total
1.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
2.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
3.	0.0	0.0	5.9	0.0	0.0	0.0	0.0	0.0	64.9	0.0	29.2	100.0
	(0.0)	(0.0)	(7.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(29.9)	(0.0)	(28.1)	
4.	0.0	27.3	0.0	27.5	0.0	0.0	0.0	19.6	25.6	0.0	0.0	100.0
	(0.0)	(21.8)	(0.0)	(17.1)	(0.0)	(0.0)	(0.0)	(17.4)	(17.2)	(0.0)	(0.0)	
5.	4.4	0.0	0.0	18.1	56.8	0.0	0.0	0.0	0.0	0.0	20.7	100.0
	(4.6)	(0.0)	(0.0)	(12.4)	(19.7)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(18.1)	
6.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
7.	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	100.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
8.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	100.0

	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
9.	6.1	0.0	0.0	8.2	0.0	0.0	13.3	0.0	50.8	0.0	21.7	100.0
	(5.9)	(0.0)	(0.0)	(7.8)	(0.0)	(0.0)	11.9	(0.0)	(12.9)	(0.0)	(10.8)	
10.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	100.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	
11.	0.0	0.0	0.0	1.0	8.3	0.0	0.0	0.0	14.3	6.8	69.6	100.0
	(0.0)	(0.0)	(0.0)	(1.0)	(5.6)	(0.0)	(0.0)	(0.0)	(6.4)	(4.9)	(9.6)	
Total	2.5	1.6	0.1	8.1	16.1	0.0	5.4	1.6	21.4	3.4	39.9	100.0
	(1.8)	(1.6)	(0.1)	(3.5)	(6.8)	(0.0)	(3.8)	(1.2)	(4.8)	(2.1)	(7.9)	

Source: NIDS Wave 5, NIDS-CRAM Wave 1 and 2, own calculations, data is weighted, standard errors in parentheses

8. References

Amra, R., Hlatshwayo, A., & McMillan, L. (2013, September). SMME employment in South Africa. In *Biennial Conference of the Economic Society of South Africa. Conference Proceedings* (pp. 25-27).

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the U.S. Labour Market. The American Economic Review, 96 (2), 189–194.

Benhura, M., & Magejo, P. (2021). Who cannot work from home in South Africa?. Evidence from wave 4 of NIDSCRAM.

Bhorat, H. (2014). Particular features of the youth unemployment challenge in South Africa. In *Keynote address presented at the Accelerating Inclusive Youth Employment Conference. Stellenbosch*.

Bhorat, H., Naidoo, K., Oosthuizen, M. and Pillay, K. (2016) Demographic, employment and wage trends in South Africa, in Bhorat, H. and Tarp, F. (eds.) Africa's Lions, Helsinki: UNU-WIDER and Brookings University Press

Bhorat, H., Thornton, A., Köhler, T., & Oosthuizen, M. (2020). Jobs and COVID-19: Measuring work-related physical interaction.

Bunz, U., Curry, C. & Voon, W. 2007. Perceived versus actual computer-email-web fluency. Computers in Human Behavior. 23(5): 2321-2344.

Casale, D. & Posel, D. 2011. English language proficiency and earnings in a developing country: the case of South Africa. The Journal of Socio- Economics.40(4): 385-393.

Casale, D., & Shepherd, D. (2020). *The gendered effects of the ongoing lockdown and school closures in South Africa: Evidence from NIDS-CRAM Waves 1 and 2. National Income Dynamics Study Coronavirus Rapid Mobile Survey (NIDS-CRAM) Working Paper*.

Claro, M., Preiss, D.D., San Martín, E., Jara, I., Hinostroza, J.E., Valenzuela, S., Cortes, F. & Nussbaum, M. 2012. Assessment of 21st century ICT skills in Chile: Test design and results from high school level students. Computers & Education. 59(3): 1042-1053.

Cole, I.J. & Kelsey, A. 2004. Computer and information literacy in post-qualifying education. Nurse Education in Practice. 4(3): 190-199.

Daniels, R. C., Ingle, K., & Brophy, T. (2021). Labour market dynamics in the era of COVID-19.

Davies, E., Nayyar, G., Reyes, S., & Torres, J. (2021). Firms through the Covid-19 pandemic: Evidence from sub-Saharan Africa. *Shaping Africa's Post-Covid Recovery*, 19-30.

De la Fuente, A. & Ciccone, A. 2003. Human capital in a global and knowledge-based economy, Universitat Autònoma de Barcelona, Departament d'Economia i d'Història Econòmica, Unitat Fonaments de l'Anàlisi Econòmica.

De Lannoy, A., Graham, L., Patel, L., & Leibbrandt, M. (2020). Why Is Youth Unemployment So Intractable in South Africa? A Synthesis of Evidence at the Micro-Level. *Journal of Applied Youth Studies*, *3*(2), 115-131.

Department of Co-operative Governance and Traditional Affairs (2020a). Disaster Management Act (57/2002): Regulations made in terms of Section 27(2) R. 398, Government Gazette No. 43148.

Department of Co-operative Governance and Traditional Affairs, 2020a2. Regulations issued in terms of section 27(2) of Disaster Management Act (57/2002), NO. R. 446, 2 April 2020.

Department of Co-operative Governance and Traditional Affairs, 2020b. Regulations issued in terms of section 27(2) of Disaster Management Act (57/2002), NO. R. 480, 29 April 2020.

Department of Co-operative Governance and Traditional Affairs, 2020c. Disaster Management Act, 2002, Determination of Alert Levels and Hotspot, 28 May 2020.

Diga, K. (2020). Information and communication technologies for development: Reshaping poverty in South Africa.

Digital Economy Report (*2019)*. *Unctad*. *United Nations* Conference On Trade And Development. Value Creation And Capture: Implications For Developing Countries

Govindasamy, P.-L. (2013). Computer literacy, employment and earnings: A crosssectional study on South Africa using the National Income Dynamics Study 2008. (Masters), University of KwaZulu-Natal, Durban.

Gujarati, D. N., & Porter, D. (2009). Basic Econometrics McGraw-Hill International Edition. Chapter 15 *'Qualitative Response Models'*, 541-589.

Hawke, A. 1998. Gender differences in wage returns to computer skills in Australia. Prometheus. 16(1): 5-12.

Heeks, R. (2017). Decent work and the digital gig economy: a developing country perspective on employment impacts and standards in online outsourcing, crowdwork, etc. *Development Informatics Working Paper,* (71).

Heeks, R., Eskelund, K., Gomez-Morantes, J. E., Malik, F., & Nicholson, B. (2020). Digital Labour Platforms in the Global South: Filling or Creating Institutional Voids?.

Ingle, K., Brophy, T., Daniels, R.C., 2021. National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM) 2020 - 2021 Panel User Manual. Release July 2021 Version 1. Cape Town: Southern Africa Labour and Development Research Unit

Katchova, A (2020). Probit and Logit models. Econometrics Academy. https://sites.google.com/site/econometricsacademy/

Krueger, A. B. (1993). How computers have changed the wage structure: evidence from microdata, 1984–1989. *The Quarterly Journal of Economics, 108*(1), 33-60.

Krueger, A.B. 1993. How computers have changed the wage structure: evidence from microdata, 1984–1989. The Quarterly Journal of Economics.108(1): 33-60

Kudyba, S. (2020). COVID-19 and the Acceleration of Digital Transformation and the Future of Work. *Information Systems Management*, *37*(4), 284-287.
Lane, M., & Conlon, G. (2016). The impact of literacy, numeracy and computer skills on earnings and employment outcomes.
Lekena M (2006) Youth employment in the Cape Town area: insights from the Cape Area Panel Study. (Doctor of Philosophy) University of Cape Town. Retrieved from

Mabanza, N. (2020). Effectiveness of Pedagogical Interface Agents in Enhancing Adult Computer Literacy Training. *Editors: Dr UG Singh (University of KwaZulu-Natal, South Africa) Prof CS Nair (Victorian Institute of Technology, Australia) e-ISBN: 978-1-990901-49-2*, 104.

Matli, W., & Ngoepe, M. (2020). Capitalizing on digital literacy skills for capacity development of people who are not in education, employment or training in South Africa. *African Journal of Science, Technology, Innovation and Development*, *12*(2), 129-139.

Mbaye, A. A., Gueye, F., Beye, A., Dia, A. K., & Mbaye, M. (2021). Employment Creation Potential, Labor Skills Requirements, and Skill Gaps for Young People: A Senegal Case Study.
Melia, Elvis (2020). African jobs in the digital era: Export options with a
focus on online labour. Discussion Paper, No. 3/2020, ISBN 978-3-96021-114-3, Deutsches Institut für Entwicklungspolitik (DIE), Bonn, http://dx.doi.org/10.23661/dp3.2020
Meng, V. 2013."The Ultimate Guide to Coding Bootcamps: The Most Selective Bootcamps." SkilledUp. http://archive.fo/YCwEA#selection-145.0-145.68.
Mincer, J. (1970). The Distribution of Labor Incomes: A Survey With Special Reference to the Human Capital Approach. Journal of Economic Literature, 8 (1), 1–26.

Morissette, R., & Drolet, M. 1998. Computers, fax Machines and Wages in Canada: What Really Matters? Analytical Studies Branch, statistics Canada. 126: 1-25.
Mulas, V., Paradi-Guilford, C., & Cerdan-Infantes, P. (2018) World Bank. Coding Bootcamps for Youth Employment : Evidence from Colombia, Lebanon, and Kenya. World Bank, Washington, DC. https://openknowledge.worldbank.org/handle/10986/29742 License: CC BY-NC-ND 3.0 IGO.
Naidoo, K. 2020. Innovation, digital platform technologies and employment: an overview of key issues and emerging trends in South Africa. Future of Work(ers) SCIS Working Paper Number 9.

National Youth Commission Act, 1996 (No. 19 of 1996). Government Gazette, 1996-04-19, Vol. 370, No. 17130, 15

Non, M., Dinkova, M., & Dahmen, B. (2021). *Skill Up Or Get Left Behind?: Digital Skills and Labor Market Outcomes in the Netherlands*. CPB Netherlands Bureau for Economic Policy Analysis.
Oosterbeek, H., & Ponce, J. (2011). The impact of computer uses on earnings in a developing country: Evidence from Ecuador. *Labour Economics*, *18*(4), 434-440.
Ranchhod, V. & Daniels, R. (2020b) Labour market dynamics in South Africa in the time of COVID-19: Evidence from Waves 1 and 2 of the NIDS-CRAM survey. *National Income Dynamics Study Coronavirus Rapid Mobile Survey (NIDS-CRAM) Working Paper*.

Ranchhod, V. & Daniels, R. C (2020a) Labour market dynamics in the time of COVID-19. *National Income Dynamics Study Coronavirus Rapid Mobile Survey (NIDS-CRAM) Working Paper*.
Rao, S. S. (2005). Bridging digital divide: Efforts in India. *Telematics and informatics*, *22*(4), 361-375.

Thinyane, M., Slay, H., Terzoli. A. and Clayton, P. 2006. A Preliminary Investigation into the Implementation of ICTs in Marginalized Communities. Department of Computer Science, Rhodes University, Grahamstown, South Africa.

Yu, K. (2016). *Do informal workers suffer an earnings penalty? A panel data analysis of earnings gaps in South Africa* (Doctoral dissertation).

Ziphorah, R. M. (2011). The provision of basic levels of computer literacy and education to the neediest community in South Africa. *International Journal for e-Learning Security*, *1*(3/4), 96-103.

Zoghi, C. & Pabilonia, S.W. 2007. Which workers gain upon adopting a computer? Canadian Journal of Economics/Revue canadienne d'économique. 40(2): 423-444