Who are the Robots Coming For? The Evolving Task Content of Employment in South Africa

Haroon Bhorat, Robert Hill, Timothy Köhler, Jabulile Monnakgotla and François Steenkamp

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DSI/NRF SOUTH AFRICAN RESEARCH CHAIR IN INDUSTRIAL DEVELOPMENT

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Abstract

In this paper, we examine how the task content of employment in South Africa, a developing country, has evolved in the post-apartheid period. By investigating the South African labour market's evolving task content, we are able to assess whether there is evidence of increased utilisation of automation and other 4IR technologies. We find that the South African labour market in the formal private sector has undergone a pattern of *relative de-routinisation* through a relative contraction in routine manual jobs and an expansion of non-routine cognitive analytical jobs. In absolute terms, although employment within all task content component groups grew over the period, non-routine jobs experienced far greater rates of jobs growth relative to routine jobs. Despite representing just 4% to 6% of workers, employment in non-routine cognitive analytical jobs more than doubled. Employment in routine jobs, which represents most workers (75% to 81%), also grew, but at a much slower rate. In relative terms, the share of routine manual jobs shrunk significantly over time, while those of all other task content component groups grew, especially non-routine cognitive analytical jobs. Most of these changes occurred between 2000 and 2010. This aggregate pattern of *relative de-routinisation* is driven by similar trends in the mining, manufacturing, construction, transport, storage and communication, and community, social and personal services industries. We also observe this pattern in both small and large firms alike. We find similar evidence when considering trends in annual entries into employment; that is, while the number of recent entries has grown within all task content components, those into non-routine cognitive (analytical) jobs has grown the fastest. While we do not find evidence of *relative de-routinisation* when considering employment exits, this does not necessarily invalidate our previous findings, given data comparability concerns across the survey instruments. Finally, we document considerable variation in the demographic and labour market characteristics of workers across these groups of occupations.

Keywords: Fourth Industrial Revolution, Automation, Labour market, task intensity, employment

JEL codes: J21; J24; O12

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1 Introduction

For several centuries, the notion that "robots are coming to take our jobs" has raised fears of the displacement of workers. In fact, the word *robot* originates from *robota* – the Slavic-language word for work – thus making the purpose of machines clear. Throughout modern history, however, the principle of automation – for a machine to complete a task, a programmer must first fully understand how the task is performed, and then write an appropriate program to guide the machine – has not changed. Yet what has changed is the cost of automation, and the speed at which it has changed. Between 1850 and 2006, the real cost of performing a standardised set of computational tasks is estimated to have fallen by at least 1.7 trillion-fold, with most of this reduction occurring within the last 30 years (Nordhaus 2007). As a result of this downward trend in costs, fears of automation have regained prominence – especially in the context of the Fourth Industrial Revolution – as they create simple but powerful incentives for employers to substitute their relatively expensive workers with computer capital.

Technology is thus reshaping the skills needed for work. However, given that different jobs require different sets of skills, jobs face varying degrees of risk to automation. As such, the labour market effects of technology are believed to be distributed unevenly across workers of varying skill sets. In the literature, there are two broad theoretical approaches to understanding the potential impacts of technological change on the labour market. The dominant theory – referred to as 'skill-biased technological change' (SBTC) – proposes that, in the last few decades, technological development has increased the demand for high-skilled workers at a rate far greater than the increase in the supply of such workers, resulting in higher returns to high-skilled jobs. In other words, technology is biased in favour of high-skilled workers. A large empirical literature now exists in support of this theory, leading it to be argued as a primary cause of rising wage inequality in many countries (Berman and Machin 2000; Berman et al. 1998; Card and DiNardo 2002).[1]

The primary shortcoming of the SBTC hypothesis is that it can only explain changes in the demand for high-skilled labour at the top of the wage distribution. However, there is a more recent and developing literature that describes how labour markets in developed countries in particular have evolved in such a manner that new computer-based technologies have displaced workers in the middle of the distribution, and have created jobs at the top and bottom ends. This phenomenon is known as labour market polarisation (Autor and Dorn 2013; Autor et al. 2003; Goos et al. 2014). Hence, the emergence of the second theoretical approach to understanding the impacts of technological change on the labour market – Autor et al.'s (2003) routinisation hypothesis.

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[1] A formalised version of this model, which Acemoglu and Autor (2011) describe as the canonical model, but which is also known as the Tinbergen model of labour demand, can be found in Tinbergen (1974, 1975).

The routinisation hypothesis, also referred to as ‘routine-replacing technical change’ or ‘routine-biased technological change’, proposes that technological development has concurrently decreased the demand for workers in jobs with high levels of ‘routine’ task content (tasks that follow explicit rules that can be accomplished by machines and are thus substitutable to technology) and increased the demand for workers in jobs with high levels of ‘non-routine’ task content (tasks that are not sufficiently well understood to be specified in computer code and are thus complementary to technology). ‘Routine’ jobs tend to be concentrated in the *middle* of the wage distribution, while ‘non-routine’ jobs tend to be concentrated at the *bottom* (and tend to be more manual in nature while requiring situational adaptability, such as truck driving through traffic or janitorial work) and at the *top* (which tend to be more cognitive in nature and include several professional and managerial occupations). The evidence, primarily from the analysis of developed countries, largely supports this theory, with many empirical studies highlighting a relative rise in non-routine-intensive employment and a fall in routine-intensive employment in recent decades (Acemoglu and Autor 2011; Autor 2015; Autor et al. 2003; Frey and Osborne 2017; Goos and Manning 2007).

While the majority of studies are concentrated on developed countries, there is a growing body of work on developing countries. However, evidence of changes in the nature of work in developing and emerging economies is mixed (Lewandowski et al. 2022). In line with trends in developed countries, there is some evidence of job de-routinisation in developing countries (Maloney and Molina 2016). For example, Hardy et al. (2016) document that all Central and Eastern European economies have experienced such de-routinisation in recent years. However, in their study of 21 developing countries (including South Africa), Maloney and Molina (2016) find evidence of de-routinisation for only two countries. Lewandowski et al. (2020) find that the average routine task intensity of jobs in developing countries has been relatively constant for the last two decades, in contrast to the developed country finding of a shift away from routine to non-routine work.

There is limited research aimed at simply detailing the changing task content of South Africa’s employment profile.[2] Where it does exist, it generally focuses on specific sectors, such as manufacturing (Allen Whitehead et al. 2021), or conducts a broader cross-country study (Lewandowski et al. 2020; Maloney and Molina 2016). Recent work by Davies and Van Seventer (2020) find mild evidence of employment polarisation, but their analysis does not view employment through the task content lens, instead focusing on trends in employment across broad occupational categories.

We contribute to this literature by, firstly, examining how the task content of employment in South Africa, a developing country, has evolved in the post-apartheid period. By investigating the South African labour market’s evolving task content, we are able to assess whether there is evidence of increased utilisation of automation and other 4IR technologies. Further, we

[2] There are a couple of studies that have focused on wage polarisation in South Africa, such as those by Bhorat et al. (2020) and Van der Linde (2015).

profile the composition of employment across task content categories by examining various individual and job characteristics. Finally, given the evolving task content profile of the South African labour force, we briefly discuss some policy implications associated with the impending Fourth Industrial Revolution.

We examine the evolving task content of the South African labour market from 2000 to 2019 by using occupation-level task content data derived from the Occupation Information Network (O*NET), and individual-level employment data from the Post-Apartheid Labour Market Series (PALMS). We construct task content measures following Acemoglu and Autor (2011) and generate a routine task intensity index following Lewandowski et al. (2022). These are then mapped, using pre-existing crosswalks, to South Africa labour market data from PALMS. We focus on four mutually exclusive groups of occupations based on their task content: 'routine manual', 'routine cognitive', 'non-routine cognitive (analytical)', and 'non-routine cognitive (personal)'. We examine the evolution of employment across these groups over time through three lenses: first, through aggregate employment; second, through annual entries into employment; and third, through annual exits from employment. Thus, despite not having access to panel data, the latter two lenses help generate a view of the impact of routinisation from the perspective of labour market churn.

There is clearly a policy imperative to understand the potential impacts of automation in the context of the Fourth Industrial Revolution, given the widely understood twin challenges of high levels of inequality and endemic unemployment in South Africa. The narrow unemployment rates have increased steadily, from approximately 16.2% in 1993 to the most recent estimate, of 35.1%, at the end of 2021 (Kerr et al. 2019; Statistics South Africa 2022), while inequality, as measured by the Gini coefficient, has fluctuated from 0.66 in 1993 to a high of 0.70 in 2008 (Leibbrandt et al. 2012).[3] As shown by Leibbrandt et al. (2012), the main driver of this inequality is differences in labour market income, and thus the functioning of the labour market plays a key role in shaping both unemployment and household income inequality in South Africa. The Fourth Industrial Revolution (4IR) is set to potentially exacerbate these twin challenges.[4] With respect to inequality, we know that the 4IR is likely to bring about great benefits to society, but we also know that it is unlikely that these benefits will be enjoyed equally across society, especially in the case of a society already overwhelmed by high inequality. Similarly, with respect to unemployment, these technological developments, while bringing about job creation, are also likely to bring about job destruction or job displacement, which is a major concern in a high-unemployment context. The increasing ability of new digital technologies to displace human labour in domains that were considered 'human terrain' raises concerns about the effects of new digital technologies on the labour market (Fossen and Sorgner 2022). To this end, it becomes important to understand the

[3] At last measure, South Africa was ranked the most unequal country in the world (World Population Review 2022).

[4] The 4IR is described as a period of fast-advancing technologies in the physical, biological and digital worlds that will ultimately reshape how economies see and grapple with development (World Economic Forum 2022).

evolution of South Africa's labour market in relation to the emergence and increasing uptake of 4IR technologies.

The paper is structured as follows: In Section 2, we detail the two key data sources used in the analysis, along with our empirical approach to examining the evolving task content of the South African labour market. In Section 3, we present the results of our analysis of the task content of three employment measures: aggregate employment, entries, and exits. We provide a brief policy discussion in Section 4, and Section 5 concludes.

2 Data and Methodology

Our analysis makes use of two distinct data sources: the Post-Apartheid Labour Market Series (PALMS) and the Occupational Information Network (O*NET). The PALMS is a harmonised series of cross-sectional, nationally representative household surveys in South Africa during the post-apartheid period until 2019. Unfortunately, no household survey in South Africa contains data on occupational task content. As such, we use four-digit occupation codes to merge the PALMS with the O*NET, which is a survey of detailed occupational demands and provides information on the task content of occupations gathered via interviews with incumbent employees and occupational experts in the United States of America. We restrict our analysis to the period from 2000 to 2019 period, and by using relevant crosswalks to harmonise the occupation codes between the two datasets we are able to produce measures of task content for each occupation in the South African labour market. The sections below describe these two data sources, as well as the crosswalks used to link them, along with our subsequent methodology.

2.1 The Occupational Information Network (O*NET) Dataset

The O*NET dataset is drawn from a United States (US) survey of a comprehensive set of occupational descriptors based on labour market demand, such as work activities, abilities and work context, and is updated every quarter (O*NET 2019). Almost 1 000 standardised occupations are included, and these are compiled drawing on input from a wide range of employees in each occupation and moderated by a set of occupational analysts. Our analysis uses Version 24.0 from August 2019.

The application of this data to non-US contexts is common in the literature; however, one concern is how appropriate the application is to developing country labour markets in particular, including South Africa. Although notable differences across labour markets are well documented, Hardy et al. (2018) show that the data are broadly appropriate for use in developing country contexts. As such, without the existence of alternative data, we continue with our use of the O*NET, which also allows comparability of estimates with the broader literature.

We make use of the Work Activities, Abilities, and Work Context modules of the O*NET database in order to calculate an occupation-level routine task intensity (RTI) index. Work activities are generalised statements based on the aggregation of a set of 19 450 detailed task statements. Our analysis makes use of generalised work activities, which comprise 41 unique activities in the data and include work activities such as: handling and moving objects; inspecting equipment, structures, or material; and thinking creatively. The abilities database comprises 20 different abilities, including elements such as oral comprehension, written comprehension, and deductive reasoning. Information on both the 'level' and 'importance' of each of the work activities and abilities are included in the data.[5] There are also 20 alternative types of work context, and a set of values (or context categories) for each of these. For example, values for 'face-to-face discussions' range from 1 = 'never' to 5 = 'every day'. Each of these values is assigned a frequency. If a specific work context element has five values, each value is assigned a frequency based on the share of people who reported that value. These frequencies sum to 100.

2.2 The Post-Apartheid Labour Market Series (PALMS) Dataset

The PALMS dataset, developed by Kerr et al. (2019), is a harmonised series of South African household survey data for the years 1994 through 2019. The original data for the series are based on nationally representative, cross-sectional household surveys conducted by Statistics South Africa, and comprises three survey instruments: the October Household Surveys (1994 to 1999), the Labour Force Surveys (2000 to 2007), and the Quarterly Labour Force Surveys (2008 to present). We restrict our analysis to the period from 2000 to 2019, meaning that the data comes from the Labour Force Surveys and the subsequent Quarterly Labour Force Surveys. To deal with issues of seasonality and unexpected shocks, we average the data across all survey waves in a given year.[6] In addition, for reasons outlined in Section 2.5 below, our analysis requires data on some variables for the unemployed not included in the PALMS. These include previous occupation, previous industry, the month and year of one's previous job, and the reason for no longer working at said job. As such, we merge in the data from the LFS and QLFS for each wave during the period.

As discussed in more detail in Section 2.5 below, our analysis comprises three components for which we make use of two samples: a sample of the employed (n = 662 078), and one of the unemployed (n = 101 247). For the former, we restrict the sample to wage earners in the formal private sector (who represent the majority of workers in the South African labour market), and exclude all private household workers so as to harmonise definitions of the formal sector across the two surveys. For the latter, we restrict the sample to the

[5] For example, while the ability of `information ordering' is very important for both mechanical engineers and file clerks; engineers are required to have a higher level of information ordering; while the level of information ordering required of file clerks is average.
[6] The Labour Force Survey (LFS) (2000 to 2007) was run twice a year, while the Quarterly Labour Force Survey (QLFS) is run four times a year. Thus, to get year-level estimates we divide the sampling weights in the LFS by two and those in the QLFS by four. The only exception is for 2019, when PALMS only included up to the end of 2019Q2, and thus we divide the 2019 QLFS sampling weights by two in order to get a year-level weight.

unemployed,[7] and again exclude all individuals whose previous occupation was in a private household. For both samples, we restrict the sample to working-aged (15 to 64 years) individuals.

2.3 Linking Datasets Through Crosswalks

We combine the O*NET task content data with the South African labour force data in the PALMS by making use of a set of 'crosswalks' that bridge the gap between the two different occupation nomenclatures, namely the eight-digit Standard Occupational Classifications 2010 (O*NET-SOC10) used in the O*NET data, and the four-digit International Standard Classification of Occupations (ISCO-88) used in PALMS. These crosswalks are a combination of those obtained from both O*NET and the Institute for Structural Research (Institute for Structural Research [IBS] 2016; O*NET 2019). The merging of O*NET and PALMS was carried out both for current occupations among the employed, which resulted in a match of 94.7% of occupations, as well as previous occupations among the unemployed, which resulted in a match of 97.5% of occupations – both at the four-digit level. Unmatched occupations are those not observed in both datasets, which is not unexpected. An adjustment is made to some of the occupation labels to account for differences between the PALMS ISCO-88 four-digit occupation labels and those used in the crosswalks; however, this makes no material difference to our analysis.

2.4 Constructing the Routine Task Intensity (RTI) Index

To facilitate the comparability of our results with the larger body of literature, we follow Acemoglu and Autor (2011) and use data on Work Activities, Abilities, and Work Context within the O*NET to create task content indicators for the level of routine cognitive, routine manual, non-routine cognitive analytical, and non-routine cognitive personal tasks exhibited for each occupation. The specific elements used by Acemoglu and Autor (2011) to construct these indicators are presented in Table 1 below.

Table 1: Definition of routine and non-routine task content indicators

Intermediate indicator	O*NET elements
Routine cognitive	• 4.C.3.b.7 Importance of repeating the same tasks • 4.C.3.b.4 Importance of being exact or accurate • 4.C.3.b.8 Structured vs unstructured work (scored in reverse)
Routine manual	• 4.C.3.d.3 Pace determined by speed of equipment • 4.A.3.a.3 Controlling machines and processes • 4.C.2.d.1.i Spend time making repetitive motions

[7] We refer to the unemployed broadly as any individual not currently working. As such, this includes the unemployed by either the narrow or broad definition, as well as the economically inactive.

Intermediate indicator	O*NET elements
Non-routine cognitive analytical	• 4.A.2.a.4 Analysing data/information • 4.A.2.b.2 Thinking creatively • 4.A.4.a.1 Interpreting information for others
Non-routine cognitive interpersonal	• 4.A.4.a.4 Establishing and maintaining personal relationships • 4.A.4.b.4 Guiding, directing and motivating subordinates • 4.A.4.b.5 Coaching/developing others

Source: Reproduced from Acemoglu and Autor (2011).

To create these four indicators for analysis, we follow the approach of Acemoglu and Autor (2011) as follows. Elements in the Work Activities file on O*NET are measured using a level and importance measure. To collapse these two measures into a single indicator for each task, importance and level values are combined according to a Cobb-Douglas function, in which 'importance' is assigned a weight of two-thirds, and 'level' a weight of one-third.[8] Work Context measures are captured by multiplying the reported frequency by level. The calculation of the routine task content indicator, $r_{h,i}$, can be summarised in the system of equations (1a) to (1d), as follows:

$$r_{h,i} = \sum_{k=1}^{A_h} WA_{k,h,i} + \sum_{l=1}^{C_h} WC_{l,h,i} \tag{1a}$$

with components defined as

$$WA_{k,h,i} = \frac{\overline{WA}_{k,h,i} - WA_{\min}}{\max\,(\overline{WA}_{k,h,i} - WA_{\min})} \tag{1b}$$

and

$$WC_{l,h,i} = \frac{\sum_{V_{i,l}=1}^{5}(V_{i,l} \times F_{V_{i,l}})\ - 100}{400} \tag{1c}$$

where

$$\overline{WA}_{k,h,i} = I_{i,k}^{\frac{2}{3}} L_{i,k}^{\frac{1}{3}} \tag{1d}$$

Note that $WA_{\min}$ is the minimum value of the $\overline{WA}_{k,h,i}$ distribution. The transformations described in equations (1b) and (1c) simply ensure that the relevant values of $WA_{k,h,i}$ and $WC_{l,h,i}$ lie between 0 and 1, so that the final value of $r_{h,i}$ is equally weighted across all elements comprising the indicator. Furthermore, $r_{h,i}$ is the task content indicator for

[8] These weight values are used to be consistent with the available literature (Bhorat et al. 2020; Blinder 2009; Firpo et al. 2011).

occupation i, and h represents the category of task under consideration.[9] A_h is the number of Work Activity elements comprising intermediate indicator $r_{h,i}$; C_h is the number of Work Context elements comprising intermediate indicator $r_{h,i}$; I_{ik} is the importance of work activity k in occupation i; while L_{ik} is the level of work activity k required in occupation i. V_{il} is the value of Work Context element l in occupation i, which ranges from 1 to 5; and $F_{V_{i,l}}$ is the frequency reported for each corresponding element of $V_{i,l}$. The intermediate indicator, $r_{h,i}$, is then scaled to lie in the interval $[0; 1]$. This rescaling serves no analytical purpose except to facilitate the construction of a conglomerate routine-task intensity (RTI) index, similar to the one proposed by Autor et al. (2003) and Autor and Dorn (2013).

We suggest the construction of this RTI index using the formulation put forward by Lewandowski et al. (2020), which includes measures of routine cognitive, non-routine cognitive analytical, and non-routine cognitive interpersonal tasks, which we augment to also include a measure for routine manual tasks, as defined by Acemoglu and Autor (2011) above. Specifically, this formulation is described by equation (2) below:

$$RTI_i = \ln\left(\frac{r_{cognitive,i} + r_{manual,i}}{2}\right) - \ln\left(\frac{nr_{analytical,i} + nr_{interpersonal,i}}{2}\right) \tag{2}$$

where $r_{cognitive,i}$, $r_{manual,i}$, $nr_{analytical,i}$ and $nr_{interpersonal,i}$ are the level of routine cognitive, routine manual, non-routine cognitive analytical, and non-routine cognitive interpersonal tasks required for occupation i, respectively. This formulation of the RTI is then again normalised to lie between 0 and 1, where a value of 0 indicates that a particular occupation is completely non-routine, while a value of 1 indicates that an occupation is completely routine. After constructing a task content indicator and RTI index for each occupation present in the O*NET database, we merged them into the PALMS. For example, as shown in Table A1 in the Appendix, the top 10 most routine occupations in the formal private South African labour market over the period largely comprise a variety of machine and plant operators, while the top 10 most non-routine occupations include religious professionals; directors, chief executives, and other management occupations; higher education teaching professionals; and traditional medicine practitioners.

2.5 Empirical Approach

Our baseline approach is to analyse aggregate employment trends in the South African private formal-sector labour market between 2000 and 2019 across the distribution of routine task intensity. As laid out in our hypotheses above, if there is evidence of increased utilisation of automation and other 4IR technologies, and routinisation has indeed taken place, we expect to observe a rising (declining) relative importance of occupations comprising more non-routine (routine) tasks. In addition to considering aggregate or net employment changes, we

[9] There are four distinct values for h: routine manual ($h = manual$), routine cognitive ($h = cognitive$), non-routine cognitive analytical ($h = analytical$), and non-routine cognitive personal ($h = personal$).

analyse trends in recent employment ‘entries’ and ‘exits’ as two alternative approaches to analysing the impact of routinisation from the perspective of labour market churn and worker flows. For a given survey wave, we define a recent entry as, conditional on employment, an individual having started their job within the previous year. A recent exit is defined, conditional on unemployment (broadly defined to include the searching, discouraged, and economically inactive), as an individual having last worked within the last year and not currently working due to retrenchment. As such, our analysis of exits is restricted to those unemployed who have previously worked, equivalent to 42% of the non-employed working-age population in 2019. If routinisation has taken place, then for ‘entries’ we expect to observe a rising (declining) relative importance of job entries into occupations comprising more non-routine (routine) tasks. Correspondingly, for exits we expect to observe a rising (declining) relative importance of job exits from occupations comprising more routine (non-routine) tasks.

Importantly, while our analysis of trends in aggregate employment and recent entries covers the whole period from 2000 to 2019, our analysis of trends in exits is restricted to the period from 2008 to 2019 due to important differences in the relevant question across the survey instruments. Specifically, the phrasing of the question on the reason an individual was not currently working and the available response options differed between the LFS and QLFS. In the LFS, the question was phrased as, “Why did you not work during the past seven days?” and the option indicating retrenchment was simply “retrenchment”, with no other, similar options. On the other hand, in the QLFS the question was phrased as, “What was the main reason you stopped working in your last job/business?” and the relevant option for retrenchment was “Lost job/job ended/laid off/business sold/closed down”. Arguably, the options available in the QLFS capture more of the relevant group, as individuals displaced by automation may not consider themselves retrenched, and thus the more generic “lost job” option better serves our purposes. We believe that these differences explain the considerably larger sample of recent exits in the QLFS, which range from 1 831 to 2 606 observations in a given wave, compared to the LFS, which range from 57 to 310 observations in a given wave.

While the single RTI index described above is helpful in summarising the routine task content of a job into a single number, it lacks nuance in understanding the drivers of employment change attributable to routinisation. As such, for each of our three approaches, we analyse trends for each of the four intermediate indicators (also known as task content components in the literature), $r_{h,i}$, described above. To do so, we follow Fonseca et al. (2018) and classify each occupation into one of the four task content components that make up our chosen composite RTI: ‘routine manual’, ‘routine cognitive’, ‘non-routine cognitive (analytical)’, or ‘non-routine cognitive (personal)’. We assign each occupation to the component for which the occupation ranks highest in intensity. Given that all components are normalised to lie between 0 and 1, this allows for a meaningful comparison of their values. This process was straightforward given the absence of cases where two or more components were equal in value (Table A3 provides a list of the top 20 occupations that fall within each of these task content categories).

For each of our three approaches, we first estimate and examine absolute and relative trends by task content component group, and thereafter exploit the range of demographic and labour market data in the PALMS to describe the composition of individuals across and within these components over the period. All estimates are weighted using the year-specific sampling weights described in Section 2.2, and account for the complex survey design.

3 Results

In this section, we start by examining trends in the task content of employment in South Africa through three lenses – aggregate employment, recent entries in employment, and recent exits from employment. By investigating South Africa's evolving task content of employment, we are able to assess whether there is evidence of increased utilisation of automation and other 4IR technologies. We then profile the composition of employment across task content components by examining the distribution of employment within these components across various individual and job characteristics. We also consider the extent to which this composition has changed over time.

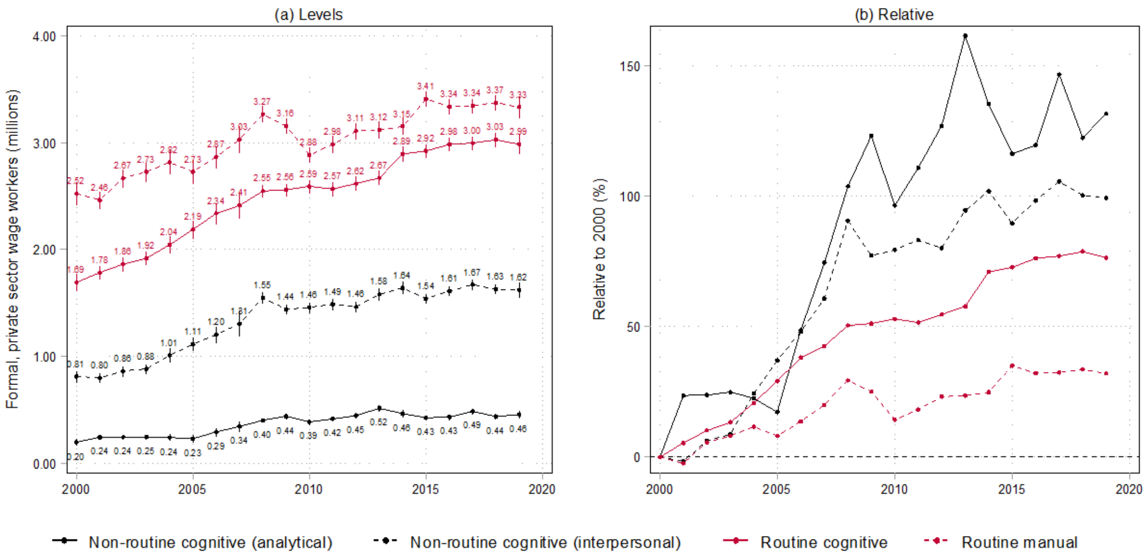
3.1 Trends in the Task Content of Aggregate Employment

Routine task-intensive jobs are dominant within the formal private sector in South Africa, and have remained as such over the 20-year period. As shown in panel (a) of Figure 1 – which presents time series of employment level estimates by task content component – we estimate that, of the 5.2 million workers in 2000, 81% (4.2 million) were in either routine manual or routine cognitive jobs. These jobs remained dominant in 2019, representing 75% of 8.4 million workers.

While routine jobs grew by 50% over the period in absolute terms, we observe a pattern of routine job sub-group convergence over time. Throughout the period there were a greater number of routine manual jobs than routine cognitive jobs; however, the number of routine manual jobs was just 32% higher in 2019 compared to 2000, while the number of routine cognitive jobs was 76% higher. Put differently, in absolute terms there were 831 000 more routine manual jobs than routine cognitive jobs in 2000, but in 2019 this difference had more than halved, to just 346 000.

We also find evidence of a pattern of what we refer to as *relative de-routinisation* in the formal private sector labour market. Although employment within all task content component groups grew over the period in absolute terms, non-routine jobs experienced far greater rates of jobs growth relative to routine jobs – see panel (b) of Figure 1. Notably, the pace of growth of non-routine cognitive analytical jobs exceeded all other task component groups. Despite representing the minority of workers throughout the period, the estimated number of non-routine cognitive analytical jobs more than doubled (132%) over the period, from 197 000 workers in 2000 to 457 000 in 2019. It appears that most of this growth took place between 2005 and 2009, where thereafter, employment levels fluctuated around an overall upward trend. Non-routine cognitive interpersonal jobs grew at a similar rate until 2008, and hence grew faster than both routine occupation groups. However, they then fluctuated around a relatively constant level.

Figure 1: Absolute and relative employment levels by task content component, 2000 to 2019

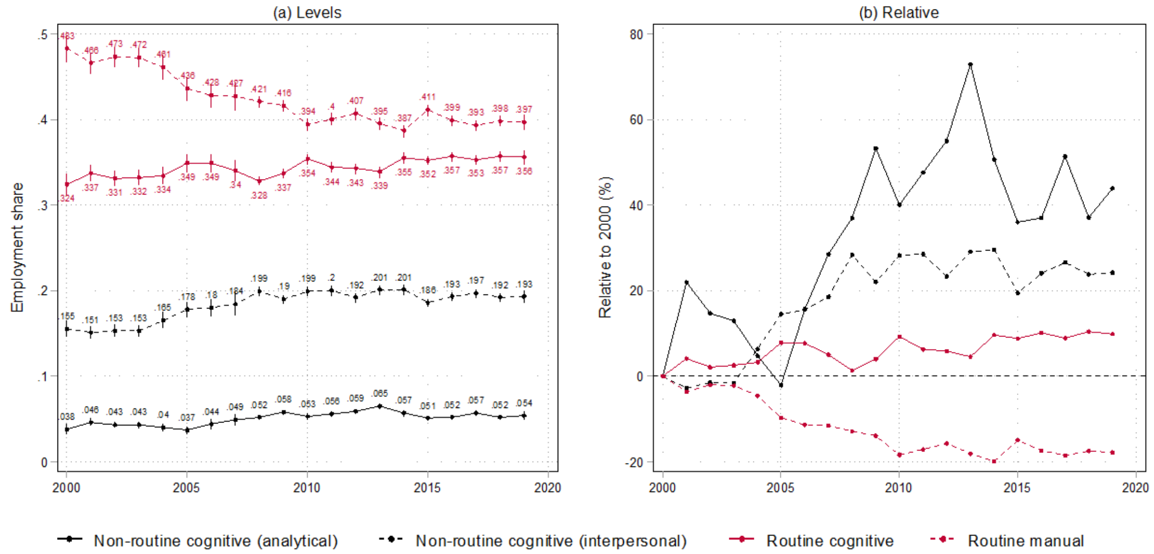


Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

This observed pattern of *relative de-routinisation* is more pertinent when considering changes in employment shares. Panel (a) of Figure 2 presents estimates of employment shares by task content component group over the period. As previously noted, while routine manual jobs have persisted to represent the majority of workers in the formal private sector labour market, their relative contribution has shrunk significantly over time. Just under half (48.3%) of employees worked in these jobs in 2000, but, some 20 years later, this share had contracted by 18% to represent 39.7% of all employees in the formal private South African labour market. Most of this contraction appears to have occurred between 2000 and 2010, while the group's employment share remained relatively constant thereafter. At the same time, the employment shares of all other task content component groups grew. Similar to the absolute trends above, the share of routine cognitive jobs grew at a slower rate compared to non-routine cognitive interpersonal jobs over the period, while the growth of non-routine cognitive analytical jobs far outstripped all groups. These latter jobs accounted for just 3.8% of workers in 2000, expanding by a notable 44% to reach 5.4% in 2019. Again, most of the growth for this group took place between 2005 and 2009, followed by a minor contraction in 2010, before continuing to grow to reach a peak of 6.5% in 2013, and fluctuating thereafter.

Figure 2: Absolute and relative employment shares by task content component, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

We also observe this pattern of *relative de-routinisation* by looking at employment growth incidence curves (GIC) that plot the variation in annual average growth rates of employment across the RTI distribution. We estimate these RTI quantile-specific growth rates and plot them in Figure 3 below, smoothing the curves using local linear (lowess) functions. We disaggregate the estimates for three distinct periods given the above observed variation in growth rates over time.

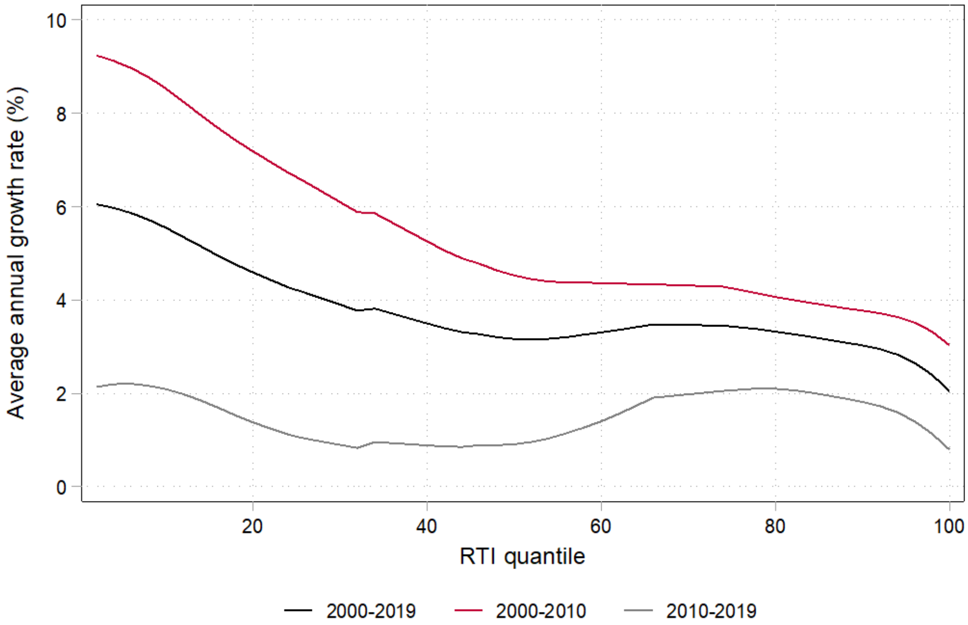
Over the whole period from 2000 to 2019, employment grew across the entire RTI distribution. However, growth was fastest for less routine jobs (low RTI), and slowest and relatively constant for those above the 40th percentile. It is clear that these changes were driven by changes between 2000 and 2010, given the equivalent but steeper GIC for the period.

Consistent with the employment patterns observed in developed economies, the latter – 2010 to 2019 – sub-period exhibits a mild 'hollowing out' of the distribution, which is suggestive of technology-induced employment polarisation.[10] It is evident from Figure 3, that over this latter period, growth rates were still positive across the entire distribution, but were much smaller, reflecting the general trend of sluggish employment growth in South Africa during this decade (Adams and Yu 2022). Across the distribution, growth rates remained heterogenous, but were now lowest (and close to zero) around the middle of the RTI

[10] For example, Autor and Dorn (2013), Goos and Manning (2007) and Goos et al. (2009) find evidence of technology-induced employment polarisation in United States, United Kingdom and Europe, respectively.

distribution, but similar around both tails – indicative of a mild 'hollowing out' of the distribution. However, it should be emphasised that such polarisation is only marginal, given the small magnitudes and low variation of growth rates during this period.

Figure 3: Employment growth incidence curves across the RTI distribution, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Curves plotted using local linear smooth plots (lowess).

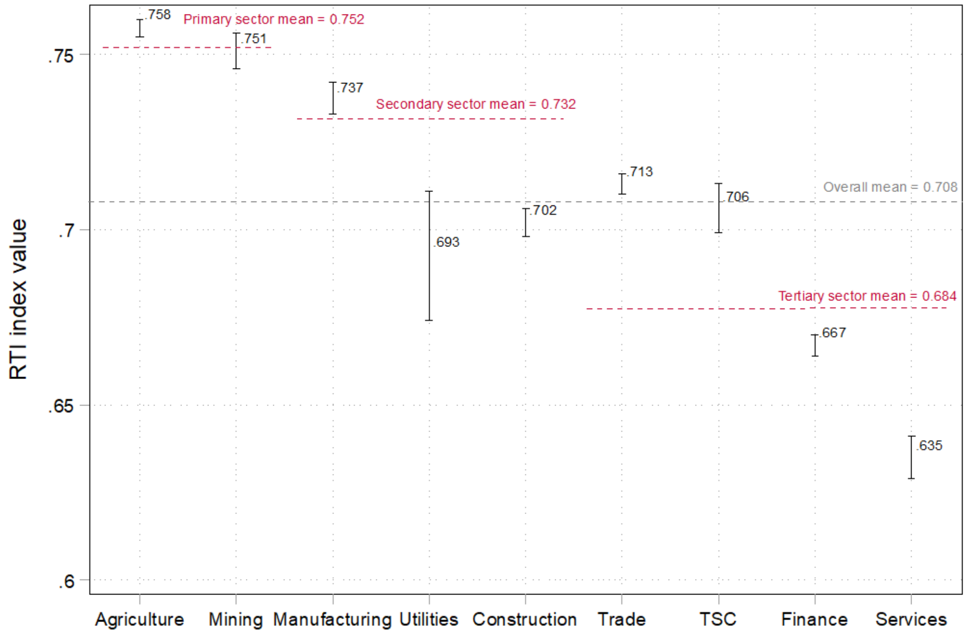
In line with the broader literature, the preceding figures strongly suggest that employment growth has favoured non-routine jobs over routine jobs. However, as we show later in this analysis, jobs of varying task content are unevenly distributed across several worker and job characteristics. The sector of employment serves as one key covariate of interest, given that de-routinisation may be explained either by structural change or alternatively be a within-industry phenomenon (Autor 2015; Bárány and Siegel 2018).[11]

Indeed, jobs across sectors vary considerably with respect to the degree of routine intensity. As shown in Figure 4, jobs in the primary sector, on average, are more routine than those in other sectors. Further, there exists significant heterogeneity in the average routine task intensity of jobs within sectors and across industries. While agriculture and mining and quarrying within the primary sector exhibit similar RTI values, within the secondary sector, jobs in the manufacturing industry are, on average, substantially more routine-intensive than those in other industries within the sector. The tertiary sector exhibits the most industry-level variation, with the finance and community, social and personal (CSP) services industries

[11] In a recent study of Italy's labour market, Intraligi et al. (2021) find that the disappearance of routine jobs is primarily a within-industry phenomenon.

exhibiting relatively low RTI values, and the trade and transport, storage, and communication (TSC) industries exhibiting relatively high values.

Figure 4: Routine task intensity by sector and industry

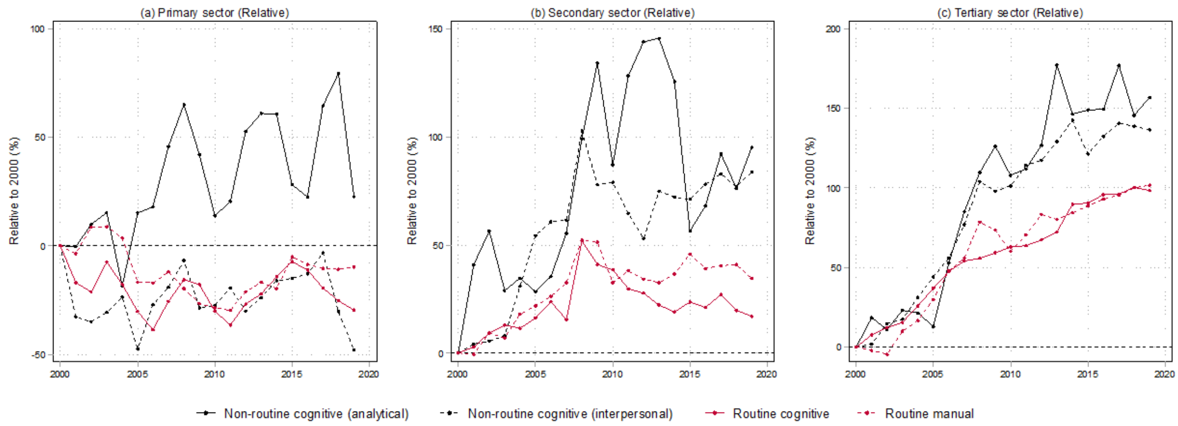


Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector. Pooled sample for 2000 to 2019 used. All estimates are weighted using sampling weights and account for the complex survey design. Capped spikes represent 95% confidence intervals. TSC = Transport, Storage, and Communication; Services = Community, Social, and Personal services.

Employment trends varied significantly by the task content component, both within and across sectors over the period. In Figure 5 we plot trends in employment levels by task content component and sector relative to 2000. While routine manual jobs are dominant in both the primary and secondary sectors, routine cognitive jobs are dominant in the tertiary sector, and non-routine cognitive analytical jobs are the minority in every sector (see the absolute employment levels by sector in Figure A1 in the Appendix). The growth of the latter task content component exceeds that of all other components, regardless of sector. However, the *relative de-routinisation* pattern observed above appears to have been driven by the tertiary sector, in which both groups of non-routine jobs grew the fastest, while both groups of routine jobs grew the slowest. In the secondary sector, the number of routine jobs grew until approximately 2008, and thereafter stalled or contracted, depending on the type. Non-routine jobs grew at a faster pace but experienced a similar pattern. In the primary sector, all job groups other than non-routine cognitive analytical jobs contracted over the period – however, most estimates of this latter group do not differ statistically significantly from one another.

Figure 5: Relative employment levels by task content component and sector, 2000 to 2019

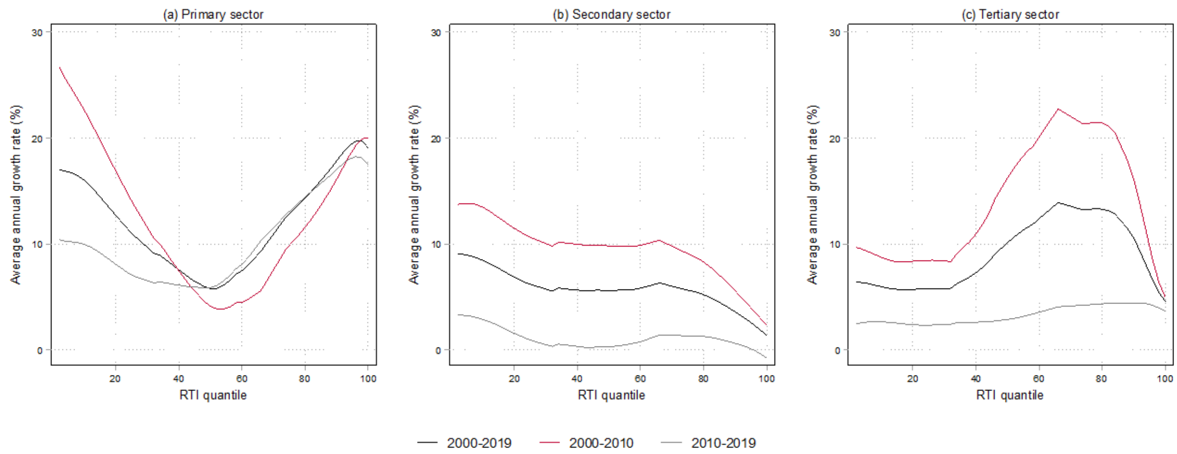


Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design.

In Figure 6 we plot sector-specific employment GICs. It is again clear that employment growth across the RTI distribution over the period varied considerably by sector. As shown in panel (a), the distribution of jobs growth in the primary sector is U-shaped – indicative of job polarisation. In other words, growth was highest at the bottom and top of the RTI distribution over the whole period. This pattern appears driven by the period from 2000 to 2010, whereas growth thereafter favoured more routine jobs. On the other hand, jobs growth favoured non-routine work in the secondary sector throughout the period, as shown in panel (b). In the tertiary sector, as shown in panel (c), jobs growth varied across the RTI distribution, but appears higher among more routine jobs.

Figure 6: Sector-specific employment growth incidence curves across the RTI distribution, 2000 to 2019

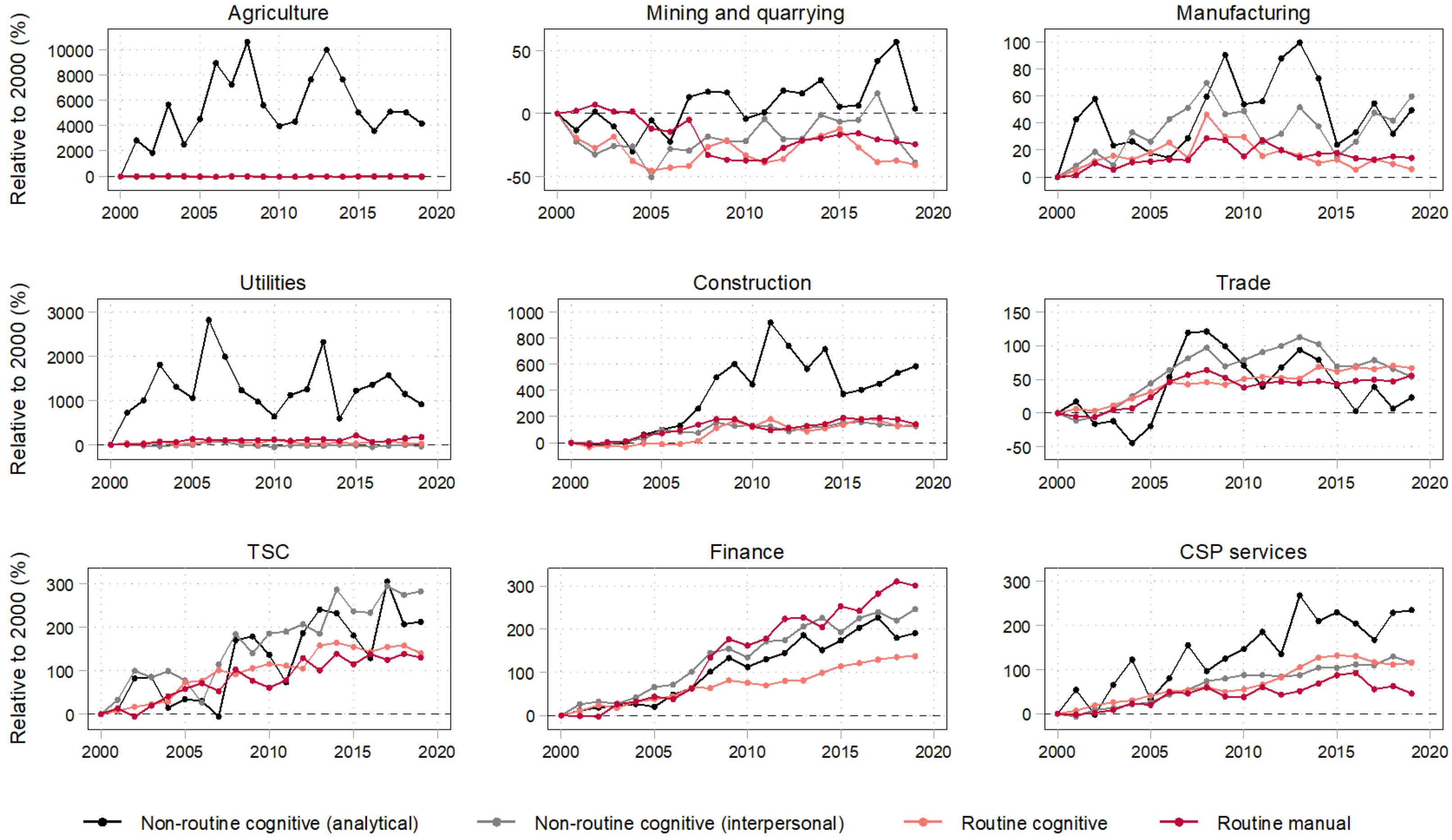


Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Curves plotted using local linear smooth plots (lowess).

Disaggregating the relative sector-specific employment trends in Figure 5 to the industry level in Figure 7 highlights significant between-industry heterogeneity. While all industries within the primary and secondary sectors are dominated by routine manual jobs (see the absolute employment levels in Figure A2 in the Appendix), those within the tertiary sector are primarily routine cognitive. This is consistent with the sectoral-level analysis above. Notably, we find evidence of *relative de-routinisation* in five industries: mining and quarrying, manufacturing, construction, transport, storage, and communication (TSC) services, and community, social, and personal (CSP) services. Together, these industries accounted for 63% of aggregate employment in 2019. While employment trends in mining and quarrying fluctuated widely over the period, the number of non-routine cognitive analytical jobs remained constant in 2019 relative to 2000, and that of routine jobs contracted. In the remaining de-routinising industries, we observe faster employment growth of non-routine cognitive analytical jobs relative to all other groups. Other industries show no clear pattern of *relative de-routinisation*.

Figure 7: Relative employment levels by task content component and industry in South Africa, 2000 to 2019

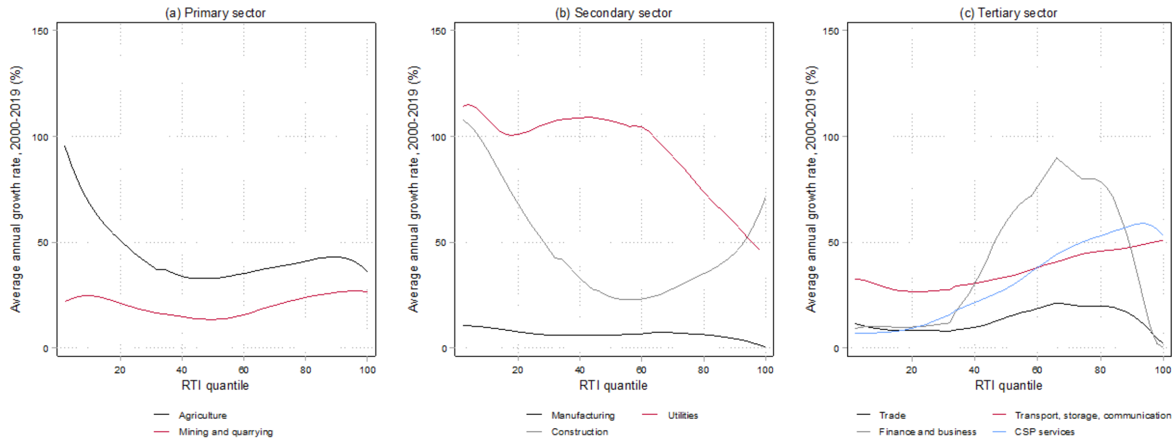


Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design.

The industry-specific employment GICs in Figure 8 are consistent with the trends observed in Figure 7. The observed polarisation in the primary sector observed in Figure 6 appears to be explained by growth in non-routine jobs in the agriculture industry, combined with growth in both routine and non-routine jobs in the mining and quarrying industry. There is considerable industry-level heterogeneity within the secondary sector. We do not find evidence of routine-biased jobs growth in the manufacturing industry, given the relatively constant growth rates across the RTI distribution, despite jobs in the industry being more routine on average relative to all other industries within the sector, as shown in Figure 4. In contrast, jobs growth in the utilities industry appears to be concentrated among non-routine jobs, and we again observe a pattern of job polarisation in the construction industry. Within the tertiary sector, all industries within the sector experienced higher growth rates among more routine jobs.

Figure 8: Industry-specific employment growth incidence curves across the RTI distribution, 2000 to 2019



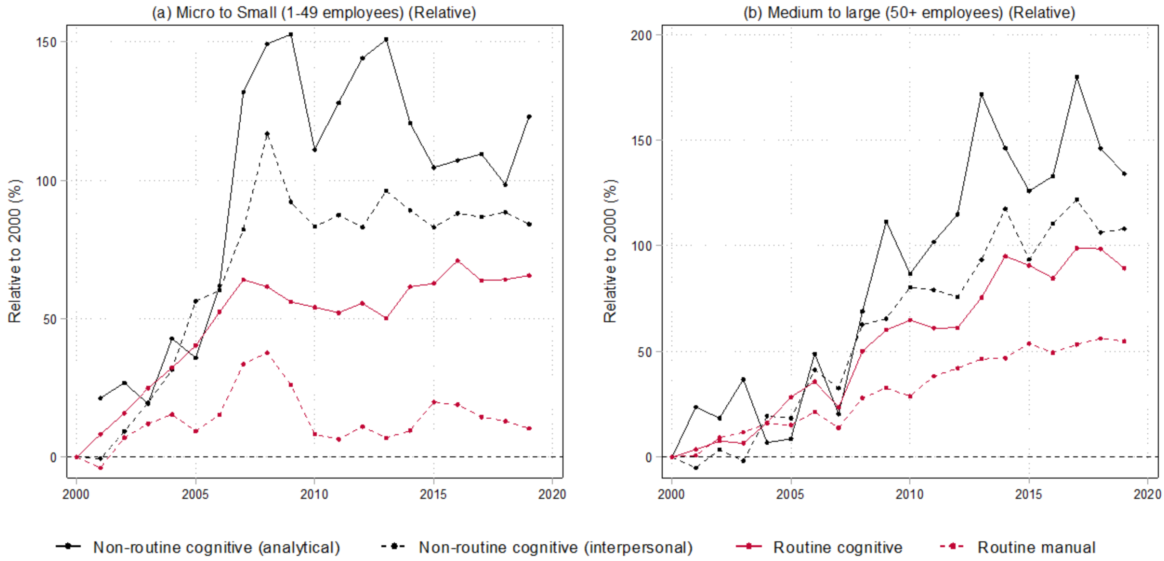
Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Curves plotted using local linear smooth plots (lowess). CSP services = Community, Social, and Personal services.

Firm size also serves as another covariate of interest when looking at employment patterns across task content components. In Figure 9 below, we plot trends in employment levels by task content component and firm size category relative to 2000.[12]

[12] The manner in which firm size data is captured by the QLFS survey instrument is limiting in that one is not able to identify individuals working in firms that are especially large. The large firm lower bound is 50 employees, which is not particularly large, and is more in line with a small to medium-sized firm. As such, this cut-off limits our ability to interrogate employment patterns across task content components for the larger firms – for example in excess of 200 employees – where technology take-up may be more prevalent, and hence where de-routinisation trends may be more visible than in small firms.

Figure 9: Relative employment levels by task content component and firm size in South Africa, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

The pattern of *relative de-routinisation,* where the growth rate for non-routine jobs exceeds that for routine jobs, is evident across both small and large firms.[13] This is consistent with our findings for employment on aggregate – as observed in Figure 2 above. We note that, in the case of micro- and small firms, most of the changes to employment occurred during the initial period from 2000 to 2010, after which employment growth across the task content components remained constant. In the case of medium to large firms, the employment growth across the task content components persisted throughout the period, but with growth in the non-routine components accelerating and outstripping the routine task content components – particularly routine manual – from 2007/2008 onward.

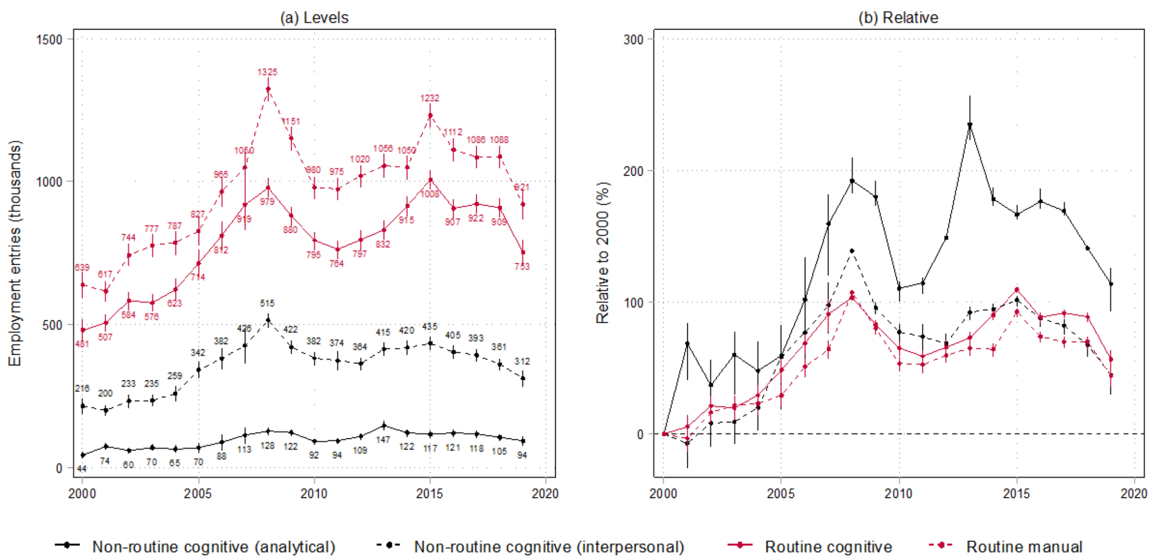
3.2 Trends in the Task Content of Employment Entries

We now consider the task content of recent employment entries – as defined in Section 2.5 – over time. Entries serve as a measure of worker flows and labour demand and, if there has been an increasing take-up of automation and other 4IR-type technologies, then we should observe a rising relative share of job entries into occupations comprising more non-routine tasks, and a declining relative share of job entries into occupations comprising more routine tasks.

[13] It is worth noting that, consistent with employment on aggregate, routine task-intensive jobs in both small and larger firms account for the majority share of employment, while non-routine cognitive analytical task-intensive jobs account for the minority share of jobs (see Appendix Figure A3).

As shown in Figure 10, we again find evidence of *relative de-routinisation*, as previously observed through the aggregate employment lens in Section 4.1. While the number of recent entries has grown both overall and within all task content components over time, those into non-routine cognitive (analytical) jobs has grown the fastest, while those into routine manual jobs has grown the slowest – see panel (b). Recent entries into routine manual occupations are dominant throughout the period, with approximately 640 000 such workers having started their work within the previous year as of 2000 (representing nearly half (46%) of total recent entries), rising to a peak of over 1.3 million workers in 2008 (45%). As shown in Figure A4 in the Appendix, the share of workers entering these occupations did not grow or contract consistently, but instead fluctuated between 42% and 47% over the period.

Figure 10: Absolute and relative employment entry levels by task content component in South Africa, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Recent employment entry defined as having commenced employment within the previous year. Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

Importantly, as shown in panel (b), despite the rise in entries into routine jobs over time, their rate of growth was the slowest. On the other hand, the growth rates of non-routine cognitive (analytical) occupations were highest across task component groups. While this group consistently represents the minority of recent entries from 2000 to 2008, the number of recent entries into these jobs tripled, from just 44 000 workers in 2000 (3.2% of total recent entries) to 128 000 workers in 2008 (4.3%). Similar to the other task component groups, the number of entries contracted from 2008 to between 2010 and 2012, and thereafter fluctuated to reach a peak of 147 000 entries in 2013, before again contracting thereafter. By 2019, the number of entries into non-routine cognitive (analytical) occupations was similar to its 2010 and 2011 levels. In relative terms with respect to entry shares, as shown in Figure A3, the share of recent entries into these occupations fluctuated between 3.2% and 6% over the period. Despite representing the minority of entries, the entry shares of this group relative to their share in 2000 were consistently the largest relative to other task component groups.

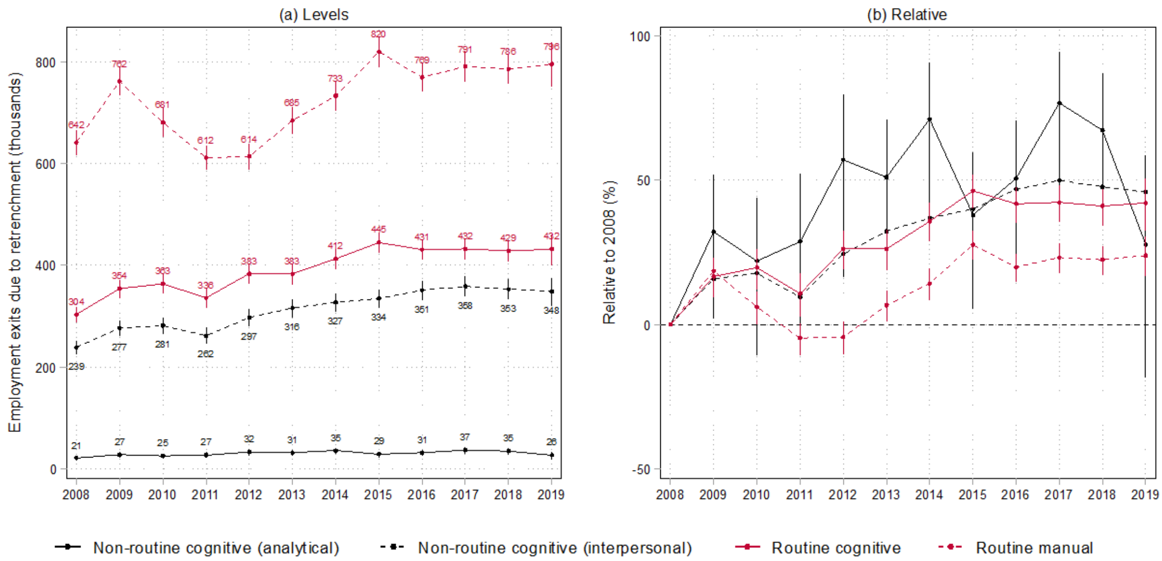
3.3 Trends in the Task Content of Employment Exits

In this section we present our estimates of recent employment exits, as defined in Section 2.5, by task content component over time. If there has been an increase in take-up of automation and other 4IR-type technologies, we should be able to observe, through this lens, a rising relative share of job exits from occupations comprising more routine tasks, and a declining relative share of job exits from occupations comprising more non-routine tasks. Importantly, the comparisons to trends in aggregate employment and recent entries above should bear in mind that here we only consider recent exit estimates derived from the QLFS, hence from 2008 onwards, due to between-instrument data comparability concerns, as described in Section 2.

It is worth first documenting the amount of churn in the labour market. The number of employment exits as shown in Figure 6, combined with the number of entries in Figure 5, suggests that worker flows among employees in the South African private formal labour market are extensive. In 2019, given that 2.1 million workers started their jobs and 1.6 million left their jobs in the previous year, worker flows then amounted to a total of 3.7 million – equivalent to 44% of all employees in this portion of the labour market. Between 2010 and 2019, this rate varied between 44% and 53%, indicating that close to one in every two job matches either forms or breaks up every year, which is higher than most European countries, but lower than the few developing countries for which data is available (Bellmann et al. 2011; Davis and Haltiwanger 1999). Despite the use of different data and methods, these estimates are consistent with Kerr (2018), who examines flow rates between 2011 and 2014 among workers in income tax-registered firms – a similar group of workers compared to those in this analysis. These rates are indicative of low labour market rigidities in hiring and firing, and suggest that such rigidities may not be as much of a concern as had previously been thought (Kerr 2018) – at least in this portion of the labour market.

As shown in Figure 11, we do not find evidence of *relative de-routinisation* using this measure, in contrast to the aggregate employment and recent entries analysis. Recent exits from routine manual occupations due to retrenchment did grow over the period, but so too did all other task component groups. While exits from routine manual occupations are dominant throughout the period, representing nearly 800 000 workers in 2019 (equivalent to just under 50% of all recent exits), the number of exits from other task content component occupations grew at a faster rate over the period. These exits from routine manual occupations are not surprising, given the dominance of these occupations among the employed (see Figure 1), and were approximately 24% higher relative to one decade earlier. Our estimates actually show that, from 2008 to 2014, recent exits from non-routine cognitive (analytical) occupations grew the most, which is not supported by the de-routinisation hypothesis. Thereafter, exits from these occupations fluctuated between 26 000 and 37 000 in a given year. Interestingly, exits from non-routine cognitive (interpersonal) and routine cognitive occupations show similar trajectories throughout the period. Similarly, we do not find evidence of de-routinisation when considering these trends in relative terms through the use of exit shares, as presented in Figure A5.

Figure 11: Absolute and relative employment exit levels by task content component in South Africa, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Recent employment exit is defined as having stopped working at one's previous job within the previous year due to retrenchment. Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector who have worked before. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

It should be emphasised that our lack of evidence for *relative de-routinisation* using the exits measure does not invalidate the evidence for *relative de-routinisation* when aggregate employment or the entries measure is used alternatively. This is because, as shown in Sections 3.1.1 and 3.2.1, most of the observed changes using aggregate employment for the entries measure occur prior to 2010. This unfortunately is a period mostly excluded here due to data comparability concerns across the survey instruments.

3.4 Profile of Employment Across Task Content Categories

We now profile the composition of employment across task content components by examining the distribution of employment within these components across various individual and job characteristics. Table 2 provides the share of employment within each of the four task content components by demographic characteristics. We also include an employment share ratio, which captures the ratio of the share of employment for a given characteristic in a given task content component, relative to the share of employment for a given characteristic on aggregate. The ratio provides insight into the distribution of employment for a given sub-group of the labour market across the four task content components, thereby highlighting patterns of over- or under-representation of these sub-groups across task content components.

Men account for the major share of employment in occupations intensive in non-routine cognitive analytical, non-routine interpersonal, and routine manual tasks. In Table 2, we observe that, in 2019, approximately three in five workers in the formal private sector are men (60.8%), and that this majority share is further reflected in the non-routine cognitive analytical (63.4%), non-routine interpersonal (61.3%), and routine manual (70.2%) task content components. The corresponding employment share ratios for men in these task content components – 1.04, 1.01 and 1.15, respectively – point to an over-representation of men in these components. However, this is not the case for the routine cognitive task content component, where women account for a higher relative share. The corresponding employment share ratio of 1.28 reflects an over-representation of women in this task content component.

The deleterious impacts of technology-induced *de-routinisation* – should they occur to a substantial degree – are set to be most acute for the African and Coloured population groups. The estimates in Table 2 indicate that, in terms of racial composition, there are substantial disparities across task content components. Africans constitute the vast majority of the employed in the formal private sector, accounting for 68.6% of employment, followed by Whites (14.5%), Coloureds (12.9%), and Indians (4%). However, the employment ratios indicate that Africans are under-represented in occupations intensive in non-routine cognitive analytical (0.63) and non-routine cognitive interpersonal (0.71) tasks, while Whites are over-represented in these non-routine task content components (corresponding ratios of 2.69 and 2.63, respectively). We also observe Indians and Coloureds being over- and under-represented in the two non-routine task content components, respectively. Africans are over-represented in occupations that are intensive in routine cognitive (1.03) and routine manual (1.16) tasks, while Coloureds are over-represented in occupations intensive in routine manual tasks (1.19). Whites are under-represented in both routine task content components.

In terms of age, the youth – particularly the youngest age cohort – are more likely to work in routine task-intensive occupations, while the non-youth are more likely to work in non-routine task-intensive occupations – with some distributional nuances among the two youth cohorts.[14] The non-youth represent the bulk share of formal private employment (54.4%), an almost equal share of non-routine cognitive analytical jobs (53.7%), and a much larger share of non-routine cognitive interpersonal jobs (62.6%), and hence over-representation in this latter non-routine task content component. For the youngest youth cohort, which represents 8.1% of formal private sector employment, we see an over-representation in both routine

[14] Of course, employees classified as youth at this particular point in time, 2019, may transition to other occupations less intensive in routine tasks as they gain experience, formal learning, and/or non-formal on-the-job training.

cognitive and routine manual occupations (both exhibit employment ratios in excess of unity). Further, the youngest youth cohort is under-represented in non-routine task-intensive jobs. This pattern is also evident for the oldest youth group, which, while accounting for 37% of formal private employment and a corresponding share of routine manual jobs, accounts for 40% of routine cognitive jobs. This pattern of youth being over-represented in routine jobs is somewhat surprising, given the notion that younger generations would be more familiar with technologies that are linked to non-routine tasks. However, we do see an over-representation of the older youth cohort in non-routine cognitive analytical occupations, which could suggest that there is some linkage between education, age, and propensity to allocate into non-routine occupations.

Table 2: Employment by demographic characteristics and task content components, 2019

Characteristics	Total		Non-routine cognitive analytical		Non-routine cognitive interpersonal		Routine cognitive		Routine manual	
	Number ('000)	Share (%)	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio
Gender										
Male	5 104	60.80	63.40	1.04	61.30	1.01	49.70	0.82	70.20	1.15
Female	3 291	39.20	36.60	0.93	38.70	0.99	50.30	1.28	29.80	0.76
Race										
African	5 759	68.60	43.50	0.63	48.80	0.71	70.90	1.03	79.60	1.16
Coloured	1 083	12.90	9.20	0.71	10.30	0.80	12.30	0.95	15.30	1.19
Indian/Asian	336	4.00	8.20	2.05	7.10	1.78	4.70	1.18	1.30	0.33
White	1 217	14.50	39.00	2.69	33.80	2.33	12.20	0.84	3.80	0.26
Age										
15-24	680	8.10	6.60	0.81	5.10	0.63	9.10	1.12	8.80	1.09
25-34	3 148	37.50	39.70	1.06	32.30	0.86	40.20	1.07	37.40	1.00
35-65	4 567	54.40	53.70	0.99	62.60	1.15	50.70	0.93	53.80	0.99
Education										
Primary or less	957	11.40	1.30	0.11	5.30	0.46	5.20	0.46	21.30	1.87
Incomplete secondary	2 401	28.60	4.50	0.16	14.70	0.51	26.60	0.93	40.40	1.41
Complete secondary	3 282	39.10	27.20	0.70	33.70	0.86	52.10	1.33	31.80	0.81
Tertiary	1 679	20.00	66.20	3.31	45.30	2.27	15.70	0.79	5.30	0.27

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design.

Consistent with Lewandowski et al. (2022), we observe that individuals with higher and lower levels of education are more likely to work in occupations intensive in non-routine and routine tasks, respectively. While individuals with a tertiary qualification account for 20% of the formal private sector workforce, they account for 66.2% and 45.3% of those employed in non-routine cognitive analytical and non-routine cognitive interpersonal occupations, respectively. Hence, the corresponding employment ratios point to an over-representation of individuals with a tertiary qualification in non-routine task-intensive occupations. In contrast, individuals with less than a tertiary qualification are less likely to find themselves in such occupations. Rather, we observe that individuals with a complete secondary education are most likely to find themselves employed in occupations intensive in routine cognitive tasks, and individuals with less than a complete secondary education are most likely to find themselves in occupations intensive in routine manual tasks. To the extent that technology induces changes in the job task content, these findings highlight the Autor et al. (2003) notion that demand shifts toward non-routine jobs are biased towards education.

We now turn to examining the composition of formal private sector employment within the task content components across skill levels and their associated one-digit occupation groupings. Our estimates are presented in Table 3.

We observe that occupations intensive in non-routine tasks are primarily comprised of high-skilled or skilled occupations. The spread of formal private sector employment intensive in non-routine cognitive analytical tasks is concentrated in high-skilled professional occupations and skilled technician occupations, with employment in these two occupation groupings accounting for approximately 95% of employment that is intensive in non-routine cognitive analytical tasks. The spread of employment that is intensive in non-routine cognitive interpersonal tasks, while relatively more dispersed across occupation groupings, is still overly represented in high-skilled occupations – 44% and 12% of employment that is intensive in non-routine cognitive interpersonal tasks are in manager and professional occupations, respectively. As such, manager and professional occupations are overly represented in the non-routine cognitive interpersonal task content component. We also observe that skilled technician and craft and related trade occupations are overly represented in the non-routine cognitive interpersonal task content component.

With respect to occupations intensive in routine tasks, we find that occupations intensive in routine cognitive tasks are predominantly skilled occupations, while those intensive in routine manual tasks are mainly low-skilled occupations. The majority of employment intensive in routine cognitive tasks is found in skilled clerical (40.35%) and service (43.66%) occupations. Employment intensive in routine manual tasks is predominantly found in skilled craft and related trade (22.63%) and plant and machine operator (24.52%) occupations, and low-skilled elementary occupations (51.59%).

Table 3: Employment by occupation and task content components, 2019

Characteristics	Total		Non-routine cognitive analytical		Non-routine cognitive interpersonal		Routine cognitive		Routine manual	
	Number ('000)	Share (%)	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio
High skilled	***1 072***	***12.77***	***33.31***	***2.61***	***56.45***	***4.42***	***0.18***	***0.01***	***0.00***	***0.00***
Managers	718	8.55	0.00	0.00	44.32	5.18	0.00	0.00	0.00	0.00
Professionals	354	4.22	33.31	7.90	12.13	2.88	0.18	0.04	0.00	0.00
Skilled	***5 445***	***64.87***	***66.69***	***1.03***	***41.73***	***0.64***	***95.51***	***1.47***	***48.41***	***0.75***
Technicians	714	8.51	62.03	7.29	13.61	1.60	6.88	0.81	0.16	0.02
Clerical	1 205	14.35	0.00	0.00	0.00	0.00	40.35	2.81	0.00	0.00
Services	1 477	17.59	0.00	0.00	9.26	0.53	43.66	2.48	0.70	0.04
Skilled agric.	18	0.21	0.00	0.00	0.27	1.29	0.00	0.00	0.40	1.89
Craft	1 103	13.13	4.65	0.35	18.59	1.42	0.88	0.07	22.63	1.72
Operators	929	11.07	0.00	0.00	0.00	0.00	3.75	0.34	24.52	2.22
Low skilled	***1 877***	***22.36***	***0.00***	***0.00***	***1.82***	***0.08***	***4.31***	***0.19***	***51.59***	***2.31***
Elementary occup.	1 877	22.36	0.00	0.00	1.82	0.08	4.31	0.19	51.59	2.31

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design.

The sectoral composition of employment within task content components for the services (tertiary) sector reflects the occupational heterogeneity of this broad sector.[15] In Table 4 we note that this sector accounts for 61.82% of formal private sector employment. We also note that the sector accounts for correspondingly larger shares of employment for individuals in occupations falling within the non-routine cognitive analytic (73.66%), the non-routine cognitive interpersonal (67.98%), and the routine cognitive (86.34%) task content components – consistent with employment ratios in excess of unity. We also observe a further level of heterogeneity in the distribution of employment within these task content components for the services sub-sectors. Employment ratios indicate that the finance and CSP industries are over-represented in the non-routine cognitive analytic task content component, with the latter industry also being over-represented in the non-routine cognitive interpersonal task content component. Similarly, the wholesale and retail trade, transport and finance are over-represented in the routine cognitive task component. However, the services sector and its constituent sub-sectors are under-represented in the routine manual task content component.

To the extent that routine task-intensive occupations are at greater risk of technological substitution through routinisation, employment in primary and secondary sector industries

[15] As expressed in Bhorat et al. (2019), South Africa is a *de facto* services based economy.

appear to be the most exposed to this risk. We observe that employment in these sectors and their constituent sub-sectors is over-represented in occupations intensive in routine manual tasks. For instance, while the agriculture, mining and manufacturing industries account for 7.7%, 4.39% and 17.64% of formal private sector employment, these sectors constitute 18.21%, 8.74% and 26.95% of employment in routine task-intensive occupations, respectively. A similar pattern emerges for the construction and utilities industries.

Table 4: Employment by industry and task content components, 2019

Characteristics	Total		Non-routine cognitive analytical		Non-routine cognitive personal		Routine cognitive		Routine manual	
	Number ('000)	Share (%)	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio
Primary sector	***1 014***	***12.08***	***3.04***	***0.25***	***2.38***	***0.20***	***2.14***	***0.18***	***26.96***	***2.23***
Agriculture	646	7.70	0.48	0.06	0.82	0.11	0.81	0.10	18.21	2.37
Mining	368	4.39	2.57	0.58	1.56	0.36	1.33	0.30	8.74	1.99
Secondary sector	***2 189***	***26.07***	***23.30***	***0.89***	***29.61***	***1.14***	***11.48***	***0.44***	***37.81***	***1.45***
Manufacturing	1 481	17.64	16.37	0.93	14.09	0.80	9.38	0.53	26.95	1.53
Utilities	32	0.39	0.53	1.36	0.41	1.07	0.20	0.52	0.52	1.34
Construction	676	8.05	6.40	0.80	15.10	1.88	1.91	0.24	10.35	1.29
Tertiary sector	***5 190***	***61.82***	***73.66***	***1.19***	***67.98***	***1.10***	***86.34***	***1.40***	***35.23***	***0.57***
W&R trade	1 971	23.48	8.72	0.37	14.03	0.60	37.97	1.62	17.11	0.73
Transport	443	5.28	5.39	1.02	5.28	1.00	6.43	1.22	4.24	0.80
Finance	1 964	23.40	46.36	1.98	24.66	1.05	32.83	1.40	11.19	0.48
CSP service	811	9.66	13.18	1.36	24.01	2.49	9.12	0.94	2.69	0.28

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design.

While the majority of the employed in the formal private sector are not union members, union membership is more likely for individuals in routine manual occupations – those most at risk of automation. Table 5 shows that close to three in every four workers are not part of a union (71.21%), and individuals in non-routine cognitive analytical (77.99%) and non-routine cognitive interpersonal (78.04%) occupations are even less likely to have union membership – reflected in employment ratios in excess of unity. The employment ratio for union membership in the routine manual task content component is 1.17, thus indicating a greater propensity for this group to enter into union membership.

There is no discernible pattern to emerge when looking at the distribution of employment across firm size categories within the task content component. We observe that formal private employment is relatively evenly distributed between micro-small (49.94%) and medium-large (43.08%) firms. Employment in medium-large firms is over-represented in the non-routine cognitive analytical and routine manual task content components, while employment in micro-small firms is over-represented in non-routine cognitive interpersonal and routine cognitive task content components.

Table 5: Employment by union status, firm size and task content components, 2019

Characteristics	Total		Non-routine cognitive analytical		Non-routine cognitive personal		Routine cognitive		Routine manual	
	Number ('000)	Share (%)	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio	Share (%)	Ratio
Union status										
Union member	2 063	24.57	17.91	0.73	18.34	0.75	24.31	0.99	28.74	1.17
Non-union	5 978	71.21	77.99	1.10	78.04	1.10	70.61	0.99	67.51	0.95
Firm size										
Micro to small (1-49 employees)	4 192	49.94	46.42	0.93	52.67	1.05	56.00	1.12	43.67	0.87
Medium to large (50+ employees)	3 616	43.08	46.23	1.07	40.44	0.94	36.26	0.84	50.04	1.16

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design.

In summary, we observe that individuals working in jobs intensive in routine manual tasks are more likely to be young African or Coloured males with at most an incomplete secondary education, working in elementary, plant and machine operator, or craft and related trade occupations in the agricultural, mining, manufacturing, utilities or construction industries. Individuals working in jobs intensive in routine cognitive tasks are more likely to be young African or Coloured females with a complete secondary education working in clerical or services occupations in the services sector industries, such as wholesale and retail trade, transport and finance. With respect to jobs intensive in non-routine cognitive interpersonal tasks, individuals are more likely to be older, Indian or White males with a tertiary education, working in managerial, professional, technician or craft and related trade occupations, in the community, social and personal services industry. Individuals working in jobs intensive in non-routine cognitive analytical tasks are more likely to be older Indian or White male youths with a tertiary education, working in professional or technician occupations in the finance, utilities or community, social and personal services industries.

Consistent with looking at the evolving task content of employment in South Africa, we now consider changes in the profile of individuals working in occupations falling within each of the task content components. We present these estimates in Table 6, where we report the percentage point change in the share of a given individual or job characteristic within a task content component for the period 2000 to 2019. We shade statistically significant growing or declining shares in green and red, respectively. In addition to reporting the percentage point share changes in Table A2 in the Appendix, we include the respective employment shares for each of the characteristics in the years 2000 to 2019.

Table 6: Composition of employment share changes by task content component, 2000 to 2019

Characteristics	Non-routine cognitive analytical	Non-routine cognitive interpersonal	Routine cognitive	Routine manual
Gender				
Male	-6.7	-6.7	-0.1	-2.4
Female	6.7	6.7	0.1	2.4
Race				
African	19.4	11.1	21.9	7.8
Coloured	1.1	-3.3	-2.7	-3.6
Indian/Asian	3.4	1.4	-1.8	-1.6
White	-23.0	-8.9	-17.3	-2.5
Age				
15-24	-9.6	-5.5	-8.1	-1.9
25-34	6.9	-1.0	3.4	4.4
35-65	2.7	6.5	4.7	-2.5
Education				
Primary or less	-3.4	-14.8	-12.1	-36.3
Incomplete secondary	-9.0	-6.0	-3.6	14.5
Complete secondary	-0.1	6.2	12.8	17.9
Tertiary	12.5	14.6	2.9	3.9
Primary sector	***-2.7***	***-6.9***	***-3.2***	***-12.6***
Agriculture	0.5	-3.6	-0.6	-6.1
Mining	-3.2	-4.0	-2.7	-6.6
Secondary sector	***-4.4***	***-3.0***	***-5.9***	***0.6***
Manufacturing	-9.0	-3.8	-6.3	-4.3
Utilities	0.4	-0.9	-0.1	0.3
Construction	4.2	1.6	0.5	4.6
Tertiary sector	***7.1***	***9.8***	***9.1***	***12.1***
W&R trade	-7.7	-4.4	-2.4	2.5
Transport	1.4	2.5	1.7	1.8
Finance	9.4	10.3	8.3	7.5
CSP service	7.1	9.8	9.1	12.1
Union status				
Union member	0.7	-3.0	0.1	-7.0
Non-union	0.7	4.3	0.6	8.4
Firm size				
Micro to small (1-49 employees)	-1.8	-4.3	-3.7	-8.6
Medium to large (50+ employees)	0.5	1.7	2.5	7.4

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: (i) The estimates are the percentage point change in the shares between 2000 and 2019 by covariates. (ii) Shaded regions denote statistically significant changes in the shares between 2000 and 2019 at the 95% confidence level. (iii) The green backgrounds reflect statistically positive change in the shares, and the red backgrounds reflect statistically negative change in the shares.

Compositional changes in the task content of employment exhibit the following patterns: First, there is evidence of a shift toward greater female representation – feminisation – in formal private sector employment: however, this compositional shift is only statistically significant in the case of occupations intensive in non-routine cognitive interpersonal tasks.[16] Second, we observe a strong compositional shift of formal private sector employment toward Africans and away from other population groups, and this shift is present across all four task content components. Third, consistent with high youth unemployment rates in South Africa, there is a shift in employment share away from the youngest youth cohort, which is evident across all four task content components. Fourth, there is a compositional shift toward an increasingly educated labour force, as evidenced by rising employment shares for individuals with a tertiary qualification across all four task content components, and rising employment shares for those with a complete secondary education in all task content components, apart from the non-routine cognitive analytical task component. Fifth, consistent with South Africa's long-term trend in structural change, the rising employment shares in the services sector and declining employment shares in manufacturing point to the continued tertiarisation and deindustrialisation of the South African economy (Bhorat et al. 2022). Declining employment shares for manufacturing are present across all four task content components, while rising employment shares for the tertiary sector are present in all task content components apart from the non-routine cognitive analytical task component. Sixth, as detailed in Kerr and Wittenberg (2021) – who show that unionisation rates have declined in South Africa since a peak in 1999 – we show a decline in union membership among those employed in occupations intensive in routine manual tasks (the task content component most likely to have union members, as alluded to in Table 5). Finally, we observe declining employment shares in occupations intensive in routine tasks, both cognitive and manual, in micro- to small firms, alongside rising employment shares for occupations intensive in routine manual tasks in medium to large firms.

4 Policy Discussion

We find evidence of *relative de-routinisation* – that is, greater growth of non-routine jobs relative to routine jobs, which – tentatively – suggests that there is a degree of technology take-up that is shifting the relative demand for workers across these two broad job groupings. Not only does this deepen our understanding of how the nature of work has changed in the (formal private sector) South African labour market during the post-apartheid period, but these divergent trends have important policy implications, such as follows:

First, investments in skills relevant to non-routine work are necessary to ensure that workers previously employed in routine occupations are able to continue accessing opportunities in

[16] This is consistent with the pattern of labour market feminisation, detailed by Casale (2004) and Casale and Posel (2002), in South Africa in the 1990s. However, as detailed in these studies, the feminisation of the South African labour market was felt most through increased female labour force participation relative to increased female employment.

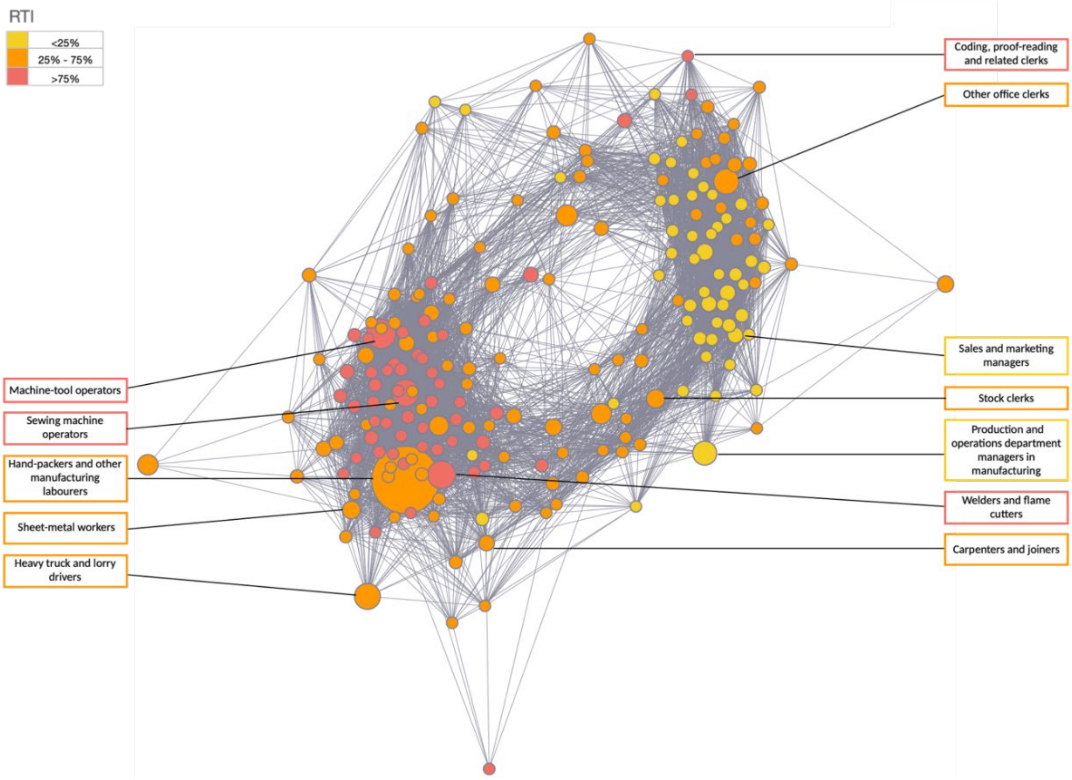
the labour market, particularly employment in non-routine occupations that are relatively hard to automate.

Second, a key challenge to such skills development interventions aimed at ameliorating employment displacement effects resulting from greater technology uptake by firms is that it is likely to be substantial in magnitude. This is a result of the fact that the majority of workers in the formal private sector work in routine task-intensive jobs – 75% of jobs in 2019. Further, this pattern of relative de-routinisation is evident across a number of industries in the economy – mining, manufacturing, construction, transport, storage and communication, and community, social and personal services industries – which means the scope of such interventions are not restricted to any single industry, but must rather be economy-wide.

Third, if such skills development interventions are not implemented, then those adversely affected are most likely to be those associated with the worst labour market outcomes, and this is likely to exacerbate existing labour market inequalities. For example, those working in jobs intensive in routine manual tasks are more likely to be young African or Coloured males with at most an incomplete secondary education. Such individuals are typically associated with higher levels of unemployment. If such skills investments are not adequately made, and the demand for routine work continues to decline, then the average worker employed in a routine occupation faces a growing risk of unemployment that can become structural in nature. This, of course, goes against the policy goals of reducing the already extreme unemployment levels in South Africa, and has obvious inequality (and poverty) implications, given the dominance of the labour market (both unemployment and the distribution of earnings among the employed) in driving overall income inequality.

Finally, skills development interventions aimed at shifting individuals out of routine task-intensive jobs and into non-routine task-intensive jobs are likely to require substantial educational and skill input – i.e. the jump to a new occupation is big. This can be visually depicted using the *occupation space* for the South African manufacturing sector – as developed by Allen Whitehead et al. (2021) – depicted in Figure 12. Each node represents an occupation, which is shaded according to its RTI score, with occupations intensive in routine tasks being shaded red, occupations intensive in non-routine tasks being shaded yellow, and occupations moderately intensive in routine tasks shaded in orange. Each edge (line connecting nodes) represents the relatedness, in terms of similar tasks and skills, between pairs of occupations. Thus, if occupations (nodes) are connected and close (short edges), then there is substantial overlap between the skills and tasks required by each occupation, which means that shifts between such occupations require relatively minor skills development interventions. Conversely, if occupations (nodes) are disconnected and far from one another, then shifts between such occupations require substantial skills development interventions.

Figure 12: South African manufacturing sector occupation space – shaded by RTI score



Source: Authors' calculations from PALMS v3.3 (Kerr et al. 2019) and O*NET (2020), and taken from Allen Whitehead et al. (2021).

Notes: 1. Occupations with a value of the RTI equal to or lower than the 25th percentile of the RTI distribution are classified as 'non-routine' or 'low risk', and shaded yellow. 2. Occupations with an RTI between the 25th and 75th percentile (exclusive) of the RTI distribution are classified as 'intermediate' or 'medium risk', and shaded orange. 3. Occupations with an RTI above the 75th percentile of the RTI distribution are classified as 'routine' or 'high risk', and shaded red. 4. Node size is proportional to overall share of manufacturing employment in a given occupation.

The *occupation space* network for the South African manufacturing sector is polarised, with a cluster of predominantly non-routine task-intensive occupations (yellow nodes) to the right, and a cluster of predominantly routine task-intensive occupations (red nodes) to the left. These two occupation clusters are distant and relatively disconnected from one another, thus indicating that shifts between the clusters, particularly from routine to non-routine task-intensive occupations, would require substantial skills development interventions.

5 Conclusion

Concerns surrounding the labour market effects of technology and automation have regained prominence in recent years. However, given wide variation in the skills demanded across jobs, these effects are likely to be unevenly distributed across workers. The routinisation hypothesis, which is dominant in the literature, posits that technological development reduces the demand for workers in jobs characterised by 'routine' tasks, while increasing the demand for workers in jobs characterised by 'non-routine' tasks. Empirical evidence largely supports this theory; however, it is concentrated in developed-country contexts. In South

Africa in particular, no evidence exists that simply describes the distribution of employment by task content and how it has evolved over time. Such an analysis has notable policy implications, given the potential effects of automation on exacerbating the country's already extreme levels of unemployment and inequality.

In this paper, we construct and apply task content measures to the South African context by making use of occupation-level task content data derived from the Occupation Information Network (O*NET) database, and individual-level labour market data from the Post-Apartheid Labour Market Series (PALMS), to analyse the evolution of the task content of employment in the formal private sector labour market in South Africa from 2000 to 2019. We do so by considering trends in aggregate employment as well as employment entries and exits.

We find that the labour market has experienced a pattern of *relative de-routinisation* through a relative contraction of routine manual jobs and an expansion of non-routine cognitive analytical jobs over time. While employment within all task content component groups grew over the period, non-routine jobs (which represent the minority of workers) experienced far greater rates of jobs growth relative to routine jobs (which represent the majority of workers). Consequently, the employment share of routine manual jobs has shrunk significantly. Most of these changes occurred between 2000 and 2010. This aggregate pattern of *relative de-routinisation* is driven by similar such trends in the mining, manufacturing, construction, transport, storage and communication, and community, social and personal services industries – accounting for approximately two-thirds of total formal private employment. We observe this pattern in both small and large firms alike. Our analysis of employment entries is consistent with the *relative de-routinisation* finding, while that of exits is inconclusive due to data limitations.

The demographic and labour market profiles of workers differ significantly across these groups of occupations. Individuals working in jobs intensive in routine manual tasks are more likely to be young African or Coloured males with at most an incomplete secondary education. They generally work in elementary, plant and machine operator, or craft and related trade occupations, in the agricultural, mining, manufacturing, utilities or construction industries. Individuals working in jobs intensive in routine cognitive tasks are more likely to be young African or Coloured females with a complete secondary education working in clerical or services occupations in the services sector industries, such as wholesale and retail trade, transport and finance. With respect to jobs intensive in non-routine cognitive interpersonal tasks, individuals are more likely to be older, Indian or White males with a tertiary education, working in managerial, professional, technician or craft and related trade occupations in the community, social and personal services industry. Finally, individuals working in jobs intensive in non-routine cognitive analytical tasks are more likely to be older Indian or White male youth with a tertiary education, working in professional or technician occupations in the finance, utilities or community, social and personal services industries.

References

Acemoglu, D. & Autor, D. (2011). Chapter 12: Skills, tasks and technologies: Implications for employment and earnings. In D. Card & O. Ashenfelter (eds), *Handbook of labor economics, Volume 4, Part B* (pp. 1043-1171). Amsterdam: Elsevier.

Adams, C. & Yu, D. (2022). Labour market trends in South Africa in 2009-2019: A lost decade? Stellenbosch Economic Working Paper WP03/2022. Department of Economics, Stellenbosch University, Stellenbosch.

Allen Whitehead, C., Bhorat, H., Hill, R., Köhler, T. and Steenkamp, F. 2021. The Potential Implications of the Fourth Industrial Revolution Technologies: The Case of the Manufacturing, Engineering and Related Services Sector. Development Policy Research Unit Working Paper 202106. DPRU, University of Cape Town.

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.

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. H. & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5): 1553-1597

Bárány, Z. L. & Siegel, C. (2018). Job polarization and structural change. *American Economic Journal: Macroeconomics*, 10(1): 57-89.

Bellmann, L., Gerner, H. & Upward, R. (2011). Job and worker turnover in German establishments. IZA Discussion Papers 6081. Institute for the Study of Labor (IZA), Bonn, Germany.

Berman, E., Bound, J. & Machin, S. (1998). Implications of skill-biased technological change: International evidence. *The Quarterly Journal of Economics*, 113(4): 1245-1279.

Berman, E. & Machin, S. (2000). Skill-biased technology transfer around the world. *Oxford Review of Economic Policy*, 16(3): 12-22.

Bhorat, H., Rooney, C. & Steenkamp, F. (2019). Understanding and characterizing the services sector in South Africa: An overview. In R. Newfarmer, J. Page & F. Tarp (eds), *Industries without smokestacks: Industrialisation in Africa reconsidered* (275-295). Oxford: Oxford University Press.

Bhorat, H., Lilenstein, K., Oosthuizen, M. & Thornton, A. (2020). Wage polarization in a high-inequality emerging economy: The case of South Africa. WIDER Working Paper 2020/55. UNU-WIDER, Helsinki.

Bhorat, H., Lilenstein, K., Oosthuizen, M. & Steenkamp, F. (2022). Economic growth, rising inequality, and deindustrialisation: South Africa's Kuznetsian tension. In A. S. Alisjahbana, K. Sen, A. Sumner & A. A. Yusuf (eds), *The developer's dilemma: Structural transformation, inequality dynamics, and inclusive growth* (pp. 180-202). Oxford: Oxford University Press.

Blinder, A. S. (2009). How many US jobs might be offshorable? *World Economics*, 10(2): 41-78.

Card, D. & DiNardo, J. E. (2002). Skill-biased technological change and rising wage inequality: Some problems and puzzles. *Journal of Labor Economics*, 20(4): 733-783.

Casale, D. (2004). What has the feminisation of the labour market 'bought' women in South Africa? Trends in labour force participation, employment and earnings, 1995-2001. *Journal of Interdisciplinary Economics*, 15(3-4): 251-275.

Casale, D. & Posel, D. (2002). The continued feminisation of the labour market in South Africa: An analysis of recent data and trends. *South African Journal of Economics*, 70(1): 156-184.

Davies, R. & Van Seventer, D. (2020). Polarization in the South African labour market: Economy-wide scenarios. WIDER Working Paper 2020/121. UNU-WIDER, Helsinki.

Davis, S. J. & Haltiwanger, J. (1999). Gross job flows. In O. Ashenfelter and D. Card (eds). *Handbook of* *labor economics, Volume 3B, Chapter 41* (pp. 2711-2805). Amsterdam: Elsevier.

Firpo, S., Fortin, N. M. & Lemieux, T. (2011). Occupational tasks and changes in the wage structure. IZA Discussion Paper No. 5542. Institute for the Study of Labor, Bonn.

Fonseca, T., Lima, F. & Pereira, S. C. (2018). Job polarization, technological change and routinization: Evidence for Portugal. *Labour Economics*, 51: 317-339.

Fossen, F. M. & Sorgner, A. (2022). New digital technologies and heterogeneous wage and employment dynamics in the United States: Evidence from individual-level data. *Technological Forecasting and Social Change*, 175: 121381. https://doi.org/10.1016/j.techfore.2021.121381

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.

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. and Salomons, A. (2009). Job polarization in Europe. American Economic Review, 99(2): 58-63.

Goos, M., Manning, A. & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8): 2509-2526.

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, IBS Working Paper Series. Institute for Structural Research (IBS), Warsaw.

Hardy, W., Lewandowski, P., Park, A. & Yang, D. (2018). The global distribution of routine and non-routine work. Institute for Structural Research Working Paper, No. 5. Institute for Structural Research (IBS), Warsaw.

Institute for Structural Research (IBS). (2016). Occupation classification crosswalks – from O*NET-SOC to ISCO [dataset]. Available from: https://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/

Intraligi V., Vittori, C. & Ricci, A. (2021). Job polarization in Italy: Structural change and routinization. Inapp Working Paper Number 75. Inapp, Rome. Available from: https://oa.inapp.org/xmlui/handle/20.500.12916/3405

Kerr, A. (2018). Job flows, worker flows and churning in South Africa. *South African Journal of Economics*, 86(S1): 141-166.

Kerr, A. & Wittenberg, M. (2021). Union wage premia and wage inequality in South Africa. *Economic Modelling*, 97: 255-271.

Kerr, A., Lam, D. & Wittenberg, M. (2019). Post-Apartheid Labour Market Series [dataset], Version 3.3. Cape Town: DataFirst [producer and distributor].

Leibbrandt, M., Finn, A. & Woolard, I. (2012). Describing and decomposing post-apartheid income inequality in South Africa. *Development Southern Africa*, 29(1): 19-34.

Lewandowski, P., Park, A. & Schotte, S. (2020). The global distribution of routine and nonroutine work. WIDER Working Paper 2020/75. UNU-WIDER, Helsinki.

Lewandowski, P., Park, A., Hardy, W., Du, Y. & Wu, S. (2022). Technology, skills, and globalization: Explaining international differences in routine and nonroutine work using survey data. *The World Bank Economic Review*, 36(3): 687-708.

Maloney, W. F. & Molina, C. (2016). *Are automation and trade polarizing developing country labor markets, too?* Washington, DC: The World Bank.

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

O*NET. (2019). *O*NET OnLine* [dataset]. Available from: https://www.onetonline.org

Statistics South Africa. (2022). *Quarterly Labour Force Survey: Quarter 4 2021*. *Statistical Release P0211*. Pretoria: Statistics South Africa.

Tinbergen, J. (1974). Substitution of graduate by other labour. *Kyklos: International Review for Social Sciences*, 27(2): 217-226.

Tinbergen, J. (1975). *Income differences: Recent research*. Amsterdam: North-Holland Publishing Company.

Van der Linde, M. (2015). An analysis of the polarisation of the South African labour market. MCom dissertation. Potchefstroom: North West University.

World Economic Forum. (2022). *Fourth Industrial Revolution*. Available from: https://www.weforum.org/focus/fourth-industrial-revolution

World Population Review. (2022). *Gini coefficient by country 2022*. Available from: https://worldpopula-tionreview.com/country-rankings/gini-coefficient-by-country

Appendix

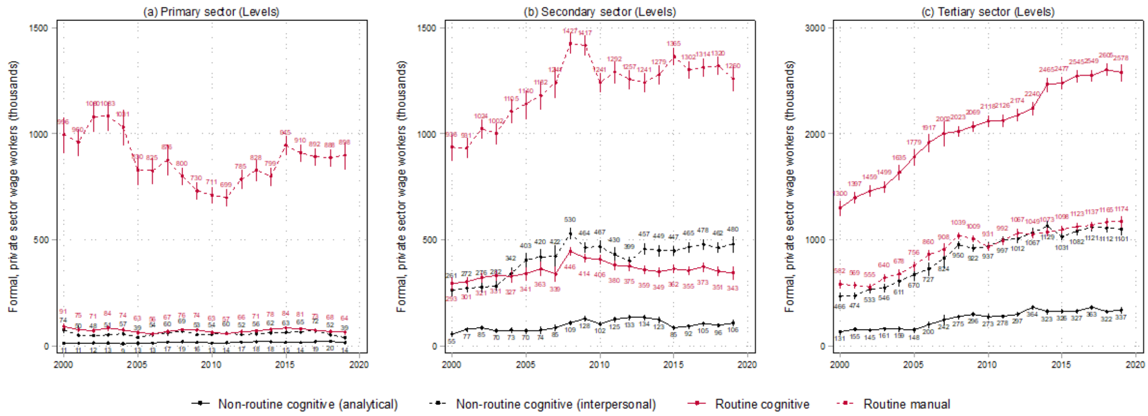
Table A1: Top 10 routine and non-routine occupations in the private formal South African labour market

Occupation title	ISCO-88 code	RTI (composite)	RTI (non-routine analytical)	RTI (non-routine interpersonal)	RTI (routine cognitive)	RTI (routine manual)
Panel (a): Top 10 non-routine occupations						
Religious associate professionals	3480	0.283	0.668	0.893	0.112	0.116
Street vendors (non-food products)	9112	0.318	0.200	0.715	0.096	0.061
Stall and market salespersons	5230	0.318	0.200	0.715	0.096	0.061
Religious professionals	2460	0.345	0.610	0.715	0.166	0.094
Directors and chief executives	1210	0.407	0.786	0.876	0.296	0.149
Sales and marketing department managers	1233	0.416	0.681	0.859	0.325	0.095
Sociologists, anthropologists, and related professionals	2442	0.423	0.901	0.661	0.302	0.151
Managing directors and chief executives	1120	0.423	0.756	0.918	0.324	0.156
College, university, and higher education teaching professionals	2310	0.432	0.798	0.740	0.289	0.182
Traditional medicine practitioners	3241	0.433	0.714	0.683	0.335	0.082
Panel (b): Top 10 routine occupations						
Weaving- and knitting-machine operators	8262	0.931	0.121	0.305	0.568	0.778
Rubber-products machine operators	8231	0.927	0.165	0.337	0.689	0.880
Fibre preparers	7431	0.920	0.174	0.284	0.586	0.779
Fur- and leather-preparing machine operators	8265	0.918	0.137	0.307	0.566	0.759
Textile-, fur- and leather-products machine operators not elsewhere classified	8269	0.911	0.220	0.192	0.433	0.756
Wood-processing plant operators	8141	0.904	0.192	0.287	0.548	0.778
Woodworking machine setters and setter-operators	7423	0.904	0.192	0.287	0.548	0.778
Vehicle, window, and related cleaners	9142	0.897	0.073	0.264	0.459	0.448
Astrologers and related workers	5151	0.896	0.000	0.455	0.759	0.459
Shoemaking and related machine operators	8266	0.893	0.215	0.331	0.644	0.777

Authors’ own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector. ISCO = International Standard Classification of Occupations code at the four-digit level. Occupations ordered by composite RTI (routine task intensity) index value.

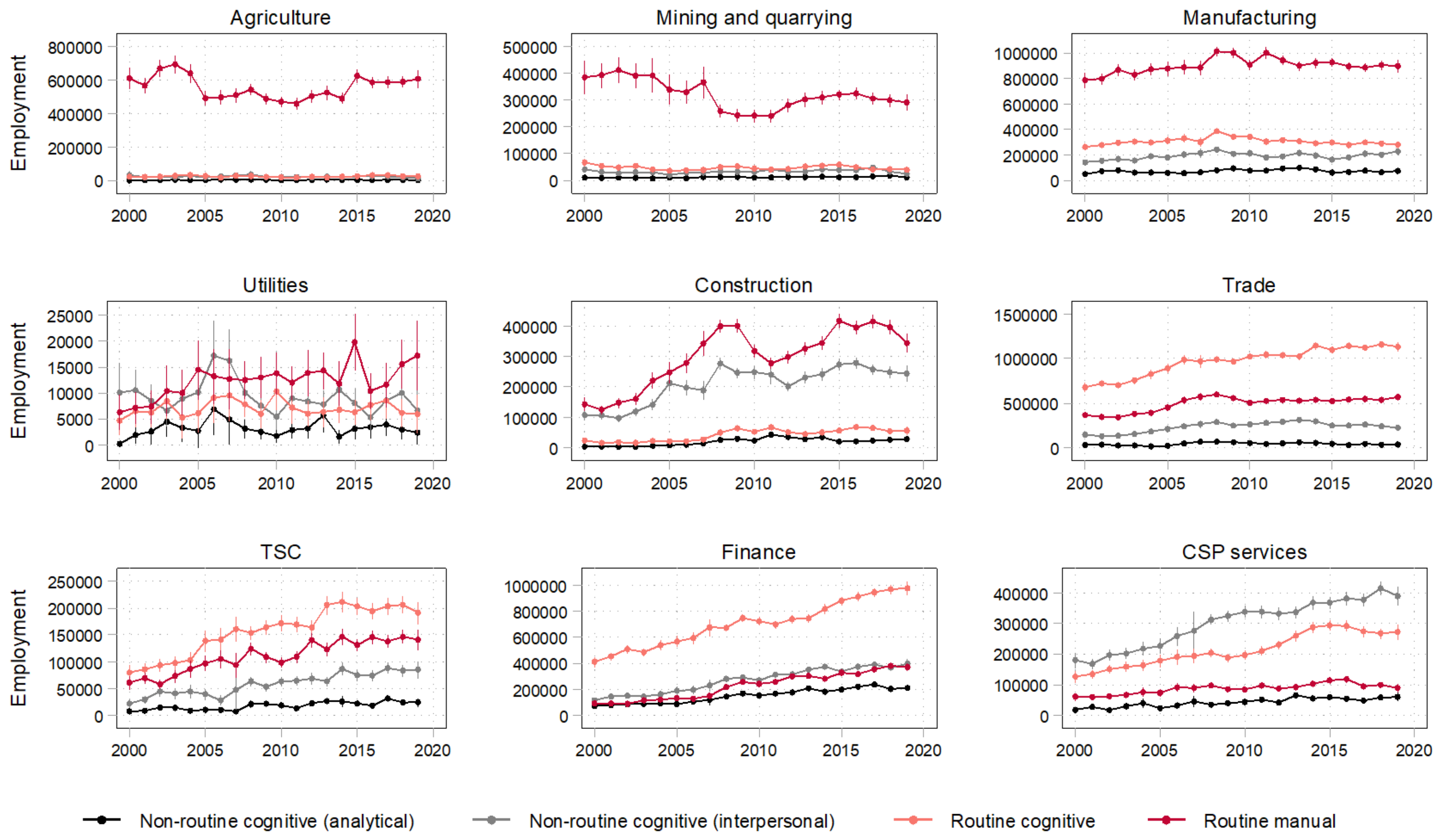
Figure A1: Absolute employment levels by task content component and sector in South Africa, 2000 to 2019



Authors’ own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

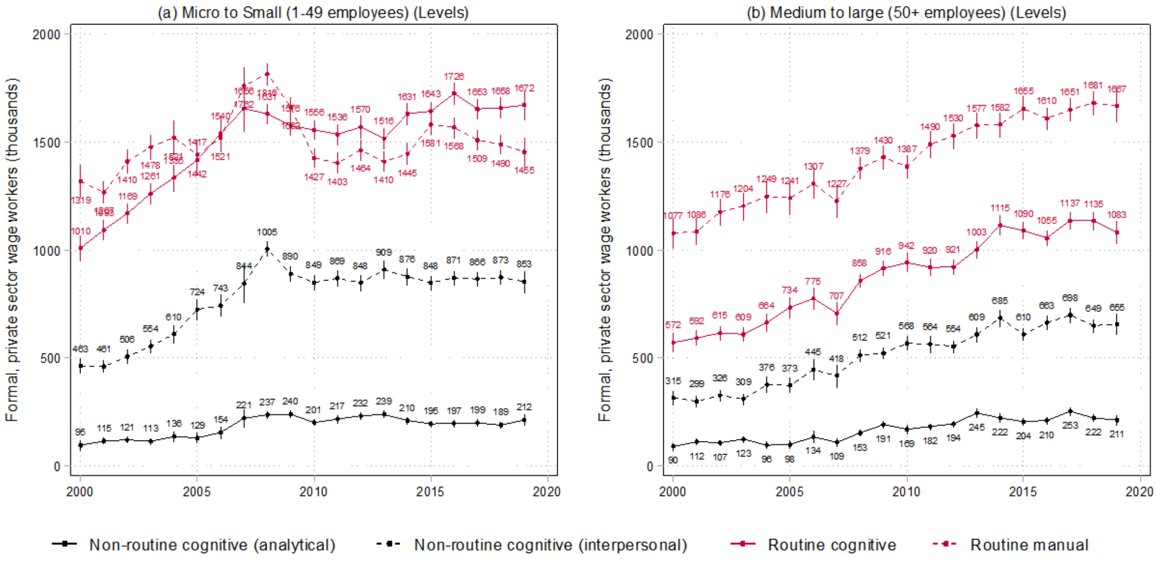
Figure A2: Absolute employment levels by task content component and industry in South Africa, 2000 to 2019



Authors’ own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

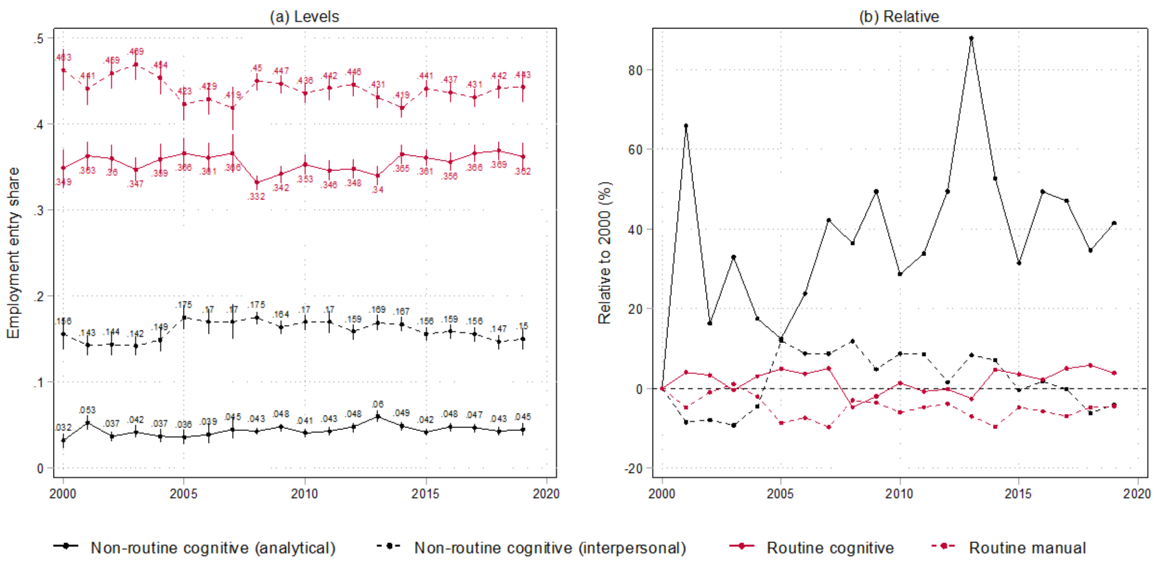
Figure A3: Absolute employment levels by task content component and firm size in South Africa, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

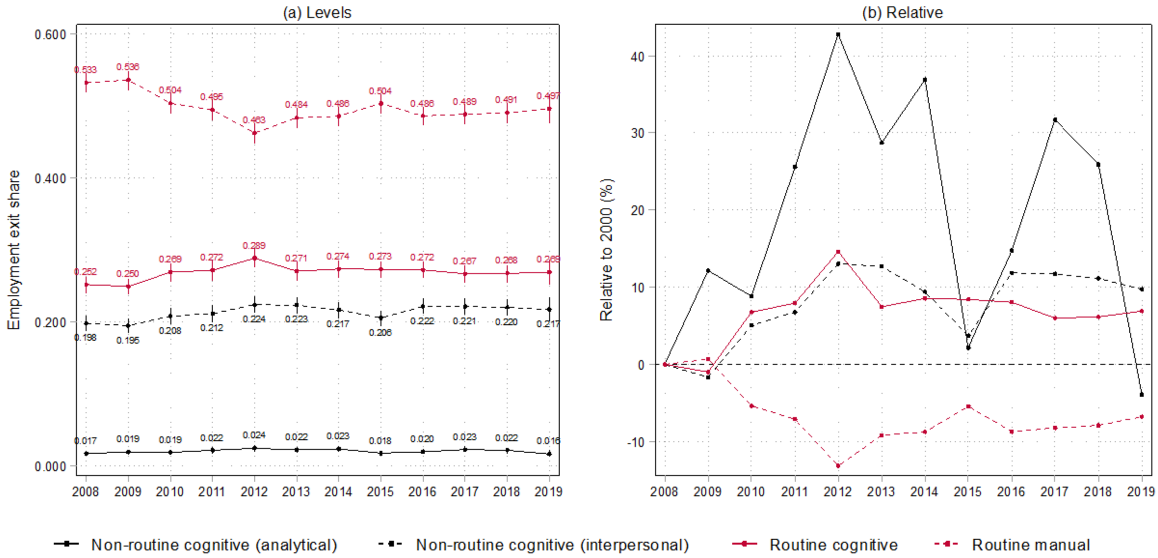
Figure A4: Absolute and relative employment entry shares by task content component in South Africa, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Recent employment entry is defined as having commenced employment within the previous year. Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

Figure A5: Absolute and relative employment exit shares by task content component in South Africa, 2000 to 2019



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Recent employment exit is defined as having stopped working at one's previous job within the previous year due to retrenchment. Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector who have worked before. All estimates are weighted using sampling weights and account for the complex survey design. Spikes represent 95% confidence intervals.

Table A2: Task content components by employment characteristics, 2000 to 2019

Characteristics	Non-routine cognitive analytical			Non-routine cognitive interpersonal			Routine cognitive			Routine manual		
	2000 Share (%)	2019 Share (%)	%Point Change (2000-2019)	2000 Share (%)	2019 Share (%)	%Point Change (2000-2019)	2000 Share (%)	2019 Share (%)	%Point Change (2000-2019)	2000 Share (%)	2019 Share (%)	%Point Change (2000-2019)
Gender												
Male	70.1	63.4	-6.7	68.0	61.3	-6.7	49.8	49.7	-0.1	72.6	70.2	-2.4
Female	29.9	36.6	6.7	32.0	38.7	6.7	50.2	50.3	0.1	27.4	29.8	2.4
Race												
African	24.2	43.5	19.4	37.7	48.8	11.1	49.0	70.9	21.9	71.8	79.6	7.8
Coloured	8.1	9.2	1.1	13.5	10.3	-3.3	14.9	12.3	-2.7	18.9	15.3	-3.6
Indian/Asian	4.9	8.2	3.4	5.7	7.1	1.4	6.4	4.7	-1.8	2.9	1.3	-1.6
White	62.0	39.0	-23.0	42.7	33.8	-8.9	29.5	12.2	-17.3	6.3	3.8	-2.5
Age												
15-24	16.2	6.6	-9.6	10.6	5.1	-5.5	17.3	9.1	-8.1	10.7	8.8	-1.9
25-34	32.9	39.7	6.9	33.3	32.3	-1.0	36.7	40.2	3.4	33.1	37.4	4.4
35-65	51.0	53.7	2.7	56.1	62.6	6.5	46.0	50.7	4.7	56.3	53.8	-2.5
Education												
Primary or less	4.7	1.3	-3.4	20.2	5.4	-14.8	17.3	5.2	-12.1	57.8	21.6	-36.3
Incomplete secondary	13.6	4.6	-9.0	20.9	14.9	-6.0	30.3	26.7	-3.6	26.4	40.9	14.5
Complete secondary	27.6	27.4	-0.1	27.8	34.0	6.2	39.5	52.3	12.8	14.3	32.2	17.9
Tertiary	54.2	66.7	12.5	31.1	45.8	14.6	12.9	15.7	2.9	1.5	5.4	3.9

Characteristics	Non-routine cognitive analytical			Non-routine cognitive interpersonal			Routine cognitive			Routine manual		
	2000 Share (%)	2019 Share (%)	% point change (2000-2019)	2000 Share (%)	2019 Share (%)	% point change (2000-2019)	2000 Share (%)	2019 Share (%)	% point change (2000-2019)	2000 Share (%)	2019 Share (%)	% point change (2000-2019)
Primary sector	**5.8**	**3.0**	**-2.7**	**9.3**	**2.4**	**-6.9**	**5.4**	**2.1**	**-3.2**	**39.6**	**27.0**	**-12.6**
Agriculture	0.0	0.5	0.5	4.1	0.5	-3.6	1.4	0.8	-0.6	24.3	18.2	-6.1
Mining	5.7	2.6	-3.2	5.2	1.2	-4.0	4.0	1.3	-2.7	15.3	8.7	-6.6
Secondary sector	**27.7**	**23.3**	**-4.4**	**32.6**	**29.6**	**-3.0**	**17.4**	**11.5**	**-5.9**	**37.2**	**37.8**	**0.6**
Manufacturing	25.4	16.4	-9.0	17.8	14.1	-3.8	15.7	9.4	-6.3	31.3	26.9	-4.3
Utilities	0.1	0.5	0.4	1.3	0.4	-0.9	0.3	0.2	-0.1	0.3	0.5	0.3
Construction	2.2	6.4	4.2	13.5	15.1	1.6	1.4	1.9	0.5	5.7	10.3	4.6
Tertiary sector	**66.6**	**73.7**	**7.1**	**58.1**	**68.0**	**9.8**	**77.2**	**86.3**	**9.1**	**23.2**	**35.2**	**12.1**
W&R trade	16.4	8.7	-7.7	18.5	14.0	-4.4	40.4	38.0	-2.4	14.6	17.1	2.5
Transport	4.0	5.4	1.4	2.8	5.3	2.5	4.7	6.4	1.7	2.4	4.2	1.8
Finance	37.0	46.4	9.4	14.4	24.7	10.3	24.6	32.8	8.3	3.7	11.2	7.5
CSP service	9.1	13.2	7.1	22.5	24.0	9.8	7.5	9.1	9.1	2.4	2.7	12.1
High skilled	**41.8**	**33.3**	**-8.5**	**46.7**	**56.5**	**9.8**	**0.4**	**0.2**	**-0.2**			**0.0**
Managers				35.8	44.3	8.5						
Professionals	41.8	33.3	-8.5	10.9	12.1	1.3	0.4	0.2	-0.2			
Skilled	**58.2**	**66.7**	**8.5**	**49.8**	**41.7**	**-8.0**	**94.8**	**95.5**	**0.7**	**58.9**	**48.4**	**-10.5**
Technicians	56.3	62.0	5.7	16.3	13.6	-2.7	10.5	6.9	-3.6	0.0	0.2	0.1
Clerical							42.9	40.4	-2.6			
Services				6.9	9.3	2.3	34.4	43.7	9.3	0.2	0.7	0.5
Skilled agricultural workers				1.6	0.3	-1.4				2.7	0.4	-2.3
Craft	1.9	4.7	2.7	24.9	18.6	-6.3	3.1	0.9	-2.2	23.7	22.6	-1.1

Characteristics	Non-routine cognitive analytical			Non-routine cognitive interpersonal			Routine cognitive			Routine manual		
	2000 Share (%)	2019 Share (%)	% point change (2000-2019)	2000 Share (%)	2019 Share (%)	% point change (2000-2019)	2000 Share (%)	2019 Share (%)	% point change (2000-2019)	2000 Share (%)	2019 Share (%)	% point change (2000-2019)
Operators							4.0	3.7	-0.2	32.4	24.5	-7.8
Low skilled				**3.6**	**1.8**	**-1.7**	**4.8**	**4.3**	**-0.5**	**41.1**	**51.6**	**10.5**
Elementary occupations				3.6	1.8	-1.7	4.8	4.3	-0.5	41.1	51.6	10.5
Union status												
Union member	17.2	17.9	0.7	21.3	18.3	-3.0	24.3	24.3	0.1	35.7	28.7	-7.0
Non-union	77.3	78.0	0.7	73.7	78.0	4.3	70.0	70.6	0.6	59.1	67.5	8.4
Firm size												
Micro to small (1-49 employees)	48.2	46.4	-1.8	57.0	52.7	-4.3	59.7	56.0	-3.7	52.2	43.7	-8.6
Medium to large (50+ employees)	45.7	46.2	0.5	38.7	40.4	1.7	33.8	36.3	2.5	42.7	50.0	7.4

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: (i) The estimates are the percentage point change in the shares between 2000 and 2019 by covariates. (ii) Shaded regions denote statistically significant changes in the shares between 2000 and 2019 at the 95% confidence level. (iii) The green background reflects statistically positive change in the shares, and the red background reflects statistically negative change in the shares. (iii) Totals do not add up to 100 due to unspecified or no responses.

Table A3: Top 20 occupations across the four task content components, 2019

Occupation title	ISCO-88 code	Employment share (%)	RTI score
Non-routine cognitive analytical			
Technical and commercial sales representatives	3415	17.2	0.517
Securities and finance dealers and brokers	3411	7.8	0.571
Electronics and telecommunications engineering technicians, Assistants, technical and electronic engineering	3114	7.6	0.680
Computer assistants	3121	6.8	0.647
Decorators and commercial designers, Product, industrial designers, Textile/clothing/fashion designers, Interior designers, Graphics designers and Designers not elsewhere classified	3471	6.5	0.588
Computer systems designers and analysts	2131	5.3	0.582
Advocates, attorneys and related occupations, Lawyers/attorneys and related occupations, Advocates/barristers, Prosecutors and Articled clerks	2421	4.5	0.578
Mechanical engineering technicians, Technicians, engineering, mechanical, Assistants, technical and mechanical engineering	3115	4.4	0.664
Technikon, teacher training, technical and other colleges, university and other higher education institutions teaching professionals and Other post-secondary education teaching professionals	2310	4.0	0.432
Electronics fitters (including apprentices/trainees)	7242	3.8	0.651
Civil engineering technicians, Technicians, engineering, civil, Assistants, technical and civil engineering	3112	3.6	0.629
Computer programmers	2132	3.1	0.583
Electrical engineering technicians, Technicians, engineering, electrical, Assistants, technical, electrical engineering	3113	2.9	0.680
Medical practitioners, physicians, Medical specialists and Medical occupations not elsewhere classified	2221	2.5	0.536
Authors, journalists and other writers, Editors, Reporters, journalists, Writers, poets, playwrights and Other writers, commentators, proof-readers	2451	2.0	0.602
Mechanical engineers	2145	1.8	0.520

Occupation title	ISCO-88 code	Employment share (%)	RTI score
Appraisers, valuers and auctioneers	3417	1.5	0.613
Electrical engineers	2143	1.5	0.567
Architects, engineers and related professionals not elsewhere classified, Industrial/production engineers, Quantity surveyors, Architects, engineers and related professionals not elsewhere classified	2149	1.2	0.530
Life science technicians, Biological science and Medical science	3211	1.2	0.658
<u>Non-routine cognitive interpersonal</u>			
Finance and administration managers/department managers	1231	10.7	0.562
Building and related electricians (including apprentices/trainees)	7137	5.4	0..695
Bricklayers and stonemasons (including apprentices/ trainees)	7122	5.1	0.650
Production and operations managers/department managers in business services	1227	4.2	0.576
Child-care workers	5131	4.2	0.530
Accountants and related accounting occupations, Accounting occupations not elsewhere classified, Auditors and related occupations and Articled clerks with accountant/auditor	2411	3.8	0.566
Buyers	3416	3.8	0.594
Production and operations managers/department managers in wholesale and retail trade	1224	3.8	0.502
Sales and marketing managers/department managers	1233	3.5	0.416
Production and operations managers/department managers in manufacturing	1222	3.3	0.600
Directors and chief executives	1210	3.2	0.407
Business professionals not elsewhere classified, Consultants	2419	3.0	0.539
Other managers/department managers not elsewhere classified	1239	2.9	0.569
Building frame and related workers not elsewhere classified (including apprentices/trainees)	7129	2.8	0.646

Occupation title	**ISCO-88 code**	**Employment share (%)**	**RTI score**
Nursing associate professionals, Nurses, senior, student, pupil, Nurses, not elsewhere classified (nursing assistants/aids included under personal care and related workers)	3231	2.7	0.604
Production and operations managers/department managers in transport, storage and communications	1226	2.6	0.620
Carpenters and joiners (including apprentices/ trainees)	7124	2.6	0.702
Hairdressers, barbers, beauticians and related workers, Beauticians and Hairdressers	5141	2.1	0.704
Production and operations managers/department managers in hotels, restaurants and other catering and accommodation services	1225	1.9	0.673
Primary education teaching associate professionals	3310	1.8	0.598
Routine cognitive			
Protective services workers not elsewhere classified, Rangers and game wardens	5169	17.7	0.669
Shop salespersons and demonstrators, Salespersons, Petrol pump and filling station attendants	5220	14.9	0.689
Other office clerks and clerks not elsewhere classified (except customer services clerks)	4190	10.1	0.697
Cashiers and ticket clerks	4211	9.4	0.764
Cooks	5122	5.8	0.732
Stock clerks	4131	4.0	0.758
Waiters, waitresses and bartenders	5123	3.2	0.742
Receptionists and information clerks	4222	3.1	0.694
Car, taxi and van drivers	8322	2.9	0.728
Safety, health and quality inspectors, Inspectors, safety and health	3152	2.7	0.730
Accounting and bookkeeping clerks	4121	2.4	0.716
Telephone switchboard operators	4223	2.3	0.782
Freight handlers	9333	2.2	0.776
Home-based personal care workers	5133	2.1	0.702
Statistical finance clerks	4122	1.7	0.671

Occupation title	ISCO-88 code	Employment share (%)	RTI score
Messengers, package and luggage porters and deliverers	9151	1.5	0.840
Tellers and other counter clerks	4212	1.4	0.770
Insurance representatives	3412	1.4	0.638
Secretaries	4115	1.3	0.692
Data entry operators	4113	1.1	0.734
Routine manual			
Farmhands and labourers	9211	17.1	0.764
Hand-packers and other manufacturing labourers	9322	15.0	0.780
Helpers and cleaners in offices, hotels and other establishments	9132	10.8	0.767
Heavy truck and lorry drivers	8324	6.2	0.736
Building construction labourers	9313	3.5	0.741
Motor vehicle mechanics and fitters (including apprentices/trainees)	7231	3.3	0.726
Agricultural or industrial machinery mechanics and fitters (including apprentices/trainees)	7233	2.7	0.736
Machine-tool operators	8211	2.3	0.811
Mining and quarrying labourers	9311	2.3	0.796
Lifting-truck operators	8334	2.1	0.787
Sheet-metal workers (including apprentices/trainees)	7213	2.0	0.719
Sewing-machine operators	8263	1.9	0.893
Welders and flame cutters (including apprentices/ trainees)	7212	1.9	0.815
Plumbers and pipe fitters (including apprentices/ trainees)	7136	1.8	0.768
Construction and maintenance labourers: roads, dams and similar constructions	9312	1.8	0.730
Miners and quarry workers (including apprentices/ trainees)	7111	1.5	0.776
Motorised farm and forestry plant operators	8331	1.4	0.739
Crane, hoist and related plant operators	8333	1.4	0.784

Occupation title	**ISCO-88 code**	**Employment share (%)**	**RTI score**
Millers, bakers, pastry-cooks and confectionery makers (including apprentices/trainees)	7412	1.4	0.789
Butchers, fishmongers and related food preparers (including apprentices/trainees)	7411	1.2	0.813

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al. 2019) and O*NET.

Notes: Sample is restricted to working-aged (15 to 64 years) employees or wage workers in the formal private sector. ISCO = International Standard Classification of Occupations code at the four-digit level. Occupations ordered by composite RTI (routine task intensity) index value.

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