Testing Positive for Automation: Labour-replacing Technology and Job Loss during the COVID-19 Pandemic in South Africa

By Angela Euston-Brown

DPRU Working Paper 202202
October 2022

DPRU
DEVELOPMENT POLICY RESEARCH UNIT

DPRU

DEVELOPMENT POLICY
RESEARCH UNIT

Testing Positive for Automation:

Labour-replacing Technology and Job Loss during the COVID-19 Pandemic in South Africa

DEVELOPMENT POLICY RESEARCH UNIT

ANGELA EUSTON-BROWN

estang001@myuct.ac.za

Working Paper 202202

ISBN 978-1-920633-94-3

October 2022

Abstract

The risk of technological job displacement represents an important component of vulnerability to job loss that has been poorly explored in the context of the COVID-19 pandemic. Expanding on the routinisation hypothesis, this paper merges O*NET occupational descriptors to South Africa's Quarterly Labour Force Survey data to investigate the role of automation risk on the likelihood of job loss between February and May 2020. Further, in a multivariate context, the interacted effects of education and automation risk on job loss probabilities are explored. The results provide preliminary evidence to suggest that high automation risk was associated with greater probabilities of job loss at the start of the pandemic in South Africa. Consequently, routine-intensive employment may have been lost to labour-replacing technology and may never be regained in future due to the accelerated adoption of automation during COVID-19. The findings highlight the importance of upskilling and retraining workers into less vulnerable occupations.

JEL codes:
E24; I25; J01; J20; O33

Keywords:
Automation; employment; task content of occupations; fourth industrial revolution; COVID-19; South Africa; education

Acknowledgements:
This long paper was produced in partial fulfilment of the requirements for the award of a Bachelor of Commerce Honours degree specialising in Economics. I would like to thank the Harry Crossley Foundation for their financial support towards my Honours degree and the Jakes Gerwel Fellowship for their role in my academic and personal development. In particular, I would like to express my gratitude to my supervisor, Robert Hill for his expert guidance, practical feedback and consistent encouragement. I would also like to thank Andrew Kerr for providing me with an unbalanced panel version of Quarterly Labour Force Survey data for 2020 quarter 1 and 2.

Working Papers can be downloaded in PDF (Adobe Acrobat) format from www.dpru.uct.ac.za. A limited number of printed copies are available from the Communications Manager: DPRU, University of Cape Town, Private Bag X3, Rondebosch, Cape Town, 7700, South Africa. Tel: +27 (0)21 650 5701, email: sarah.marriott@uct.ac.za.

Corresponding authors

Angela Euston-Brown
estang001@myuct.ac.za

Recommended citation

Euston-Brown, A. (2022). Testing Positive for Automation: Labour-replacing Technology and Job Loss during the COVID-19 Pandemic in South Africa. Development Policy Research Unit Working Paper 202202. DPRU, University of Cape Town.

Contents

1. Introduction

The COVID-19 pandemic led to staggering losses in economic activity and jobs around the world. In South Africa, the strict national lockdown and its economic consequences resulted in the loss of 2.2 to 3 million jobs between February and April/May 2020 (Spaull et al., 2020; Statistics South Africa (StatsSA), 2020b). While a host of literature has analysed the demographic and employment characteristics of the job-losers (Benhura & Magejo, 2020; Casale & Posel, 2020; Hill & Köhler, 2020; Jain et al., 2020; Köhler & Bhorat, 2020; Ranchhod & Daniels, 2020; 2021; Köhler et al., 2021), little to no research has explored whether the adoption of labour-replacing technologies contributed to the job losses experienced in South Africa. The following paper attempts to provide novel insight into the extent to which automation impacted job loss at the onset of the COVID-19 pandemic in South Africa.

The fear that machines will take over jobs and disrupt livelihoods is by no means new (World Bank, 2019). Even the famous economist John Maynard Keynes referred to the phenomenon of "technological unemployment" (Keynes, 1931). However, the threat of widespread technological job displacement is increasingly probable. Between 1969 and 2005, the real cost of computing power is estimated to have fallen by over 50% every year (Nordhaus, 2007). As tasks become more cost effectively completed by computers, robots and artificial intelligence (AI), profit driven firms will substitute human labour for technology. Furthermore, the COVID-19 public health crisis and the associated economic downturn is likely to have accelerated this trend (Blit, 2020; Georgieff & Milanez, 2021; Karr et al., 2020). There is thus concern that the pandemic has, and will, precipitate large levels of "technological unemployment". South Africa entered the pandemic with low levels of employment and weak job creation (World Bank, 2021). Thus, understanding the role (if any) that automation had to play in the widespread job loss of 2020 is critical to assist policymakers in understanding to what extent the jobs lost during the pandemic may have been permanently lost to labour-replacing technologies, and to what extent recovery from this employment shock is possible.

The degree to which workers occupy jobs with a high-risk of substitutability by automation technologies has attracted the interest of many researchers, although not yet in relation to the COVID-19 pandemic (Goos & Manning, 2007; Firpo, Fortin & Lemieux, 2011; Autor & Dorn, 2013). Skills-biased technological change (Tinbergen 1974; 1975) predicts that technology favours high-skilled workers, and displaces low-skilled workers. On the other hand, the routinisation hypothesis takes on a more nuanced, task-based approach (Autor et al., 2003). This theory suggests that technological change is routine-biased, with technology increasing the relative demand for non-routine workers, while leaving routine workers at high-risk of job displacement. These theories and the associated research emphasise the role of education in protecting against high-risk of automation. Despite these well-established theories, literature evaluating the effects of automation in the labour market is limited for developing countries, including South Africa. This analysis hopes to add preliminary insight into the unfolding dynamics of technological change in developing countries.

The paper finds evidence to suggest that routine-intense occupations were more susceptible to job loss at the onset of the pandemic in South Africa. Furthermore, the analysis indicates that occupations at high-risk of automation are predominantly occupied by South Africa's most vulnerable. This suggests that the adoption of labour-replacing technologies in South Africa may compound these vulnerabilities and exacerbate existing inequalities. In fact, the Presidential Commission on the 4th Industrial Revolution acknowledges that the acceleration of technological advances must be done in full consideration of the potential inequality-enhancing effects (Department of Communications and Digital Technologies, 2020). The strong correlation between education levels and risk of automation makes a strong case for proactive, 21st-century education as a strategy toward mitigating the future negative effects of automation – and augmenting the positive effects – on South African employment.

This paper is organised as follows: Section (2) outlines and critically analyses the theories and empirical evidence behind technological change and unemployment. Recent research on the labour market outcomes during COVID-19 is also discussed. Section (3) provides an overview of the data and methods used in the econometric investigation. Section (4) presents and discusses descriptive statistics, while Section

(5) presents regression results. Section (6) discusses the implications of the results, provides policy recommendations and identifies limitations present in the analysis. Section (7) concludes.

2. COVID-19, Accelerated Automation and the Labour Market

2.1. The COVID-19 Pandemic is Expected to Accelerate Automation

The COVID-19 pandemic is expected to accelerate the uptake of automation technologies, leading to the potential elimination of certain jobs (Georgieff & Milanez, 2021; Lund et al., 2021). Recessionary periods hasten efficiency-enhancing economic changes, as firms seek to reduce costs while retaining productive capacity, and as resources are reallocated towards the most productive firms (Blit, 2020). As consumer demand and revenues fell during the 2020 economic shutdown, firms may have replaced human labour with cheaper technology to reduce costs. After the 2008 Global Financial Crisis, the United States (US) and the European Union (EU) experienced a lasting decline in the share of routine jobs, suggesting an increase in automation (Lund et al., 2021). Automation further appears to be a practical solution to maintaining production under lockdown-constrained labour supplies, and to reducing COVID-19 transmissions to protect the health of employees and customers (Karr et al., 2020).

Going forward, firms' investment decisions will likely shift toward the faster adoption of automation technologies. This is particularly true if governments' economic stabilisation policies, such as lower interest rates, help reduce the costs of introducing automation technologies (Karr et al., 2020). In fact, according to a global survey conducted by McKinsey Global Institute, two thirds of 800 senior executives reported that they were increasing investment in automation and AI (Lund et al., 2021). This accelerated investment in automation technology will have employment ramifications.

At present, there is a local and global paucity of literature on the relationship between job loss, automation and the pandemic. However, an analysis conducted by Livanos and Ravanos (2021) on the EU finds evidence to suggest that countries with jobs facing higher risk of automation *are* expected to experience larger short-term employment loss post-COVID-19. Additionally, occupations with a greater probability of automation appear to suffer lasting employment losses (Livanos & Ravanos, 2021). Consequently, we may expect jobs with greater automation risk to have experienced higher levels of displacement at the onset of the pandemic in South Africa.

2.2. The COVID-19 Pandemic and the South African Labour Market

Research has found that job losses in South Africa during the initial lockdown were both large and concentrated amongst the already vulnerable. Ranchhod and Daniels (2021) using the NIDS-CRAM survey, estimate that approximately one in three employed people in the sample were not employed in April 2020. Analyses using the NIDS-CRAM or QLFS data find employment loss to be concentrated amongst women (Casale & Posel, 2020; Casale & Shepherd, 2020; Hill & Köhler, 2020), African/Black individuals, youth, less-educated and lower-skilled groups (Köhler et al., 2021; Ranchhod & Daniels, 2021). In addition, informal sector workers, low-wage workers, and union non-members were disproportionately negatively affected (Benhura & Magejo, 2020; Jain et al., 2020; Köhler & Bhorat, 2020; Ranchhod & Daniels, 2020; Köhler et al., 2021). Given the fact that employment is one of the most important factors affecting transitions into and out of poverty (Leibbrandt et al., 2010), understanding the key drivers behind the 2020 job losses is of preeminent importance.

Researchers have attempted to isolate various determinants of job loss during the start of lockdown. Köhler et al. (2021), using a quasi-experimental analysis, estimate that of the 2.2 million quarter-on-quarter contraction in employment, South Africa's specific lockdown policy directly accounted for 26.1% of total jobs lost. However, the magnitude of this estimate may be as low as 12.7%, and suggests that the majority of South Africa's short-term job loss may be attributable to other factors. The level of physical interaction in the workplace is one such factor (Bhorat et al., 2020b). Another unexplored factor in the job loss equation is the adoption of automation technologies. This paper will thus contribute to this growing body of literature by investigating the effect of a workers' risk of automation on their likelihood of job loss during the start of the COVID-19 pandemic in South Africa.

2.3. Theories of Technological Change in the Labour Market

The disruptive effect of technological change on the labour market is by no means a new topic in economics, and several core theories of technological change have been developed.

2.3.1. Skill-Biased Technological Change

The impact of technology on the labour market has classically been understood using Tinbergen's (1974, 1975) model of skill-biased technological change (SBTC). Under this model, technology is in favour of high-skilled workers and against low-skilled workers. While the theory is tractable, conceptually attractive and empirically successful (Berman et al., 1994; Autor et al., 1998; Autor et al., 2003; Hardy et al., 2016; Bhorat & Khan, 2018; World Bank, 2019), the theory merely labels the correlation between computerisation and increases in high-skill labour input. As such, it fails to explain what it is that technology does to cause the relatively high demand for high-skilled workers (Autor et al., 2003). In addition, the model fails to explain the simultaneous increases in demand for those in low-skill occupations (Goos & Manning, 2007; Acemoglu & Autor, 2011). Consequently, another theory has emerged which focuses on occupations' task content as a driver of technology-induced labour market change.

2.3.2. Routinisation and the Task Content of Occupations

Since the seminal paper by Autor, Levy & Murnane (2003), a more nuanced view of technological change – the routinisation hypothesis – has been formalised and well-used in literature (Goos & Manning, 2007; Firpo, Fortin & Lemieux, 2011; Autor & Dorn, 2013; Bhorat et al., 2020a). Because routine tasks can be feasibly solved using algorithms, the routinisation hypothesis suggests that technology complements non-routine tasks and substitutes routine tasks (Acemoglu & Autor, 2011). As such, technology will replace workers performing routine-intense cognitive and manual tasks, such as record-keeping, while complementing workers performing non-routine problem-solving and complex communications tasks, such as research (Autor et al., 2003). With decreases in the prices of technology, firms will invest in automation technology, thereby replacing their routine-intense labour input and increasing their demand for labour adept in non-routine tasks. Using the intensity of routine, manual and abstract task activities performed at work, Autor and Dorn (2013) provide a categorisation of occupations based on their relative automation risk. A similar task-composition based model is used in this paper's analysis. However, instead of evaluating the effects of automation at an aggregated level, such as occupations or regions, this paper provides a complementary perspective by focusing on individual outcomes.

Technology adoption inadvertently raises the relative demand for highly educated workers, who hold comparative advantage in non-routine versus routine tasks (Autor et al., 2003; Goos et al., 2014). According to Autor, Levy and Murnane (2003), the routinisation hypothesis can explain 60% of the shift in demand favoring educated labour in the late 1990s in the US. In addition, Hardy, Keister and Lewandowski (2016) find that countries in Central and Eastern Europe experienced a rising intensity of non-routine cognitive tasks in jobs, and a decreasing intensity of manual tasks, between 1998-2013. Their results suggest that workforce upskilling and tertiary education were a factor behind these changes. In South Africa, educational attainment is relatively poor (Spaull, 2013). Given the link between education and automation risk, the confluence between education and automation risk will be explored in this paper, to assist policymakers in their response to any trends of accelerated automation during and after the COVID-19 pandemic.

2.4. Past Evidence on the Impact of Automation on Employment

Evidence of the impact of automation technology on employment in advanced economies is mixed. Some studies find that automation has displaced labour (Brynjolfsson & McAfee, 2014; Acemoglu & Restrepo, 2017; Acemoglu & Restrepo, 2019). In US labour markets, Acemoglu and Restrepo (2020) estimate that one more robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points. On the other hand, many authors have concluded that automation technologies have a neutral or positive influence on labour demand, job growth and total employment (Bessen, 2016; Gregory et al., 2016; Dauth et al., 2017; Mann & Püttmann, 2018; Koch et al., 2021). Manyika et al. (2017b) estimate that while computers destroyed 3.5 million jobs in the US since 1970, they also created at least 19.3 million. Thus, in the long-run, automation may in fact create jobs and increase demand for existing ones (Autor, 2015; Manyika et al., 2017b).

In developing countries, automation technologies are not nearly as well-established (World Bank, 2016; United Nations Industrial Development Organization, 2019). Das and Hilgenstock (2018) assert that developing economies are significantly less exposed to routinisation than their developed counterparts. However, the Asian Development Bank (ADB) (2018) found that, between 2005–2015, new technologies had a net positive impact on employment, as rising labour demand more than compensated for jobs displaced by technology. On the other hand, robots have been estimated to have had significant displacement effects in China and Mexico (Artuc et al., 2019; Giuntella & Wang, 2019). Despite this, Ernst et al. (2018) argue that automation technologies in developing countries have the potential to increase productivity growth opportunities and, therefore, employment growth.

The adoption of Fourth Industrial Revolution (4IR) technologies is highly country- and industry-specific, and will likely cause some industries to decline and others to grow (Bessen, 2019; Gentili et al., 2020). Empirical evidence from advanced nations has found automation's displacement effects to be particularly strong in manufacturing due to high levels of routine, predictable physical tasks (Dauth et al., 2017; Manyika et al., 2017a, Mann & Püttmann, 2018; Acemoglu & Restrepo, 2019). However, manufacturing job losses have been found to be offset, if not outstripped, by job growth in the services sector (Dauth et al., 2017; Mann & Püttmannm, 2018). Thus, automation might not cause mass unemployment, but it may require workers to make disruptive transitions to new industries, requiring new skills and occupations (Bessen, 2016; 2019).

2.5. Predicting the Impact of Automation on Employment

Given the above employment effects of technology, the degree to which workers occupy jobs at high risk of substitutability by automation technologies has attracted the interest of many researchers. The predicted impacts for advanced nations vary widely. For example, in the US, Frey and Osborne (2017) estimate that around 47% of total employment is in occupations at high-risk of automation, while Arntz et al. (2016) find that only 9% of workers are at high-risk of automation. Developing countries, on the other hand, are likely to experience different levels of automation risk compared to advanced nations, due to different occupational distributions and a lack of economic feasibility (UNCTAD, 2017; Maloney & Molina, 2019). Thus, while the World Bank (2016) estimate that two-thirds of all jobs in developing countries are susceptible to automation, the expected unemployment effects are moderated by low wages and slow technology adoption (ADB, 2018). Consequently, while technical feasibility of automation may be present in South Africa, this does not necessarily imply that automation will ensue. However, when accounting for both technological feasibility and adoption time lags, the World Bank (2016) estimate that approximately 48% of employment in South Africa can be computerised.

In South Africa, studies on the risk of automation have focused on the manufacturing industry. Drawing on interviews with firm managers, government and union representatives in the South African apparel industry, Parschau and Hauge (2020) find that the impact of automation on unemployment has been, and will continue to be, negligible. On the other hand, Allen Whitehead et al. (2021) examine the impact of automation technologies on the Manufacturing, Engineering and Related Services Sector (MER) sector, using the task-content of occupations. The authors find that a significant share of the sector’s labour force was in high-risk occupations, and this has remained static over the past decade. Additionally, they observe an increase in the number and share of high-risk employment in the metal sector. This is concerning, as the delayed adoption of labour-displacing technologies may lead to more significant job displacement in future. Thus, this paper aims to explore whether risk of automation was a determinant of job loss at the start of the COVID-19 pandemic in South Africa.

3. Data and Method

3.1. Quarterly Labour Force Survey

This analysis uses the Quarterly Labour Force Survey (QLFS), which is a household-based, nationally representative survey[1] conducted by Statistics South Africa (Stats SA). The survey captures data on demographic and socioeconomic characteristics and labour market activities of individuals 15 years or older who live in South Africa. Prior to March 2020, the survey made use of face-to-face interviews and covered approximately 33 000 dwelling units. However, data collection was disrupted in Q1:2020 due to COVID-19 lockdown regulations. Approximately 2% of dwellings were not interviewed, and imputations were conducted using Q4:2019 data. In Q2:2020, Stats SA shifted to Computer Assisted Telephone Interviewing (CATI) for data collection. As a result, the Q1:2020 sample was also used for Q2:2020, allowing for the creation of an unbalanced panel dataset (StatsSA, 2020b). However, data was only collected from dwelling units with available contact numbers. Additionally, contact numbers that were invalid, unanswered or reached households that had relocated since Q1:2020, were considered 'non-contact'. While weights were adjusted for non-response, there were high levels of attrition between the quarters.[2] This attrition is likely to be non-random, and may create issues of selection bias. StatsSA recommends caution when comparing Q2:2020 to previous quarters (StatsSA, 2020b).

This paper's analysis uses a cross-sectional dataset for Q1:2020, with a variable capturing whether an individual lost their job by Q2:2020. The job loss variable is generated using Q2:2020 employment status information from an unbalanced panel dataset created by Kerr (2021).[3] Throughout the analysis, the QLFS survey's complex design (sample weights, clustering and stratification) is accounted for. The sample is restricted, by definition, to all those employed in Q1:2020 who are of working-age (15–

[1] With the weights released by Statistics South Africa.
[2] The Q2:2020 sample contained 19 554 fewer individuals, or approximately 70.66% of the Q1:2020 sample.
[3] Individuals in the QLFS are not identified using an individual-level unique ID across quarters. Thus, the dataset is approximated by matching individuals in the same household ID with the same person ID number. Because household composition changes, this is further cross-checked with race, gender and age.

64 years), and who have non-missing employment status information in Q2:2020. The sample is further restricted to only those in occupations with matching O*NET task data.[4] The final sample consists of 9 345 workers, representing 9 047 465 workers in the population.[5]

3.2. O*NET

The Occupational Information Network (O*NET) database is a US survey that captures standardised and occupation-specific descriptors (O*NET, 2021). The data is collected from a range of employees and occupation experts, and contains 923 occupations. The occupation taxonomy was last revised in 2019. The data is particularly useful due to the wide range of descriptors, and the possibility for quantitative comparisons across occupations. The O*NET 25.0 Database, which was updated in August 2020, is used in this paper to create a Routine Task Index (see below). However, using US data to describe South African occupations might be prone to bias. Despite this, Lewandowski et al. (2019) find that O*NET descriptors are generally appropriate for use in the context of developing countries. In the absence of readily available occupation task data for South Africa, this paper assumes the O*NET descriptors are an acceptable approximation for the purpose at hand.

3.3. Generating a Routine Task Index

Based on the routinisation hypothesis, it is assumed that occupations with more routine tasks will be at higher risk of automation. An occupation level Routine Task Index (RTI) is created as a proxy for an occupation's risk of automation. The RTI is constructed using four intermediate indicators[6] defined by Acemoglu and Autor (2011) that combine work activities, abilities, and work context descriptors from the O*NET database. The final RTI measure is based on the formulation used by Lewandowski, Park & Schotte (2020) and Lewandowski et al. (2019). However, this paper includes an additional measure of routine manual tasks, as defined by Acemoglu and Autor

[4] See Section 3.4 for explanation.
[5] See Table 1 in Section 4.
6 The intermediate indicators are routine cognitive tasks, routine manual tasks, non-routine cognitive analytical tasks, and non-routine cognitive personal tasks. Consult Acemoglu and Autor (2011) for a detailed description.

(2011), since excluding them would mischaracterise certain occupations' RTI in the South African context (Allen Whitehead et al., 2021. The RTI is defined as follows:

$$RTI = \ln\left(\frac{rc_i + rm_i}{2}\right) - \ln\left(\frac{nra_i + nrp_i}{2}\right)$$

where rc_i, rm_i, nra_i and nrp_i refer to the intermediate indicators: routine cognitive, routine manual, non-routine cognitive analytical and non-routine cognitive personal tasks required in each occupation i. The RTI is then normalised to fall between 0 and 1, where 0 indicates a completely non-routine occupation, and 1 indicates a completely routine occupation.

The RTI is subdivided into the three mutually exclusive categories: low-risk, medium-risk and high-risk. Based on the routinisation hypothesis, "routine" occupations are at high-risk of automation, while "non-routine" occupations are at low-risk. Following Autor and Dorn (2013), occupations with an RTI above the 66th percentile of the RTI distribution are considered routine-intense, and are classified as "high-risk". Occupations with an RTI between the 33rd and 66th percentile (inclusive) are referred to as "medium-risk". Occupations with an RTI equal to or lower than the 33rd percentile are considered non-routine, "low-risk".

3.4. Merging RTI with QLFS data

Mapping O*NET data to QLFS data is somewhat complex due to differences in their occupational classifications.[7] Thus, this analysis uses a publicly provided "crosswalk" created by the Institute for Structural Research (Instytut Badań Strukturalnych) to match O*NET's occupation codes to the QLFS' (IBS, 2016). However, several South African occupations, such as taxi drivers, have no identical occupation within the O*NET database. In order to avoid losing information, these occupations are re-coded as comparable occupations in the O*NET database.[8] While these amendments

[7] The O*NET database uses the Standard Occupational Classification (SOC), while the QLFS uses ISCO-88 classification codes.
[8] For example, "taxi drivers, informal" is recoded as "Car, taxi and van drivers". See Table A2 in Appendix.

ensure a 92.22% match between the datasets, this analysis ought to be reconducted when South African specific occupation data becomes available.

3.5. Methodology for predicting job loss

The aim of this paper is to explore the role of workers' automation risk, and the interaction with education level, on the probability of job loss at the start of 2020. The dependent variable is thus a binary response variable that equals to one if an individual is not employed[9] and zero if an individual is employed in Q2:2020, conditional on the individual being employed in Q1:2020. While a Linear Probability Model (LPM) is simple to estimate and use, the model's fitted values can be less than zero or greater than one and it only reports constant marginal effects (Wooldridge, 2015). Thus, this paper will use probit models. Because probit models have an inverse Gaussian link function, errors are assumed to be normally distributed. In addition, because the link function produces coefficients in the normal distribution scale, marginal effects are calculated and presented throughout the paper. The probit model takes on the following form:

$$P(jobloss_i|x_i) = \beta_0 + \alpha RISK_i + \beta EDUC_i + \gamma X_i + \delta INST_i + \eta INDUS_i + \varepsilon$$

where $jobloss_i$ represents the binary job loss variable, $RISK_i$ is the categorical variable for low-, medium- and high-risk of automation, $EDUC_i$ is the categorical variable for mutually exclusive education levels: no matric, matric and post-matric. X_i represents multiple individual-level controls, namely age[10], marital status, gender, and race. $INST_i$ represents the labour market institution framework, and contains dummy variables for union membership, public sector employment,[11] and formal sector employment. $INDUS_i$ controls for different industries.

Given that the pandemic may have accelerated automation adoption, higher automation risk is expected to increase the likelihood of job loss (Livanos & Ravanos,

[9] Not employed consists of unemployed, discouraged work seekers and other not economically active.
[10] Age is coded as a categorical variable with 4 categories: 18-24 years, 25-44 years, 45-54 years and 55-64 years.
[11] The public sector dummy variable was created based on the same variable used in the PALMS dataset (Kerr & Wittenberg, 2019).

2021). In contrast, workers' education levels are expected to have a protective effect on job loss, and be strongly correlated with risk of automation (Hardy et al., 2016). In cognisance of the education and automation risk co-movements, the above probit model is further run with an interaction term for education and automation-risk. It is expected that the protective effect of a post-matric qualification is greater amongst workers at low-risk of automation.

Given the strong observed relationship between wages and job loss during the start of the pandemic in South Africa, the lack of available earnings data will lead to issues of omitted variable bias (Ranchhod & Daniels, 2020). In addition, the model will likely suffer from inflated standard errors due to multicollinearity. For example, automation risk will likely be correlated with industries. However, the exclusion of these variables would bias coefficients, which is considered more detrimental than finding a lack of significance on individual effects (Wooldridge, 2015). Prior to running the probit models, a preliminary data analysis is conducted below.

4. Descriptive Statistics

The levels of job loss between Q1:2020 and Q2:2020 were unprecedented in South Africa. Table 1 indicates that of those employed in Q1:2020, 20.13% or 1 820 928 (1 718 984; 1 922 872)[12] individuals lost their job[13]. However, 40.37% of the employed population in Q1:2020 had missing employment status information in Q2:2020[14]. This limits the sample size and introduces issues of selection bias[15]. Despite this, when including the missing data, 12.01% of the population lost their employment going into Quarter 2. This magnitude of job loss provides a large sample to robustly investigate whether high automation risk contributed to workers' susceptibility to job loss.

Table 1. Employment status of those in Q2:2020 who were employed in Q1:2020.

Employment Status in Q2:2020	Sample frequency	Percentage	Population frequency	Percentage
1. Employed	7 380	78.97	7 226 537 (116 282)	79.87
2. Unemployed	509	5.45	489 898 (27 329)	5.41
3. Discouraged job seeker	187	2.00	172 304 (15 615)	1.90
4. Other not economically active	1 269	13.58	1 158 727 (41 427)	12.81
Total	9 345	100.00	9 047 465 (130 340)	100.00

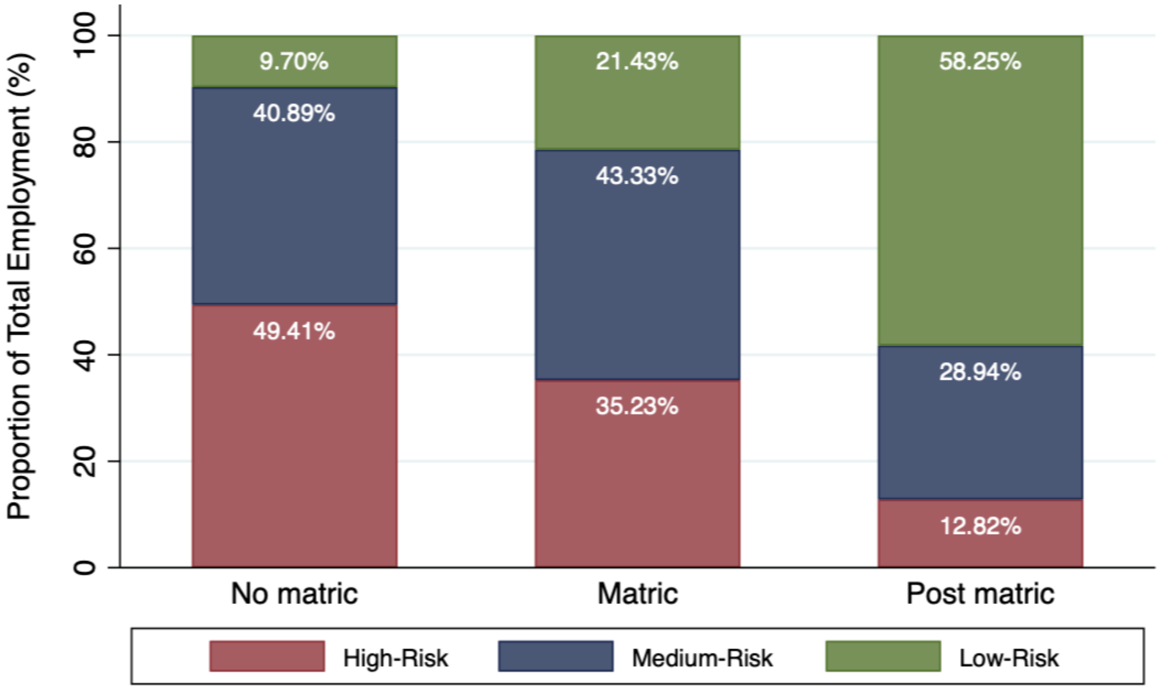
Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d)
Notes: 1. Weights have been applied to obtain population values. 2. Standard errors are reported in parentheses and are adjusted for clustering and stratification. 3. Sample is restricted to the working-age population, and those in occupations with RTI data. 4. This table captures information for those with non-missing employment status information in Q2:2020.

Figure 1 [16] below explores the share of pre-pandemic employment across worker's education status and risk of automation. The figure shows that those with no matric are 3.85 times more likely than those with post matric, and 1.40 times more likely than those with matric, to be employed in routine occupations at high-risk of automation.

[12] Confidence intervals in parentheses.
[13] This value is lower than 2.2-3 million due to restricting the sample to only those with employment information in both Q1:2020 and Q2:2020, and only those with RTI data.
[14] See Table A1 in Appendix for a replica of Table 1, but with missing observations included.
[15] A simple regression finds that the probability of having missing employment data in Q2:2020 is significantly associated with various demographic characteristics.
[16] See Table A3 in Appendix for confidence intervals.

Those with post matric predominantly work in non-routine occupations at low-risk of automation. This pattern of highly-educated workers being employed in non-routine occupations, and less-educated workers in routine occupations, matches empirical and theoretical evidence (Autor et al., 2003; Hardy et al., 2016). Furthermore, it emphasises that workers' education levels can prescribe their occupation options, and is thus a strong predictor of susceptibility to technological substitution. In South Africa, this correlation is concerning, as it suggests that the accelerated adoption of automation due to COVID-19 may exaggerate the labour market inequalities driven by existing disparities in access to quality education (Branson & Leibbrandt, 2013).

Figure 1. Pre-pandemic (Q1:2020) employment across workers' education levels and risk of automation.



Source: Author's own calculations from QLFS 2020Q1 (StatsSA, 2020c).
Notes: Weights have been used.

Table 2 further explores differences in the demographic characteristics of those in occupations at low- and high-risk of automation. Table 2 corroborates the education differential in Figure 1, showing that the proportion of workers with post matric employed in low-risk occupations is 6.8 times larger than in high-risk occupations. This aligns with Allen Whitehead et al. (2021), who find formal education levels to be a key determinant in the positioning of workers across high- and low-risk occupations in South Africa's MER sector. Table 2 further shows that women, African and Coloured individuals, the youth, rural-dwelling individuals, informal workers, non-union members, and non-government employees hold a relatively larger proportion of jobs at high-risk of automation compared to jobs at low-risk of automation. If automation adoption was accelerated by the pandemic, these figures suggest that workers in the already most vulnerable groups in South Africa would have been the most likely to have experienced technological unemployment.

Table 2. Demographic characteristics by automation risk level.

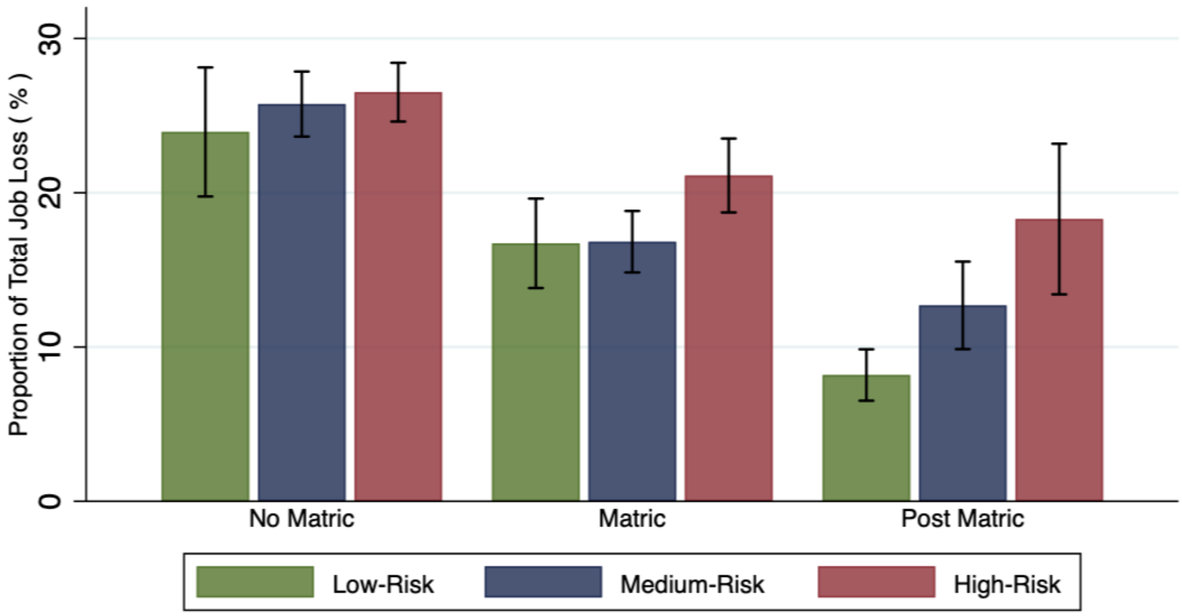
	High Risk	***Low Risk***	***P-value***
Job loss	0.242	0.136	0.000***
	(0.007)	(0.007)	
No Matric	0.581	0.172	0.000***
	(0.006)	(0.006)	
Matric	0.343	0.315	0.066*
	(0.006)	(0.008)	
Post Matric	0.075	0.513	0.000***
	(0.003)	(0.009)	
Age: 15-24 yrs	0.067	0.036	0.000***
	(0.004)	(0.003)	
Age: 25-44 yrs	0.592	0.536	0.001***
	(0.006)	(0.009)	
Age: 45-54 yrs	0.237	0.294	0.000***
	(0.005)	(0.008)	
Age: 55-64 yrs	0.103	0.134	0.002***
	(0.004)	(0.006)	
Female	0.517	0.478	0.005***
	(0.007)	(0.009)	
Married	0.327	0.584	0.000***
	(0.006)	(0.009)	
African	0.860	0.595	0.000***
	(0.005)	(0.009)	
Coloured	0.087	0.090	0.778
	(0.004)	(0.005)	
Indian/Asian	0.018	0.064	0.000***
	(0.002)	(0.004)	
White	0.035	0.251	0.000***
	(0.002)	(0.008)	
Urban location	0.746	0.818	0.000***
	(0.006)	(0.006)	
Formal	0.637	0.763	0.000***
	(0.006)	(0.008)	
Public	0.044	0.358	0.000***
	(0.003)	(0.008)	
Union	0.258	0.470	0.000***
	(0.006)	(0.010)	
Hours worked	41.831	43.849	0.000***
	(0.179)	(0.218)	
Weighted Population Size	3 237 932	2 140 864	

*Source: Authors' calculations from QLFS (StatsSA, 2020) and O*NET (2020).*

Notes: 1. Occupations with an RTI below the 33rd percentile of the RTI distribution are classified as non-routine, low-risk. Those above the 66th percentile are routine, high-risk. 2. Statistics are weighted to be representative of the population. Standard errors adjusted for clustering and stratification, and scaled to handle strata with a single sampling unit. 3. Standard errors are in parentheses. 4. Significance levels are denoted with stars: *** p<0.01, ** p<0.05, * p<0.1.

The proportion of workers who lost their job at the start of the pandemic is significantly larger for those in high-risk occupations relative to low-risk occupations. Table 2 shows that 24% of workers in high-risk occupations lost their jobs, relative to only 14% of those in low-risk jobs. This difference is significant at the 1% level. This may point to the possibility that the adoption, or anticipated adoption, of 4IR technologies prompted the loss of more jobs with a large share of routine-tasks, as put forward by the Routinisation Hypothesis (Autor et al., 2003). Given the high level of existing vulnerability amongst those working in high-risk occupations, and the strong correlation between education attainment and automation risk, it is worth assessing whether post matric education could dampen the potential job-displacing effects of being at high-risk of automation.

Figure 2. Job loss across workers' education levels and risk of automation.



Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d).
Notes: 95% Confidence Intervals in black.

Figure 2 shows that, across all three automation-risk categories, those with a post-matric education do have a lower proportion of job loss relative to those with only a matric or no matric. This may suggest that higher education can diminish the likelihood of job loss when working in highly automatable jobs. This result matches previous studies' finding that job loss at the start of the pandemic was concentrated amongst the less-educated (Köhler et al., 2021; Ranchhod & Daniels, 2021). However, Figure

2 also shows that workers at high-risk of automation had a higher proportion of job-loss, relative to workers at low-risk of automation, across all education levels. This suggests that higher education was unable to fully eliminate the potential labour-displacing effects of being at high-risk of automation at the onset of the pandemic in South Africa.

Figure 2 further illustrates an interaction between workers' education levels and automation risk level. Amongst those with a post-matric qualification, there are large differences in the proportion of job loss across the automation risk categories, compared to amongst those with no matric. This may suggest that an occupation's automation risk plays a larger role in job loss at higher levels of education. Similarly, there are smaller differences in the proportion of job loss across education levels for those in high-risk of automation occupations, compared to those in low-risk occupations. This suggests that education levels may play a stronger role in determining job loss in low-risk of automation occupations. However, the large confidence bands on job loss for those with post-matric in high-risk occupations and no matric in low-risk occupations reflects the small sample size in these groups. It further emphasises how individuals with higher education are able to select into low-risk occupations. Ultimately, Figure 2 highlights that education and automation-risk levels may interact to exacerbate inequalities in the probability of job loss.

In order to predict the effect of automation risk on job loss, other key determinants of job loss are investigated in Table 3 below. Table 3 finds that job loss differs significantly by gender amongst those working in low- and high-risk occupations, with the majority of those losing jobs being female. This is in-line with Casale and Posel (2020) and Casale and Shepherd (2020), who find employment losses to be concentrated amongst women in the first month of lockdown. On average, African/black individuals appear more likely to have lost employment, while White individuals appear more likely to have kept employment, relative to other races. In line with Benhura and Magejo (2020) and Köhler et al. (2021), those employed in the formal sector, public sector and those with trade union membership had a larger share of job-retainers. These statistics indicate that the already vulnerable were also most likely to work in high-risk of automation occupations and to have lost their jobs at the start of the pandemic. This emphasises the future social importance of understanding the extent to which automation contributed to the 2020 job-losses; particularly as technology-replaced jobs may never be regained in the post-COVID-19 economy.

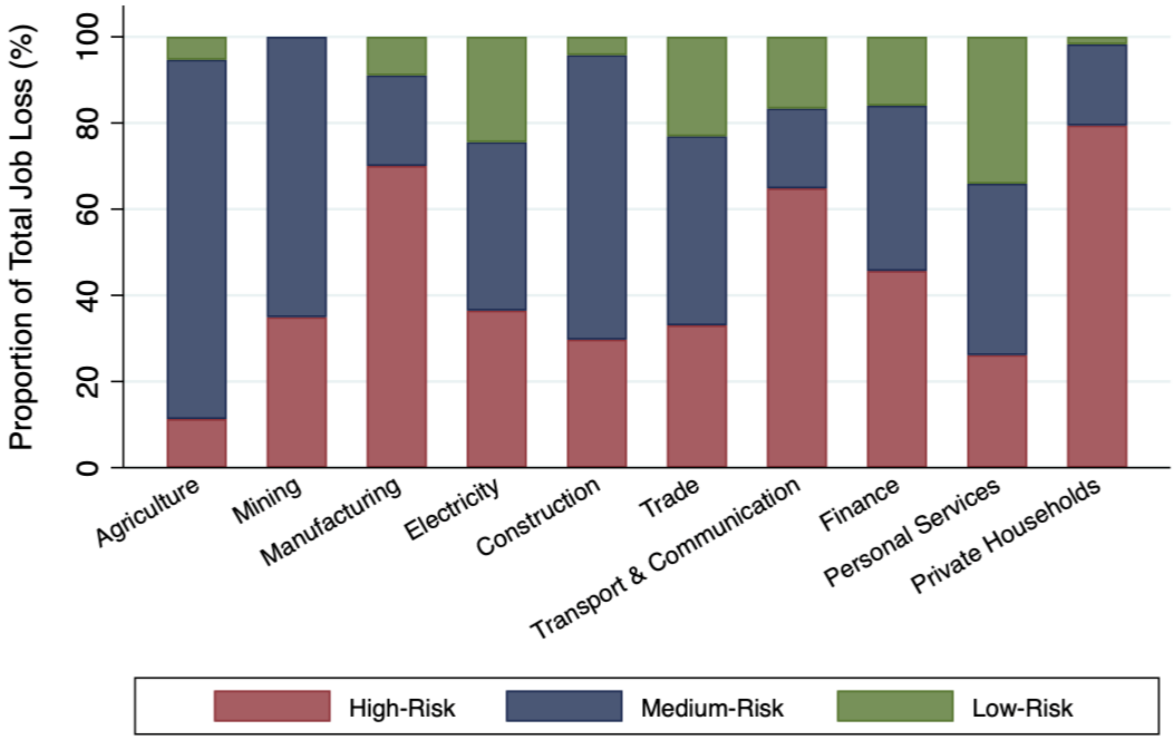
Table 3. Demographic Characteristics of the working age population by job loss status and risk of technological job displacement.

	LOW RISK			***INTERMEDIATE RISK***			***HIGH RISK***		
	Kept Job	Lost Job	P-value	Kept Job	Lost Job	P-value	Kept Job	Lost Job	P-value
No Matric	0.15	0.30	0.00***	0.42	0.57	0.00***	0.56	0.64	0.00***
Matric	0.30	0.39	0.01**	0.41	0.33	0.00***	0.36	0.30	0.01***
Post Matric	0.54	0.31	0.00***	0.17	0.10	0.00***	0.08	0.06	0.03**
15-24 years	0.03	0.08	0.00***	0.06	0.12	0.00***	0.06	0.09	0.00***
25-44 years	0.54	0.51	0.43	0.65	0.61	0.09*	0.59	0.59	0.90
45 -54 years	0.31	0.22	0.00***	0.21	0.17	0.04**	0.25	0.19	0.00***
55-64 years	0.13	0.18	0.04**	0.08	0.09	0.47	0.10	0.12	0.07*
Female	0.46	0.59	0.00***	0.39	0.38	0.69	0.51	0.55	0.05**
African	0.58	0.68	0.01***	0.78	0.82	0.08*	0.85	0.88	0.17
Coloured	0.09	0.07	0.15	0.08	0.10	0.42	0.09	0.09	0.84
Indian/Asian	0.07	0.04	0.07*	0.03	0.02	0.12	0.02	0.02	0.71
White	0.26	0.21	0.21	0.10	0.07	0.04**	0.04	0.02	0.01***
Formal	0.82	0.41	0.00***	0.79	0.52	0.00***	0.68	0.52	0.00***
Public	0.39	0.12	0.00***	0.15	0.09	0.00***	0.05	0.02	0.00***
Union	0.50	0.16	0.00***	0.33	0.11	0.00***	0.30	0.13	0.00***
Hours Worked	44.07	42.40	0.17	44.77	42.18	0.00***	42.62	39.35	0.00***
Weighted Population Size	1 848 898	291 967		2 766 859	698 460		2 454 290	783 642	

*Source: Authors' calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d) and O*NET (2020).*
Notes: 1. Occupations with an RTI below the 33rd percentile of the RTI distribution are classified as non-routine, those above the 66th percentile as routine, and those in between as intermediate. 2. Statistics are weighted to be representative of the population. Variance is adjusted for clustering and stratification. Variance scaled to handle strata with a single sampling unit. 3. *** p<0.01, ** p<0.05, * p<0.1 3.

Figure 4 demonstrates that automation-risk is industry-specific, and technology adoption will likely cause labour displacement in some industries and labour growth in others (Bessen, 2019; Gentili et al., 2020). According to Figure 4*,* private households, manufacturing and the transport and communication industries had the largest share of highly automatable jobs lost. The manufacturing industry is dominated by routine tasks, and empirical evidence from advanced nations has found automation's displacement effect to be particularly strong in manufacturing (Dauth et al., 2017; Mann & Püttmann, 2018; Acemoglu & Restrepo, 2019). The large share of high-risk occupations that were lost in private households is unique to South Africa and is likely reflecting the inability for domestic workers to access their places of work during the national lockdown.[17] The differences in job loss by automation risk across industries emphasises the importance of accounting for industries in the regression models run below.

Figure 3. Job loss across Industries by Workers' Risk of Automation.



Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d).
Notes: Weights have been used.

[17] Domestic workers are coded as high-risk, routine, according to the measures created using the O*NET database. This represents a key limitation of using US occupation data within the South African context, and is discussed in Section 6.

5. Results

Table 4: Probit Regression Estimates of the Marginal Effects of Automation Risk and Education Levels on the Probability of Job Loss.

Dependent variable: Job Loss (unemployed in Q2:2020, conditional on being employed in Q1:2020)				
	(1)	(2)	(3)	(4)
Automation risk level				
Intermediate Risk	0.065***	0.029**	0.059***	0.046 ***
	(0.012)	(0.013)	(0.014)	(0.016)
High Risk	0.106***	0.052***	0.065***	0.047***
	(0.012)	(0.014)	(0.016)	(0.017)
Education level				
Matric		-0.069 ***		-0.019*
		(0.011)		(0.012)
Post Matric		-0.133 ***		-0.052***
		(0.014)		(0.017)
Control Variables				
Individual and Employment Characteristics	No	No	Yes	Yes
Province Dummies	No	No	Yes	Yes
Industry Dummies	No	No	Yes	Yes
Observations	9,142	9,051	7,651	7,591

Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 *(StatsSA, 2020c and 2020d).*
Notes: 1. Standard errors are in parentheses and are adjusted for stratification and clustering. 2. The sample is all working-age individuals (15 to 64 years). 3. Data are weighted appropriately. 4. The base categories are low-risk for automation risk level and no matric qualification for education level. 5. See Methodology for detailed breakdown of the control variables. 6. Significance levels are denoted with stars: *** p<0.01, ** p<0.05, * p<0.1.

Table 4 presents the average marginal effects of workers' education levels and occupations' automation risk on the probability of job loss between Q1:2020 and Q2:2020. Column 1 shows that, without including any controls, being in a high-risk occupation relative to a low-risk occupation, is associated with a 10.6 percentage point increase in the probability of job loss in Q2:2020. Being in an intermediate-risk occupation also has a positive, albeit less pronounced, effect on the probability of job loss. Both estimates are significant at the 1% level. Column 2's estimates indicate that the inclusion of the education level variables reduces the magnitude of the coefficients on the automation risk variables. This suggests a strong negative correlation between education levels and an occupation's risk of automation. The correlation increases the standard errors for the automation risk effects when education is included, thereby reducing the precision of Column 2's estimates. The estimates for the variables of interest do, however, remain statistically significant.

Table 4's Columns 3 and 4 indicate that the positive effect of automation risk on job loss is robust to the inclusion of relevant explanatory variables. The estimates in Column 4 suggest that being in an intermediate- or high-risk occupation, relative to a low-risk occupation, is associated with a respective 4.6 or 4.7 percentage point rise in the likelihood of job loss. Relative to the mean job loss amongst low-risk of automation workers (14%) and high-risk of automation workers (24%), these effects are large and economically significant. However, the magnitude of these estimates has fallen in comparison to Columns 2 and 3, indicating that the inclusion of key explanatory variables removed positive omitted variable bias on the automation risk effects. Furthermore, the additional covariates have slightly reduced the precision of the estimates, due to high levels of multicollinearity. However, removing correlated variables to avoid multicollinearity would increase the potential for omitted variable bias in the coefficients of interest (Wooldridge, 2015). Given that the coefficients remain statistically significant, the slight decrease in precision is not of concern.

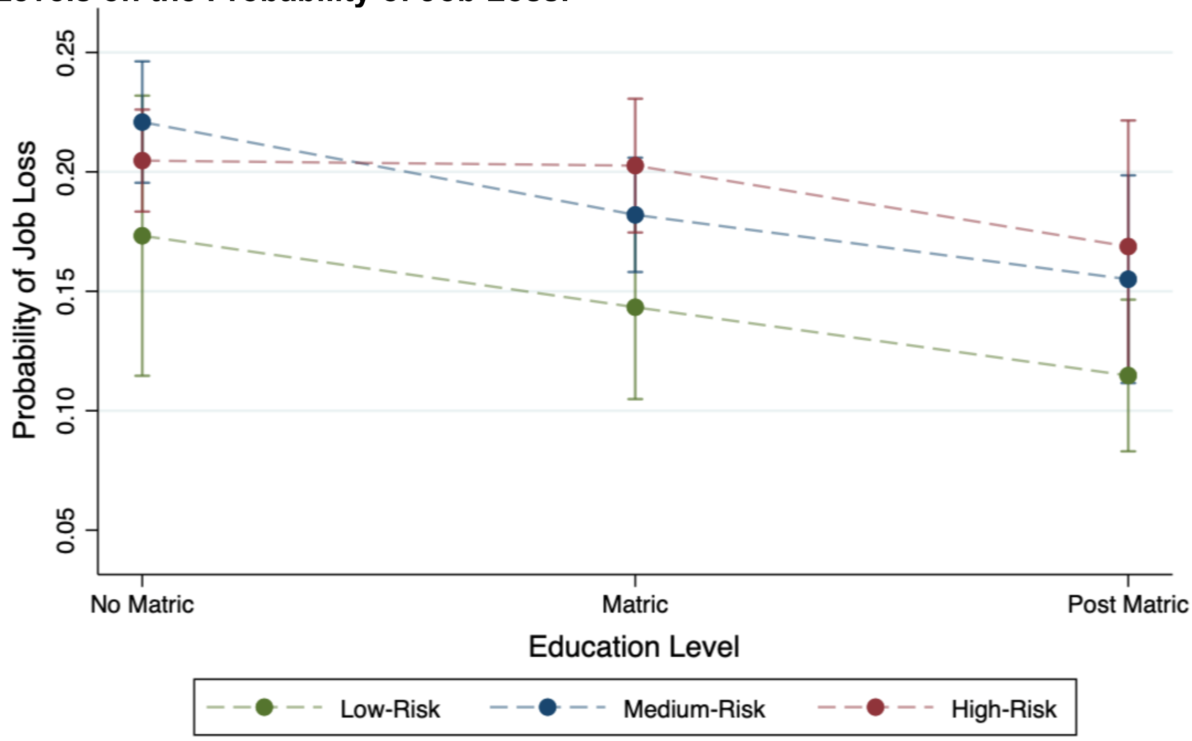
LPM estimation results for Table 4, presented in Table A4 of the Appendix, indicate that the results are robust to model selection. In addition, Column 4's estimates are robust to the categorisation of automation risk. Specifically, when re-running the probit regression in Column 4 with a risk variable constructed by dividing the RTI at the 1) 25th and 75th percentile and 2) at the median, the results do not change substantially, and are statistically and practically equivalent.[18]

Column 2 and Column 4 show that including education level variables deflates the magnitude of the automation risk coefficients, whether controls are present or not. This suggests that education levels are strongly negatively correlated with automation risk

[18] See Figure A1 in the Appendix.

levels, as observed in the descriptive analysis and in the literature. Consequently, in order to ascertain whether the effects of education on job loss compounds the automation risk effect on job loss, an interaction term is added to the probit model in Column 4. The predictive margins and the average marginal effects of automation-risk levels on the probability of job loss at different levels of education are presented in Figure 4 and Table 5 below.

Figure 4. Predictive Margins of Automation Risk levels at different Education Levels on the Probability of Job Loss.



Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 *(StatsSA, 2020c and 2020d).*
Notes: 95% Confidence Intervals included.

Table 5. Average Marginal Effects of automation risk levels on the probability of job loss at different levels of education.

Education Level	*Medium-risk*	*High-risk*
No Matric	0.048	0.032
	(0.032)	(0.032)
Matric	0.039*	0.059**
	(0.022)	(0.024)
Post Matric	0.040	0.054*
	(0.025)	(0.031)

Source: Authors' own calculations from QLFS 2020Q1 and 2020Q2 *(StatsSA, 2020c and 2020d) and O*NET (2020).*
Notes: 1. Base category for automation-risk variables is Low-risk occupation. 2. Standard errors are reported in parentheses. 3. Significance values are denoted with stars: *** p<0.01, ** p<0.05, * p<0. 4. All relevant controls are included in the regression.

Table 5 indicates that being at high-risk of automation, relative to being at low-risk of automation, increases the probability of job loss at all levels of education. When everyone has a matric or a post matric, then being at high-risk of automation relative to low-risk is associated with a 5.9 or 5.4 percentage point increase in the probability of job-loss, respectively. This result is likely statistically significant as more educated individuals are equipped to enter a variety of jobs, leading to more variation in their automation risk levels (as can be seen in Figure 1). Interestingly, when everyone has no matric, the marginal effect of being at high-risk of automation relative to being at low-risk of automation is statistically insignificant. The insignificance is likely a consequence of low variation in automation risk levels amongst those with no matric, as seen in Figure 1. However, the size of the coefficient is relatively large in relation to mean job loss, and its economic significance should not be overlooked.

Figure 4 illustrates that, when everyone is assumed to have no matric education, medium-risk of automation has the highest predicted probability of job loss, instead of high-risk of automation. This is reflected in the lower marginal effect on high-risk compared to medium-risk in Table 5. The result breaks from a seeming trend in the marginal effects, and may be reflecting a common observation in developing countries where low wages reduce the economic feasibility, and thus unemployment effects, of adopting automation technologies (World Bank, 2016; ADB, 2018; Maloney & Molina, 2019). High-routine occupations dominated by less-educated workers may be composed of low-paying jobs. Because this labour is cheaper than technology, it is unlikely to be displaced. Thus, being at high-risk, relative to low-risk, has a smaller marginal effect on job loss probability in comparison to being at medium-risk. This phenomenon may also explain why the marginal effect of being at high-risk, relative to being at low-risk, is over 2 percentage points *larger* if everyone has matric or post matric compared to everyone having no matric.

6. Discussion

The results above may provide preliminary evidence to suggest that automation adoption in response to the national lockdown contributed to early 2020 job losses in South Africa. According to Table 1's estimates, workers in occupations with higher routine-task content were more likely to have lost their job by the second quarter of 2020. Given that this aligns with the predictions of the routinisation hypothesis (Autor et al., 2003), this finding may indicate that South African workers in high-risk jobs were being replaced by automation technologies at the onset of the pandemic. This possibility is not unlikely, as economic dislocations historically precipitate cost reducing strategies, such as automation (Blit, 2020). In addition, Livanos and Ravanos (2021) establish that, due to the pandemic, occupations with a greater probability of automation will suffer more significant employment loss in the EU. Thus, while the results cannot concretely confirm whether firms chose to adopt automation technologies in South Africa, the evidence does not disprove the possibility.

Even if job loss at the start of the pandemic was not driven by automation, the significant positive correlation found between the likelihood of job loss and high automation risk should raise concern that the jobs that were lost will never be regained due to increased adoption of labour-replacing technologies. The pandemic's disruption will have affected future investment decisions and may have encouraged firms to shift toward technology-driven production processes going forward (Blit, 2020). The probit regression results indicate that high automation risk was significantly and positively correlated to job loss in early 2020. In addition, a higher proportion of those who lost their jobs were working in occupations at high-risk of automation. Consequently, while technology may not have replaced these workers in Quarter 2, the adoption of technology since Q2:2020 may eliminate the potential for these workers to regain their jobs. Fewer than 40% of the jobs lost in March 2020 had been recovered by the end of 2020 (World Bank, 2021). This suggests that there is still a possibility that many of these jobs will be eliminated by technology going forward in South Africa. Given South Africa's exceptionally high unemployment levels, this potential uptake of labour-replacing technologies should not be overlooked by policymakers.

The huge number of South Africans who recently became unemployed may have entirely lost their jobs due to technology. It is important that these individuals are supported to make successful and expeditious transitions into new lines of work (Atkinson, 2018). In the short-term, policymakers may wish to investigate the viability of a "technological unemployment income grant" to counter the immediate inequality-enhancing effects of the permanent job loss, and support workers in adapting their skills to find new work. In addition, while automation may eliminate jobs in some sectors, evidence suggests that it can encourage employment growth in other sectors (Dauth et al., 2017; Mann & Püttmannm, 2018; Bessen, 2019; 2016). Consequently, policies and efforts to encourage business activity in new sectors and support the retraining of the technologically-displaced could improve employment outcomes in the new, post-COVID era (Atkinson, 2018).

While education programmes are a common policy response toward mitigating technological unemployment (Atkinson, 2018), the interaction results in Figure 4 suggest that having a matric compared to no matric does not reduce high-risk workers' predicted probability of job loss. In addition, Table 5 shows that the marginal effect of being at high-risk of automation relative to low-risk on the likelihood of job loss is smaller when everyone has no matric[19] compared to when everyone has matric. This unexpected result may reflect employment dynamics linked to the low wages of low-skilled workers in South Africa (Leibbrandt et al., 2010). While low-skilled workers may theoretically be at high-risk of automation, their low levels of education make them cheaper than more educated workers and, most importantly, cheaper than automation technologies. In fact, automation technologies are often not rapidly adopted in developing countries due to the low economic feasibility (World Bank, 2016; Maloney & Molina, 2019; Parschau & Hauge, 2020). This may explain why those in high-risk occupations with no matric are equally as likely to lose their jobs as those with a matric, and less likely than those in medium-risk occupations. However, given the correlation between automation risk and education level, the importance of education cannot be understated.

[19] While this marginal effect is statistically insignificant, and cannot be considered conclusive, the magnitude of the effect is of economic significance.

Given the potential evidence of technological displacement, policymakers ought to explore ways to minimise the number of workers who are at risk of replacement by technology going forward. According to McKinsey Global Institute's post-COVID-19 scenario, 1 in 16 workers will need to find a different occupation by 2030 (Lund et al., 2021). The preliminary data analysis, and previous literature, shows that workers with a post matric education tend to occupy a larger share of those working in low-risk of automation occupations (Allen Whitehead et al., 2021). Consequently, education programmes and worker reskilling can minimise the number of workers who are at risk of future-displacement (Atkinson, 2018). This is particularly necessary in South Africa, as the results suggest that high-risk occupations are dominated by the most vulnerable. However, education takes time and policymakers may wish to investigate the viability of a "robot tax" to curb the future adoption of automation in South Africa. However, the efficacy of such a tax is questionable, particularly if it drives firms to move their production to other countries (Gasteiger & Prettner, 2017).

6.1. Limitations

While this paper is the first to provide evidence of a link between automation risk and the probability of job loss at the start of the pandemic in South Africa, one cannot conclude a causal relationship between automation risk and job loss due to a variety of limitations.

The probit regression results are likely biased and spuriously significant due to omitted variable bias and multicollinearity. The lack of earnings data raises significant concern for omitted variable bias, particularly as earnings and automation risk are very closely correlated. Ranchhod and Daniels (2020) find a clear negative relationship between workers' likelihood of job loss and their prior earnings level in Q2:2020. As such, without controlling for earnings data, the automation risk variables' coefficients will spuriously account for the variation in job loss that is explained by earnings levels. The significance and size of the automation risk coefficients is thus likely to be inaccurate. Work experience is another omitted variable that could bias coefficients due to correlation with education level and automation-risk. In light of this, it is strongly advised that this analysis be reconducted when earnings data becomes available.

The limitations of using US occupation descriptors to describe South African occupations cannot be understated. While the descriptors have been shown to be generally appropriate in developing country contexts (Lewandowski et al., 2019), they are not perfectly accurate within the South African context. In particular, domestic workers are considered high-risk, routine occupations according to the O*NET descriptors. However, in South Africa, while aspects of domestic work, such as dish-washing, may be automatable, a large share of domestic work includes non-routine aspects, such as childcare. Given that the occupations with the largest share of job loss in the data were domestic workers, helpers and cleaners[20], this incorrect representation of the occupation's automation risk may have overstated the impact of being at high-risk of automation on the probability of job loss. The development of a South African-specific database of occupation descriptors would support many in their endeavours to conduct analyses of employment dynamics based on occupation's task content.

It is important to note that the risk of automation variable used in this paper merely reflects the technical and theoretical feasibility of occupation automation. Automation adoption is further dependent on employers' time, money, and access to technologies. Thus, being "at risk" of automation does not mean that workers are "likely to be automated". This is particularly true in developing countries where labour tends to be cheap (ADB, 2018). Without actually obtaining direct input from industry stakeholders and experts, one cannot concretely confirm that jobs were automated at the onset of the pandemic. This analysis could be improved through the inclusion of a variable that accounts for the economic feasibility of automation adoption in different industries and occupations in South Africa.

While this paper emphasises the role of automation, other factors may be relevant in explaining the high probability of job loss among routine-intensive workers. One concern is that workers select into occupations for reasons that are correlated with labour outcomes. For example, if highly routine occupations require lower skill levels, then low-skilled workers will select into these occupations. Consequently, it may be unclear whether the observed differences in the probability of job loss between routine

[20] In total, domestic workers and helpers and cleaners in establishments made up 13.82% of total job loss in the sample by occupation.

and non-routine workers is due to automation dynamics or workers' selection on observable and unobservable skills. In addition, unobservable factors, such as levels of physical interaction, the ability to work from home, and work experience would have impacted job loss at the onset of the pandemic (Bhorat et al., 2020b). Future research on job loss during the COVID-19 pandemic could incorporate a physical interaction index and a remote work index to avoid bias in the estimation of the automation-risk effect.

Following from this, it is important to acknowledge that the COVID-19 pandemic may be unique in its effects on job loss. Consequently, the extent to which this paper's results can be can be used to explain dynamics outside of the COVID-19 lockdown context is limited. Furthermore, research has shown that the impact of automation can be highly industry-specific, so caution must be taken when generalising the above results across industries in South Africa. Despite these limitations, the reported results provide interesting, timely and relevant correlations between workers' risk of automation, education levels, and job losses. As such, automation trends should be carefully monitored in South Africa. In addition, more qualitative research, as done by Parschau & Hauge (2020), should be conducted to enable a deeper and more conclusive analysis on the effects of technological change in the South African labour market.

7. Conclusion

The future of work is one of the most critical challenges of the 21st century, particularly in the post-COVID era. While previous studies have explored who is most “at risk” of automation in South Africa, this paper is the first to investigate whether, and to what extent, a worker’s risk of automation affected their probability of job loss at the onset of the pandemic.

The results offer no conclusive evidence to indicate that automation caused job loss. However, the results find that high automation risk is positively correlated with lower education levels and higher probabilities of job loss. If the adoption of automation technologies does accelerate in response to the pandemic, then these correlations suggest that the high-risk jobs lost at the start of the pandemic may never be regained. Given South Africa’s exceptionally high unemployment levels, this shift could have significant, and concerning, macroeconomic and inequality-enhancing consequences. As such, automation adoption should not be overlooked in the post-COVID-19 policy agendas.

Further research investigating the evolution of automation adoption since March 2020 is necessary to confirm this paper’s findings and help the public and private sector anticipate skills gaps, manage job losses, and develop a more innovative and resilient post-COVID-19 economy.

References

Acemoglu, D. & Autor, D.H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Card, D. and Ashenfelter, O. (Eds.) *Handbook of Labor Economics*. Amsterdam: Elsevier.

Acemoglu, D. & Restrepo, P. (2017). Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation. *American Economic Review*, 107(5), 174-179.

Acemoglu, D. & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33 (2), 3-30.

Acemoglu, D. & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy,* 128(6), 2188-2244.

Asian Development Bank (ADB). (2018). *Asian Development Outlook (ADO) 2018: How Technology Affects Jobs.* Asian Development Bank. Available from: https://www.adb.org/sites/default/files/publication/411666/ado2018.pdf [29 October 2020].

Allen Whitehead, C., Bhorat, H., Hill, R., Köhler, T. & Steenkamp, F. (2021). The Potential Employment Implications of the Fourth Industrial Revolution Technologies: The Case of the Manufacturing, Engineering and Related Services Sector. *DPRU Working Paper 2021*. Cape Town: University of Cape Town Development Policy Research Unit.

Arntz, M., Gregory, T. & Zierahn, U. (2016). The risk of automation for jobs in OECD countries. OECD iLibrary.

Artuc, E., Christiaensen, L. and Winkler, H. J. (2019). Does Automation in Rich Countries Hurt Developing Ones? Evidence from the U.S. And Mexico. World Bank Policy Research Working Paper No. 8741.

Atkinson, R.D. (2018). How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change. Information Technology & Innovation Foundation.

Autor, D.H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3-30.

Autor, D. & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5), 1553-97.

Autor, D.H., Katz, L.F. & Krueger, A.B. (1998). Computing Inequality: Have Computers Changed the Labor Market? *The Quarterly Journal of Economics*, 113(4),1169-1213.

Autor, D.H., Levy, F. & Murnane, R.J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279-1333.

Benhura, M. & Magejo, P. (2020). Differences between formal and informal workers' outcomes during the COVID-19 crisis lockdown in South Africa. (Working Paper No.2). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 2.

Berman, E., Bound, J. & Griliches, Z. (1994). Changes in the Demand for Skilled Labor within U. S. Manufacturing: Evidence from the Annual Survey of Manufactures. *The Quarterly Journal of Economics*, 109(2), 367-397.

Bessen, J.E. (2016). How computer automation affects occupations: Technology, jobs, and skills. Boston University School of Law, Law and Economics research paper, no. 15-49.

Bessen, J. (2019) Automation and jobs: when technology boosts employment. *Economic Policy*, 34(100), 589-626.

Bhorat, H. & Khan, S. (2018). Structural change and patterns of inequality in the South African labour market. Development Policy Research Unit Working Paper 201801. University of Cape Town.

Bhorat, H., Lilenstein, K., Oosthuizen, M. & Thornton, A. (2020a). Wage Polarization in a High-Inequality Emerging Economy. WIDER Working Paper 2020/55. Helsinki: UNU-WIDER.

Bhorat, H., Thornton, A., Köhler, T. & Oosthuizen, M. (2020b). Jobs and COVID-19: Measuring Work-Related Physical Interaction. Development Policy Research Unit Working Paper 202003. University of Cape Town.

Blit, J. (2020). Automation and Reallocation: Will COVID-19 Usher in the Future of Work? *Canadian Public Policy*, 46(SII), S192-S202.

Branson, N. & Leibbrandt, M. (2013). Education Quality and Labour Market Outcomes in South Africa. *OECD Economics Department Working Papers*, No. 1021. OECD Publishing, Paris.

Brynjolfsson, E. & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.

Casale, D. & Posel, D. (2020) Gender and the early effects of the COVID-19 crisis in the paid and unpaid economies in South Africa. (Working Paper No.4.). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 1.

Casale, D. & Shepherd, D. (2021). Gendered employment dynamics during the COVID-19 pandemic. (Working Paper No.4.). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 4.

Das, M. & Hilgenstock, B. (2018). The Exposure to Routinization: Labor Market Implications for Developed and Developing Economies. *IMF working paper*, 18(135).

Dauth, W., Findeisen, S., Südekum, J. & Woessner, N. (2017). German Robots – The Impact of Industrial Robots on Workers. CEPR Discussion Papers 12306.

Department of Communications and Digital Technologies. (2020). Report of the Presidential Commission on the 4th Industrial Revolution (PC4IR). Government Gazette, No. 43834.

Ernst, E., Merola, R. & Samaan, D. (2019). Economics of artificial intelligence: Implications for the future of work. *IZA Journal of Labor Policy*, *9*(1), 1-35.

Firpo, S., Fortin, N.M. & Lemieux, T. (2011). Occupational Tasks and Changes in the Wage Structure. IZA Discussion Paper No. 5542.

Frey, C.B. & Osborne, M.A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114: 254-280.

Gasteiger, E. & Prettner, K. (2017). A note on automation, stagnation, and the implications of a robot tax. School of Business & Economics Discussion Paper.

Gentili, A., Compagnucci, F., Gallegati, M. & Valentini, E. (2020). Are machines stealing our jobs? *Cambridge Journal of Regions, Economy and Society*, 13(1), 153-173.

Georgieff, A. & Milanez, A. (2021). What happened to jobs at high risk of automation? OECD Social, Employment and Migration Working Papers, No. 255. OECD Publishing, Paris.

Giuntella, O. & Wang, T. (2019). Is an army of robots marching on Chinese jobs? IZA Discussion Papers 12281, Institute of Labor Economics (IZA).

Goos, M. & Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The review of economics and statistics*, 89(1), 118-133.

Goos, M., Manning, A. & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8), 2509-2600.

Gregory, T., Salomons, A. & Zierahn, U. (2016). Racing with or against the machine? Evidence from Europe. ZEW-Centre for European Economic Research Discussion Paper, 16-053.

Hardy, W., Keister, R. & Lewandowski, P. (2016). Technology or upskilling? Trends in the task composition of jobs in Central and Eastern Europe. HKUST IEMS Working Paper No. 2016-40.

Hill, R. & Köhler, T. (2020). Mind the gap: Analysing the effects of South Africa's national lockdown on gender wage inequality. (Working Paper No. 7). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 2.

Institute for Structural Research (IBS). (2016). Occupation classifications crosswalks – from O*NET-SOC to ISCO. Institute for Structural Research.

Jain, R., Budlender, J., Zizzamia, R. & Bassier, I. (2020). The Labour Market And Poverty Impacts Of Covid-19 In South Africa. (Working Paper No.5). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 1.

Karr, J., Loh, K. & San Andres, E.A. (2020). COVID-19, 4IR and the Future of Work. POLICY BRIEF No. 34 June 2020. APEC Policy Support Unit.

Kerr, A. & Wittenberg, M. (2019). A Guide to version 3.3 of the Post-Apartheid Labour Market Series (PALMS).

Kerr, A. (2021). QLFS Q1:2020 and Q2:2020 Unbalanced Panel Dataset.

Keynes, J. M. (1931). Economic Possibilities for Our Grandchildren. *Essays in Persuasion*, 358–74. London: Macmillan.

Koch, M., Manuylov, I. & Smolka, M. (2021). Robots and Firms. *The Economic Journal*, 131(638), 2553-2584.

Köhler, T. & Bhorat, H. (2020). Covid-19, social protection, and the labour market in South Africa: Are social grants being targeted at the most vulnerable? (Working Paper No.6). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 1.

Köhler, T., Bhorat, H., Hill, R. & Stanwix, B. (2021). COVID-19 and the labour market: Estimating the employment effects of South Africa's national lockdown. Development Policy Research Unit Working Paper 202107. University of Cape Town.

Leibbrandt, M., Woolard, I., McEwen, H. & Koep, C. (2010). Employment and Inequality Outcomes in South Africa. Southern Africa Labour and Development Research Unit (SALDRU). School of Economics, University of Cape Town.

Lewandowski, P., Park, A., Hardy, W. & Du, Y. (2019). Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data. IBS Working Paper 04/2019. Warsaw: Institute for Structural Research.

Lewandowski, P., Park, A. & Schotte, S. (2020). The global distribution of routine and non-routine work. IZA Discussion Paper No. 13384.

Livanos, I. and Ravanos, P. (2021). Job loss and COVID-19: do remote work, automation and tasks at work matter? Luxembourg: Publications Office of the European Union. Cedefop working paper; No 4.

Lund, S., Madgavkar, A., Manyika, J., Smit, S., Ellingrud, K. & Robinson, O. (2021). The future of work after COVID-19 Special Report. McKinsey Global Institute.

Maloney, W.F. & Molina, C. (2019). Is automation labour-displacing in the developing countries, too? Robots, polarisation, and jobs. Washington, D.C.: World Bank Group.

Mann, K. & Püttmann, L. (2018). Benign Effects of Automation: New Evidence from Patent Texts. *Review of Economics and Statistics*.

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Wilmott, P. & Dewhurst, M. (2017a). A future that works: AI automation employment and productivity. McKinsey Global Institute.

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R. & Sanghvi, S. (2017b). Jobs lost, jobs gained: Workforce transitions in a time of automation. McKinsey Global Institute.

Nordhaus, W.D. (2007). Two centuries of productivity growth in computing. *The Journal of Economic History*, 67(1), 128-159.

O*NET. 2020. *O*NET OnLine*. [dataset]. Available: https://www.onetonline.org [2021, 1 May].

Parschau, C. & Hauge, J. (2020). Is automation stealing manufacturing jobs? Evidence from South Africa's apparel industry. *Geoforum*, 115, 120-131.

Ranchhod, V. & Daniels, R.C. (2020). Labour market dynamics in South Africa in the time of Covid-19: Evidence from Wave 1 of the NIDS-CRAM Survey. (Working Paper No.9). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 1.

Ranchhod, V. & Daniels, R.C. (2021). Labour Market Dynamics in South Africa at the Onset of the COVID-19 Pandemic. *South African Journal of Economics*, 89(1), 44-62.

Spaull, N. (2013). South Africa's education crisis: The quality of education in South Africa 1994-2011. *Johannesburg: Centre for Development and Enterprise*, 21(1), 1-65.

Spaull, N. et al. (2020). Synthesis Report NIDS-CRAM Wave 2. (Working Paper No.1). National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave 2.

Statistics South Africa (StatsSA). (2020a). STATISTICAL RELEASE P0211 Quarterly Labour Force Survey Quarter 1: 2020.

Statistics South Africa (StatsSA). (2020b). STATISTICAL RELEASE P0211 Quarterly Labour Force Survey Quarter 2: 2020.

Statistics South Africa (StatsSA). (2020c). Quarterly Labour Force Survey 2020: Q1 [dataset]. Version 1. Pretoria: Statistics South Africa [producer]. Cape Town: DataFirst [distributor].

Statistics South Africa (StatsSA). (2020d). Quarterly Labour Force Survey 2020: Q2 [dataset]. Version 1. Pretoria: Statistics South Africa [producer]. Cape Town: DataFirst [distributor].

Tinbergen, J. (1974). Substitution of graduate by other labour. Kyklos: *International Review of Social Science*. 27, 217-226.

Tinbergen, J. (1975). Income Difference: Recent Research. North-Holland Publishing Company: Amsterdam.

United Nations Conference on Trade and Development [UNCTAD]. (2017). Trade and development report 2017–beyond austerity: Towards a global new deal.

United Nations Industrial Development Organization [UNIDO]. (2019). Industrial Development Report 2020: Industrializing in the digital age.

Wooldridge, J.M. (2015). Introductory econometrics: A modern approach. Cengage learning.

World Bank. (2016). World development report 2016: Digital dividends. Washington, D.C.: World Bank Group.

World Bank. (2019). World Development Report 2019: The Changing Nature of Work. Washington, DC: World Bank.

World Bank. (2021). South Africa Economic Update, Edition 13: Building Back Better from COVID-19 with a Special Focus on Jobs. Washington, D.C.: World Bank Group.

Appendix

Table A1. Employment status of those in Q2:2020 who were employed in Q1:2020.

Employment Status in Q2:2020	Sample frequency	Percentage	Population frequency	Percentage
1. Employed	7 380	46.94	7 226 537	47.63
2. Unemployed	509	3.24	489 898	3.23
3. Discouraged job seeker	187	1.19	172 304	1.14
4. Other not economically active	1 269	8.07	1 158 727	7.64
Missing	6 376	40.56	6 126 020	40.37
Total	15 721	100.00	15 173 485	100.00

Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d).
Notes: 1. Weights have been applied to obtain population values. 2. Sample is restricted to the working-age population, and those in occupations with RTI data. 3. This table includes the frequency of observations in the sample with missing employment status information in Q2:2020.

Table A2. List of recoded South African occupations.

Occupations That Did Not Merge			Occupations Reallocated To	
ISCO 88	Description	Percent of observations	ISCO 88	Description
3391	Teaching associate professionals	7.92%	3310	Primary education teaching associates
5124	Tavern and shebeen operators	25.65%	5123	Waiters, waitresses and bartenders
5231	Spaza shop owners	8.5%	5230	Stall and market salespersons
8320	Taxi drivers, informal	21.24%	8322	Car, taxi and van drivers
9162	Sweepers and related labourers	27.86%	9161	Garbage collectors
	TOTAL	71.97%		

Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d).
Note: South African occupations with no identical occupation within the O*NET database are reported on the left-hand side. These occupations are re-coded to comparable occupations in the O*NET database which are reported on the right-hand side of the table.

Table A3. Figure 1's pre-pandemic (Q1:2020) employment percentages and confidence intervals across workers' education levels and risk of automation.

	Automation Risk Level		
Education Level	**Low risk**	**Intermediate Risk**	**High risk**
No matric	9.70%	40.89%	49.41%
	[8.70% ;10.81%]	[39.16%; 42.65%]	[47.63%; 51.18%]
Matric	21.43%	43.33%	35.23%
	[19.79% ; 23.17%]	[41.37%; 45.32%]	[33.31%; 37.20%]
Post matric	58.25%	28.94%	12.82%
	[55.40% ; 61.03%]	[26.44%; 31.57%]	[11.22% ; 14.61%]
Total	24.24%	39.21%	36.55%

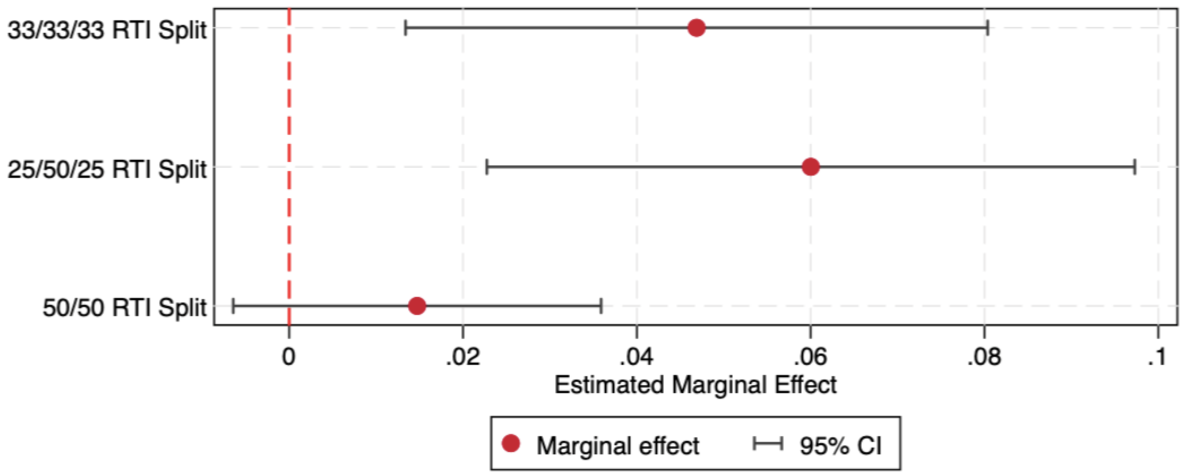
Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d).
Notes: Weights have been applied to the sample.

Table A4: LPM Estimates of the Marginal Effects of Automation Risk and Education Levels on the Probability of Job Loss.

Dependent variable: Job Loss (unemployed in Q2:2020, conditional on being employed in Q1:2020)				
	(1)	(2)	(3)	(4)
Automation risk level				
Intermediate Risk	0.065***	0.025**	0.046***	0.030**
	(0.012)	(0.013)	(0.013)	(0.014)
High Risk	0.106***	0.050***	0.052***	0.031*
	(0.012)	(0.014)	(0.015)	(0.017)
Education level				
Matric		-0.070***		-0.025**
		(0.011)		(0.012)
Post Matric		-0.131***		-0.053***
		(0.014)		(0.016)
Control Variables				
Individual and Employment Characteristic Dummies	No	No	Yes	Yes
Province Dummies	No	No	Yes	Yes
Industry Dummies	No	No	Yes	Yes
Observations	9,142	9,051	7,651	7,591

Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d).
Notes: 1. Standard errors are in parentheses. 2. Significance levels are denoted with stars: *** p<0.01, ** p<0.05, * p<0.1 3. 3. The sample is all working-age individuals (15 to 64 years). Data are weighted appropriately. Variance is adjusted for stratification and clustering. 4. The base categories are low-risk for automation risk level and no matric qualification for education level. 5. See Methodology for detailed breakdown of the control variables.

Figure A1. Coefficients on the High-risk, routine variable using different RTI categorisations (splits).



Source: Author's own calculations from QLFS 2020Q1 and 2020Q2 (StatsSA, 2020c and 2020d).
Note: Base category is Low-Risk, non-routine occupations.

Development Policy Research Unit
University of Cape Town
Private Bag, Rondebosch 7701
Cape Town, South Africa
Tel: +27 21 650 5701
www.dpru.uct.ac.za