POLICY BRIEF

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

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Background

For several centuries, the notion that 'robots are coming to take our jobs' has raised fears of the displacement of workers. Fears of automation have regained prominence in recent decades due to the speed at which the cost of automation has declined, creating simple but powerful incentives for employers to substitute their relatively expensive workers with computer capital. Thus, technology is reshaping the skills needed for work. However, the labour market effects of technology are believed to be unevenly distributed across workers, given that different jobs require different skillsets.

There are two broad theories in the literature that seek to explain these heterogenous effects. The 'skill-biased technological change' hypothesis posits that technological development increases the demand for high-skilled workers at a rate far greater than the increase in the supply of these workers, resulting in higher returns to high-skilled jobs. While a large empirical literature supports this theory,[1] its key shortcoming is that it only explains changes in the demand for high-skilled labour. Hence, the emergence of the second theory – Autor et al.'s (2003) routinisation hypothesis – which proposes that technological development has concurrently decreased the demand for 'routine' jobs and increased the demand for 'non-routine' jobs. The former comprise tasks that follow explicit rules that can be accomplished by machines, while the latter comprise tasks that are not sufficiently well understood to be specified in computer code and are thus complementary to technology.

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[1] See Berman et al. (1998); Berman and Machin (2000); Card and DiNardo (2002).

Empirical evidence largely supports the routinisation hypothesis.[2] However studies are concentrated in developed country contexts. Of those focusing on developing countries, the empirical evidence is mixed.[3] In South Africa in particular, limited research exists on simply describing the changing task content of the country's employment profile.[4] In our working paper (Bhorat et al. 2023) we use individual-level, nationally representative labour force survey data combined with occupation-level task content data to examine the evolution of the task content of employment in South Africa during the post-apartheid period to determine whether there is evidence of increased utilisation of automation and other 4IR technologies. The policy imperative of our analysis is clear, given that increased automation has the potential to exacerbate South Africa's already extreme levels of unemployment and income inequality.

Data and methodology

Our analysis makes use of two distinct datasets: the Post-Apartheid Labour Market Series (PALMS) and the Occupational Information Network (O*NET). The PALMS is a harmonised series of cross-sectional, individual-level, nationally representative household surveys in South Africa. Because no household survey in the country collects data on occupational task content, we had to use occupation codes and relevant crosswalks to merge the PALMS with the O*NET – a United States survey of a comprehensive set of occupational descriptors based on labour market demand. By doing so, we are able to produce measures of task content for each occupation in the South African labour market. We restrict our sample to employees in the formal private sector, excluding those in private households, and study the period 2000 to 2019.

Following Acemoglu and Autor (2011) and Lewandowski et al. (2022), we use this merged dataset to construct several routine-task intensity (RTI) indices to facilitate the comparability of our results with the larger literature. A composite RTI index summarises into a single number how routine the task content of each occupation is. While this single RTI index is helpful, it lacks nuance in understanding the drivers of routinisation. As such, we follow Fonseca et al. (2018) and classify each occupation into one of four task content components that make up the composite RTI index based on the component for which the occupation ranks highest in intensity. Box 1 describes each of the four task content components, accompanied by example occupations.

Evidence of de-routinisation would then manifest in a rising (declining) share of occupations comprising more non-routine (routine) tasks. 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. These latter two lenses help generate a view of the impact of routinisation from the perspective of labour market churn. We furthermore 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. The interested reader is referred to the working paper (Bhorat et al. 2023) for a much more detailed description of our data and methodology.

[2] See Autor et al. (2003); Goos and Manning (2007); Acemoglu and Autor (2011); Autor (2015); Frey and Osborne (2017).

[3] See Hardy et al. (2016); Maloney and Molina (2016); Lewandowski et al. (2020, 2022)

[4] Where it does exist, it focuses on specific sectors such as manufacturing (Allen Whitehead et al. 2021), or conducts a broader cross-country study (Maloney & Molina 2016; Lewandowski et al. 2020).

Box 1 : Descriptions and examples of task content components in South Africa

Task component	Description	Examples
Routine manual	Place importance on controlling machines and processes, the pace of work, and time spent on repetitive motions	Hand-packers; workplace cleaners; farm labourers
Routine cognitive	Place importance on task repetition and being exact or accurate	Salespersons; office clerks; cashiers
Non-routine cognitive analytical	Place importance on analysing information and thinking creatively	Finance brokers; electrical engineers; lawyers
Non-routine cognitive interpersonal	Place importance on establishing and maintaining personal relationships	Managers; childcare workers; bricklayers

Results

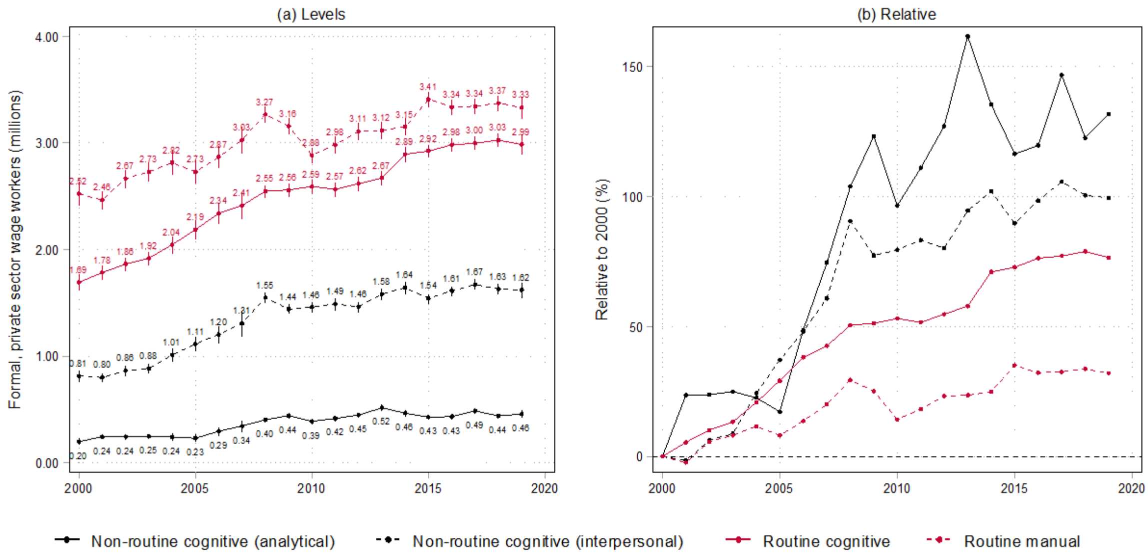
The dominance of routine jobs

We find that routine task-intensive jobs are dominant within the formal private South African labour market and have remained as such over the 20-year period. As shown in panel (a) of Figure 1, over 80% of workers were in either routine manual or routine cognitive jobs in 2000, which reduced to 75% by 2019. There has been a notable amount of routine job sub-group convergence over time: While the number of routine manual jobs exceeds that of routine cognitive jobs, by 2019 the latter group grew by 76% – more than double the growth rate of the former (32%).

Jobs growth in favour of non-routine jobs

We find evidence of *relative de-routinisation* in the labour market during the post-apartheid period. While employment within all task content component groups grew over time, non-routine jobs experienced far greater rates of jobs growth relative to routine jobs, as shown in panel (b) of Figure 1. Despite representing the minority of workers throughout the period, **the pace of growth of non-routine cognitive analytical jobs exceeded that of all other groups**, more than doubling over the period – from 197 000 workers in 2000 to just under half a million in 2019. Most growth took place between 2005 and 2009, whereafter employment levels fluctuated around an overall upward trend.

Figure 1: Employment levels by task content component in South Africa, 2000 to 2019



Source: Bhorat et al. (2023)

This pattern of *relative de-routinisation* is more pertinent when considering changes in employment shares. While routine manual jobs have persisted to represent the majority of workers, their relative contribution has shrunk significantly – from just under half (48.3%) in 2000 to 39.7% in 2019. Concurrently, the employment shares of all other task content component groups grew and, notably, the growth of non-routine cognitive analytical jobs far outstripped all other groups. This de-routinisation pattern holds when analysing growth incidence curves across the RTI distribution, which reveal that **jobs growth was fastest for less routine jobs** (i.e., those with a low RTI value). We find similar evidence when considering trends in annual entries into employment, while our analysis of employment exits is inconclusive due to data limitations.

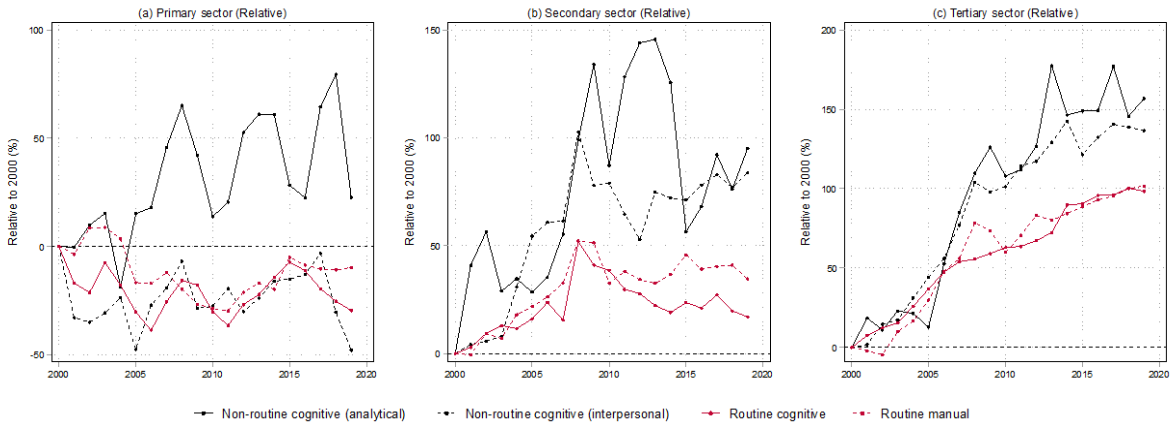
A varying profile of workers

Jobs of varying task content are unevenly distributed across several worker and job characteristics. The profile of workers differs significantly across these groups of occupations. Workers in routine manual jobs 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 trades occupations in the primary and secondary sectors. Those in routine cognitive jobs are more likely to be young, African or Coloured females with a complete secondary education, working in clerical or services occupations in the tertiary sector. On the other hand, workers in non-routine cognitive interpersonal jobs are more likely to be older, Indian/Asian or White males with a tertiary education, working in managerial, professional, technician or craft and related trade occupations in the tertiary sector, while those in non-routine cognitive analytical jobs are more likely to be older, Indian/Asian or White males with a tertiary education, working in professional or technician occupations in the tertiary sector.

De-routinisation regardless of sector

Sector of employment serves as one key covariate of interest, given that de-routinisation may be explained either by structural change or, alternatively, may be a within-industry phenomenon (Autor 2015; Bárány & Siegel 2018). Employment trends varied significantly by task content component, both within and across sectors over time. **While routine manual jobs are dominant in both the primary and secondary sectors, routine cognitive jobs are dominant in the tertiary sector**. Non-routine cognitive analytical jobs are the minority in every sector. The growth of the latter group, however, again exceeds that of all other components, regardless of sector (see Figure 2).

Figure 2: Relative employment levels by task content component and sector, 2000 to 2019



Source: Bhorat et al. (2023)

Disaggregating further to the industry level within sectors, we find evidence of *relative de-routinisation* in five industries: mining and quarrying, manufacturing, construction, transport, storage and communication (TSC), and community, social and personal (CSP) services. Together, these industries accounted for 63% of aggregate employment in 2019. Finally, we examine trends by firm size as another characteristic of interest, and find evidence of *relative de-routinisation* for both smaller and larger firms.

Policy implications

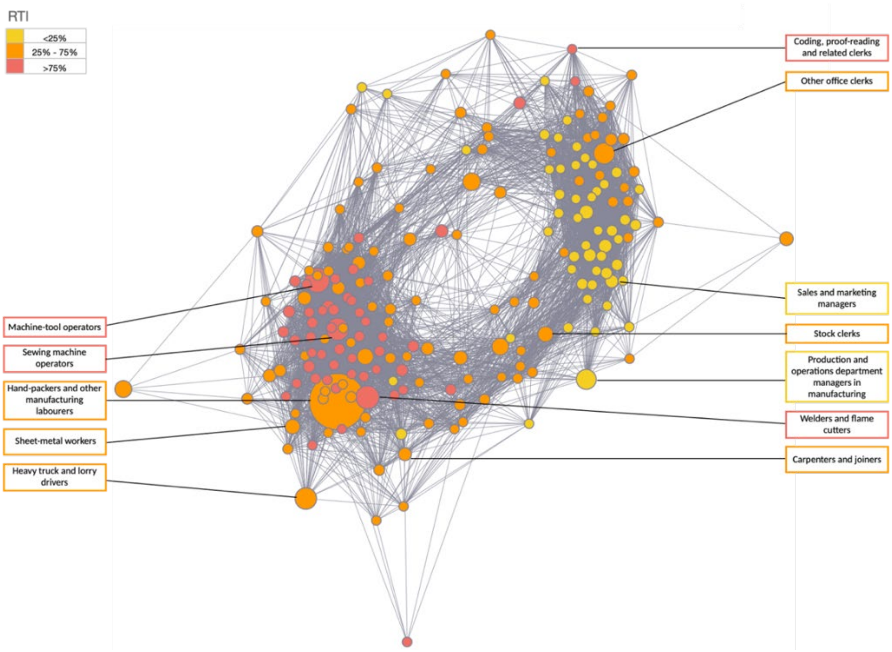
In our analysis of the evolution of the task content of employment in the formal private South African labour market, we find evidence of *relative de-routinisation* – in other words, greater growth of non-routine jobs relative to routine jobs. This suggests that automation and other 4IR technologies are shifting the relative demand for workers across these two job groupings. While this deepens our understanding of how the nature of work has changed in the country, these trends have important policy implications.

Investments in skills development relevant to non-routine jobs are necessary to ensure that workers previously employed in routine occupations are able to continue accessing opportunities in the labour market; particularly employment in non-routine occupations, which are relatively hard to automate. A key challenge to such skills development requirements is that they are likely substantial in magnitude, given that the majority of workers (75% in 2019) in the formal private sector work in routine jobs. In addition, given that *relative de-routinisation* is evident across not one but a number of industries, the scope of such interventions must be economy-wide.

If such interventions are not adequately implemented and the demand for routine work continues to decline, existing labour market inequalities will likely widen. For instance, those working in routine manual jobs are primarily young, African or Coloured, with at most an incomplete secondary education. While these demographic groups already face higher levels of unemployment, without adequate intervention their risk of unemployment will likely grow, which course goes against the policy goals of reducing the already extreme unemployment levels in the country. This has obvious inequality and poverty implications, given the dominance of the labour market in driving overall income inequality.

Finally, such interventions will likely require substantial educational and skill input. In other words, the 'jump' from a routine to non-routine occupation is big. This can be visually depicted using an *occupation space* for the South African manufacturing sector, as developed by Allen Whitehead et al. (2021) and depicted in Figure 3, where each node represents an occupation and is shaded according to its RTI score, and each line represents relatedness in terms of similar tasks and skills between pairs of occupations.[5] Thus, if occupations (nodes) are connected and close, there is substantial overlap between the skills and tasks required, which implies that shifts between such occupations require relatively minor skills development interventions. However, the figure here makes it evident that, at least for the manufacturing sector,[6] the labour market is polarised, with a cluster of predominantly non-routine task-intensive occupations (yellow nodes) to the right, relatively distant and disconnected from a cluster of predominantly routine task-intensive occupations (red nodes) to the left. This indicates that, unfortunately, shifts between the clusters, particularly from routine to non-routine jobs, would require substantial skills development interventions.

Figure 3: Occupation space for the South African manufacturing sector, shaded by RTI score



Source: Allen Whitehead et al. (2021).

[5] Occupations intensive in routine tasks are shaded in red, those intensive in non-routine tasks are shaded in yellow, and those moderately intensive in routine tasks are shaded in orange.

[6] It is important to note that the occupation space for all sectors will have the same polarised structure as that for the manufacturing sector.

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