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

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Overview

- Introduction
- Research Objective
- Motivation
- Methodology and data
- Trends in task content of employment in South Africa
- Sectoral trends in the task content of employment in South Africa
- Conclusion

Introduction

Impact of technological change on the labour market – a task content view

Introduction (1)

- The notion that "robots are coming to take our jobs" is not new.
  - In essence, the principle of automation implies that for a machine to complete a task, a programmer must fully understand how the task is performed, and then write an appropriate programme to guide the machine.
- What is new… (Nordhaus, 2007)
  - …is that the cost of automation has fallen dramatically
  - …and the speed at which is has changed has increased rapidly.
- These technological changes (unevenly) impact on the labour market
  - Technology reshapes the skills needed for work → different jobs require different sets of skills → jobs face varying degrees of risk to automation → labour market effects of technology distributed unevenly across workers of varying skill sets.

Introduction (2)

Two broad theoretical approaches to understanding the potential impacts of technological changes on the labour market:

- **Skills Biased Technological Change**
  - Technological development has increased the demand for high-skilled workers at a rate far greater than the increase in the supply of high-skilled workers, resulting in higher returns to high-skilled jobs
  - 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, Bound & Machin, 1998; Berman & Machin, 2000; Card & DiNardo, 2002).
  - But, SBTC only explains changes in the demand for high-skilled labour at the top of the wage distribution
- **Routinisation hypothesis** (Autor, Levy & Murnane, 2003)
  - Computer-based technological change has displaced workers in the middle of the distribution, and has created jobs at the top and bottom ends – i.e. labour market polarization (Autor, Levy & Murnane, 2003; Goos, Manning & Salomons, 2014; Autor & Dorn, 2013)
  - 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) – concentrated in the middle of the wage distribution
    - …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) – concentrated at the bottom and top of the wage distribution
  - Recent empirical evidence in support this theory. Highlight a relative rise in non-routine-intensive employment and a fall in routine-intensive employment in recent decades (Autor et al., 2003; Goos & Manning, 2007; Acemoglu & Autor, 2011; Autor, 2015; Frey & Osborne, 2017).

Research Objective

- Examine how the task content of employment in South Africa, a developing country, has evolved in the post-apartheid period.
  - By investigating the labour market's evolving task content, we can assess whether there is evidence of increased utilisation of automation, and other 4IR technologies.
- Examine cross-sectoral variation in the evolving task content of employment

Motivation

- Studies examining task content of employment typically focused on developed country context…
- …but there is a growing body of work on developing economies
  - Evidence on changes in the nature of work in developing and emerging economies is mixed (Lewandowski et al., 2022)
  - Some evidence of job de-routinisation in developing countries. Hardy et al. (2016) document that all Central and Eastern European economies have experienced such de-routinisation in recent years.
  - Maloney and Molina (2016) find evidence of de-routinisation for only two countries (out of 21).
  - 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.
  - Generally focused on specific sectors – e.g. manufacturing (Allen Whitehead et al., 2021)
  - or part of a broader cross-country study (Maloney & Molina, 2016; Lewandowski et al., 2020)
  - Recent work by Davies and van Seventer (2020) find mild evidence of employment polarisation,
    - Does not view employment through the task content lens, and instead focuses on trends in employment across broad occupational categories
- Policy imperative to understanding 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.

Data and Methodology

Measuring the task content of employment

Measuring Routine Task Intensity

- *Aim: Create occupation level Routine Task Index (RTI) as proxy for occupation's risk of automation*.
- Drawing on Acemoglu and Autor (2011) use 4 task measures*, h=(1,…4):*
  - Routine Cognitive Tasks
  - Routine Manual Tasks
  - Non-Routine Cognitive Analytical Tasks and
  - Non-routine Cognitive Personal Tasks.
- Using O*NET: Every occupation coded by:
  - 'Importance' and 'Level' of work activity
  - Frequency and Value assigned to work context
- Work activity (A_h) and work context (C_h) are O*NET classifications – trying to cover all task aspects of a job.
- Work Activity (A_h) : *Importance* & *Level* of skill required.
- Work Context (C_h): Combination of how often task/skill is required (*frequency*) & *value* of skill required.

- For work activities, Cobb-Douglas weight of two-thirds to 'importance' and one-third to 'level' is arbitrarily assigned, following Blinder (2007) Firpo *et al*., 2011; Bhorat et al., 2020. Work context captured by multiplying frequency by value of the level. This can be summarized as:

$$r_{h,i} = \sum_{k=1}^{A_h} I_{ik}^{\frac{2}{3}} L_{ik}^{\frac{1}{3}} + \sum_{l=1}^{C_h} F_{il} \times V_{il}$$

  - Where $r_{h,i}$ is intermediate indicator for occupation i, and h represents the task category under consideration (i.e. routine manual, routine cognitive, non-routine cognitive analytical, or non-routine cognitive personal).
  - A_h is the number of Work Activity elements; C_h is the number of Work Context elements; 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$i$; F_{il} is the frequency and V_{il} the value of Work Context element l in occupation i.
- The intermediate indicator, $r_{h,i}$ is then scaled to lie in the interval $[0;1]$. This rescaling is simply to assist in equalising the weight of intermediate indicators in the construction of the final RTI.

Measuring Routine Task Intensity

- *Example 1: Truck Driver on Numerical Skills (scale 1-10):*
  - Relatively high importance (7)
  - Level - low (2)
  - Frequency (every day-10)
  - Value (2)

  ***r* =23.11**

- *Example 2: Research Scientist on Numerical Skills (scale 1-10):*
  - Relatively high importance (10)
  - Level - high (10)
  - Frequency (every day -10)
  - Value (10)

  ***r* =122.22**

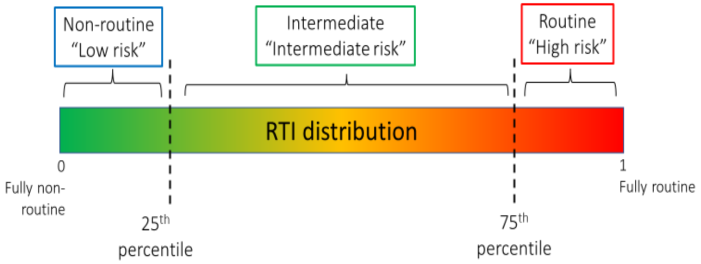
- Using above approach from O*NET, define a measure of routine task intensity (RTI) following A&A (2011) & Lewandowski, Park, Schotte (2020) in following way:

$$\boldsymbol{RTI_i = ln\left(\frac{r_{cog,i} + r_{man,i}}{2}\right) - ln\left(\frac{nr_{analytical,i} + nr_{personal,i}}{2}\right)}$$

- Where $r_{cog,i}$, $r_{man,i}$, $nr_{analytical,i}$ and $nr_{personal,i}$ are level of routine cognitive, routine manual non-routine cognitive analytical and non-routine cognitive personal tasks required for occupation i, respectively.

- RTI_i normalised to (0-1). Where value of 1 indicates occupation is completely routine.

- Following Lewandowski, Park and Schotte (2020), subdivide RTI into three mutually exclusive categories in order to categorise an occupation's risk of automation:
  - *$RTI < 25^{th}p$* = "Non-Routine".
  - *RTI 25^{th} - $75^{th}p$* (intermediate)
  - *$RTI > 75^{th}p$* = "Routine".



Data: Task Content + Employment

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Occupation Information Network (O*NET)

- Task content data
- United States data on standardised occupation-specific descriptors, including *work activities (41)*, *work context (20)* and *abilities (20)*
  - Version 24.0 August 2019
- Approx. 1 000 standardised occupations
- Occupation taxonomy O*NET SOC

\+

Post-Apartheid Labour Market Series (PALMS)

(Kerr, Lam and Wittenberg, 2019)

- South African labour market data - employment
- Harmonised series of SA surveys from 1993 to 2019.
  - 2000 to 2019
- Individual-level demographic characteristics and occupation information for the employed
- Occupations captured by SASCO code (based on ISCO-88)

Crosswalks

- Code provided by the Institute for Structural Research (IBS, 2016; O*NET, 2020)
- Map O*NET SOC code to ISCO-88 code to match O*NET data to PALMS data at the 4-digit level

Occupation-level task content information matched to SA labour force survey data

- 365 4-digit occupations (approx. 94.7% match)
- Working age wage earners in formal private sector

Constructing Routine and Non-Routine Task Content Indicators

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Occupation (4-digit ISCO-88)	**Non-routine cognitive analytical**	Non-routine cognitive interpersonal	Routine cognitive	Routine manual
Economists	**0,92**	0,58	0,29	0,08
Physicists and astronomers	**0,92**	0,58	0,37	0,18
Sociologists, anthropologists and related professionals	**0,90**	0,66	0,30	0,15
Chemical engineers	**0,86**	0,64	0,39	0,22
Geologists and geophysicists	**0,86**	0,62	0,40	0,19
Mathematicians and related professionals	**0,86**	0,61	0,40	0,16
Sanitarians	**0,84**	0,75	0,46	0,28
Statisticians	**0,84**	0,63	0,48	0,13
Philosophers, historians and political scientists	**0,83**	0,58	0,34	0,14
Computer programmers	**0,81**	0,51	0,56	0,25

Top 10 occupations by **non-routine cognitive analytical** scores

Occupation (4-digit ISCO-88)	Non-routine cognitive analytical	Non-routine cognitive interpersonal	Routine cognitive	**Routine manual**
Lifting-truck operators	0,38	0,50	0,51	**0,90**
Industrial-robot operators	0,51	0,50	0,63	**0,89**
Industrial robot controllers	0,51	0,50	0,63	**0,89**
Rubber-products machine operators	0,16	0,34	0,69	**0,88**
Miners and quarry workers	0,43	0,51	0,50	**0,86**
Metal drawers and extruders	0,34	0,53	0,62	**0,85**
Metal-heat-treating-plant operators	0,27	0,49	0,65	**0,81**
Chemical-heat-treating-plant operators	0,27	0,49	0,65	**0,81**
Metal wheel-grinders, polishers and tool sharpeners	0,31	0,42	0,53	**0,80**
Metal finishing-, plating- and coating-machine operators	0,29	0,32	0,57	**0,80**

Top 10 occupations by **routine manual** scores

Constructing Routine and Non-Routine Task Content Indicators

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Occupation (4-digit ISCO-88)	Non-routine cognitive analytical	**Non-routine cognitive interpersonal**	Routine cognitive	Routine manual
Senior officials of employers', workers' and other economic-interest organisations	0,73	**0,95**	0,36	0,19
Personnel and industrial relations department managers	0,72	**0,92**	0,35	0,16
Senior government officials	0,76	**0,92**	0,32	0,16
Religious associate professionals	0,67	**0,89**	0,11	0,12
Directors and chief executives	0,79	**0,88**	0,30	0,15
Traditional chiefs and heads of villages	0,79	**0,88**	0,30	0,15
Sales and marketing department managers	0,68	**0,86**	0,33	0,10
General managers in wholesale and retail trade	0,57	**0,85**	0,40	0,23
General managers not elsewhere classified	0,63	**0,84**	0,40	0,21
Education methods specialists	0,80	**0,84**	0,35	0,18

Top 10 occupations by **non-routine cognitive interpersonal** scores

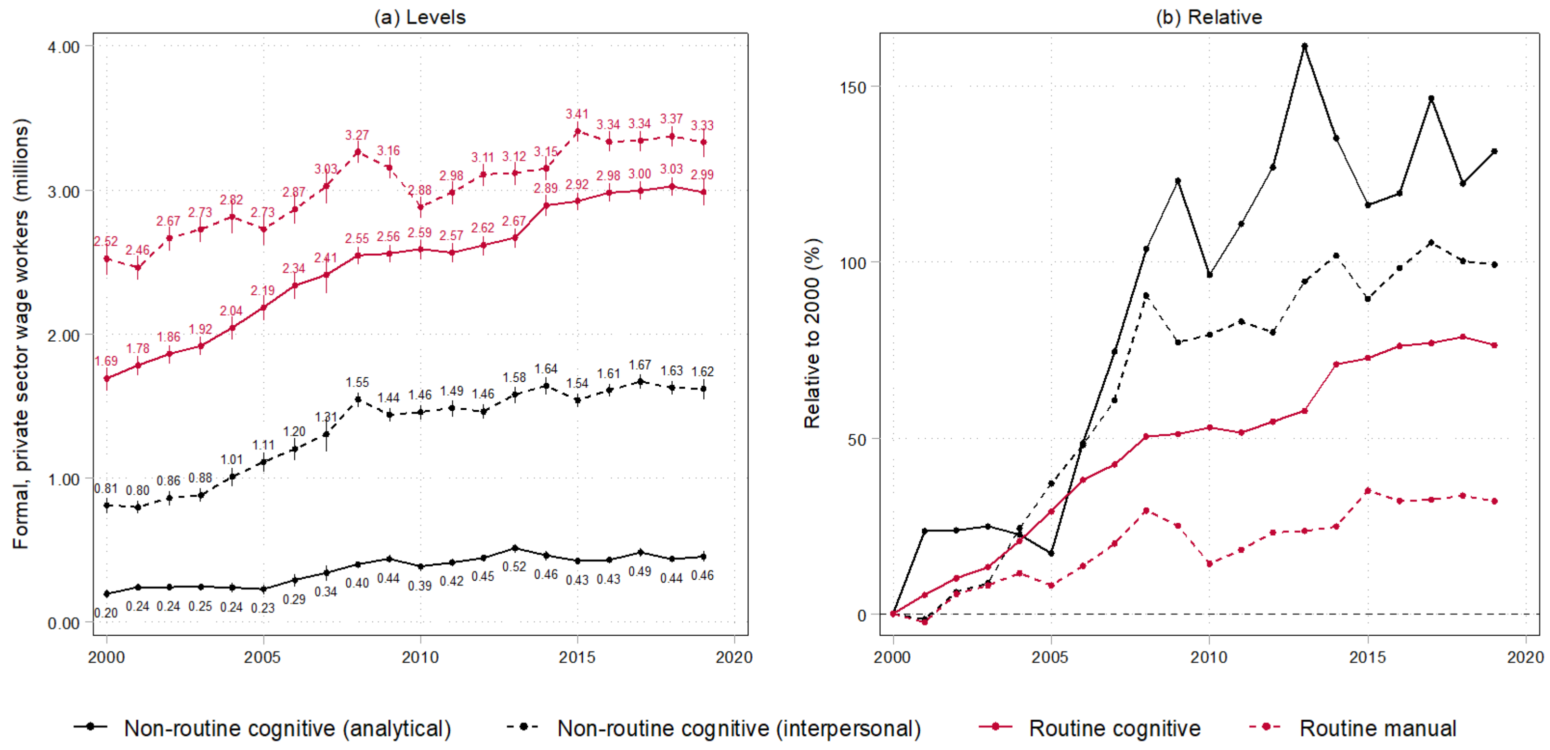
Occupation (4-digit ISCO-88)	Non-routine cognitive analytical	Non-routine cognitive interpersonal	**Routine cognitive**	Routine manual
Coding, proof-reading and related clerks	0,31	0,23	**0,85**	0,29
Telephone switchboard operators	0,36	0,45	**0,81**	0,49
Cashiers and ticket clerks	0,33	0,56	**0,79**	0,49
Tellers and other counter clerks	0,37	0,51	**0,77**	0,48
Fortune-tellers, palmists and related workers	0,00	0,45	**0,76**	0,46
Astrologers and related workers	0,00	0,45	**0,76**	0,46
Air traffic controllers	0,66	0,57	**0,76**	0,43
Bookkeepers	0,36	0,44	**0,75**	0,36
Data entry operators	0,48	0,53	**0,74**	0,51
Travel agency and related clerks	0,47	0,52	**0,72**	0,36

Top 10 occupations by **routine cognitive** scores

Task Content of Employment in South Africa: An Overview of Trends

Trends in the task content of employment

Absolute and relative employment levels by task content component, 2000 – 2019

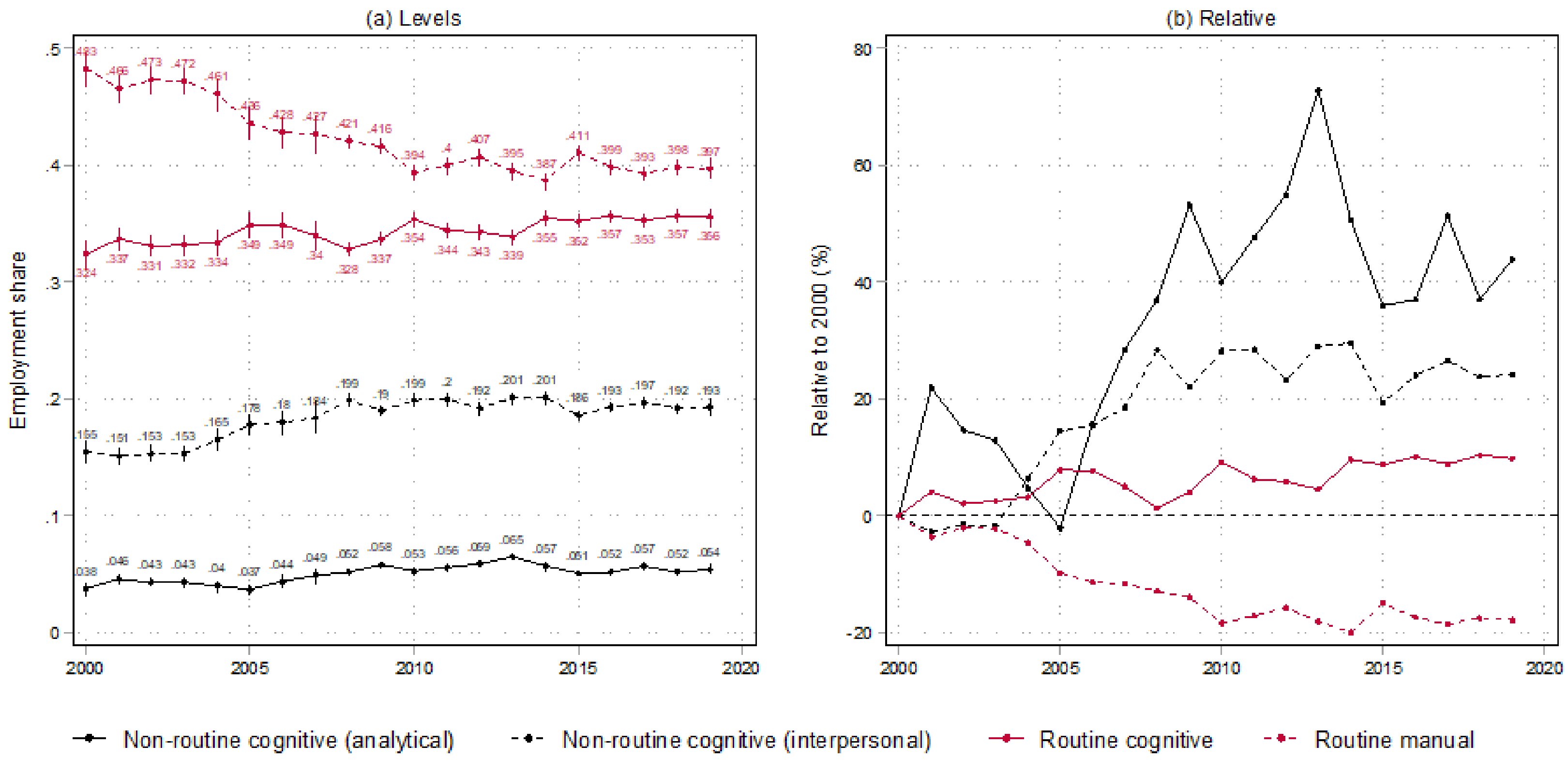


Authors' own calculations. Source: PALMS version 3.3 (Kerr et al., 2019) and O*NET.
Notes: Sample restricted working-aged (15-64 years) employees in the formal private sector. All estimates weighted using sampling weights and account for the complex survey design. Spikes represent 95 percent confidence intervals.

- Routine Task-Intensive jobs: The key form of employment in the formal private sector in South Africa:
  - 2000: 81% (4.2m)
  - 2019: 75% (6.3m)
- Evidence of a pattern of *Relative De-Routinisation*
  - Absolute employment growth in all four task content components (*Panel a*)
  - However, ***non-routine jobs experienced far greater rates of job growth relative to routine jobs*** (*Panel b*)
  - Non-Routine Cognitive Analytical: 197k in 2000 to 457k in 2019 ***growing by 132% over the period,*** with majority of growth in the mid-2000s

Trends in the task content of employment

Absolute and relative employment shares by task content component, 2000 – 2019



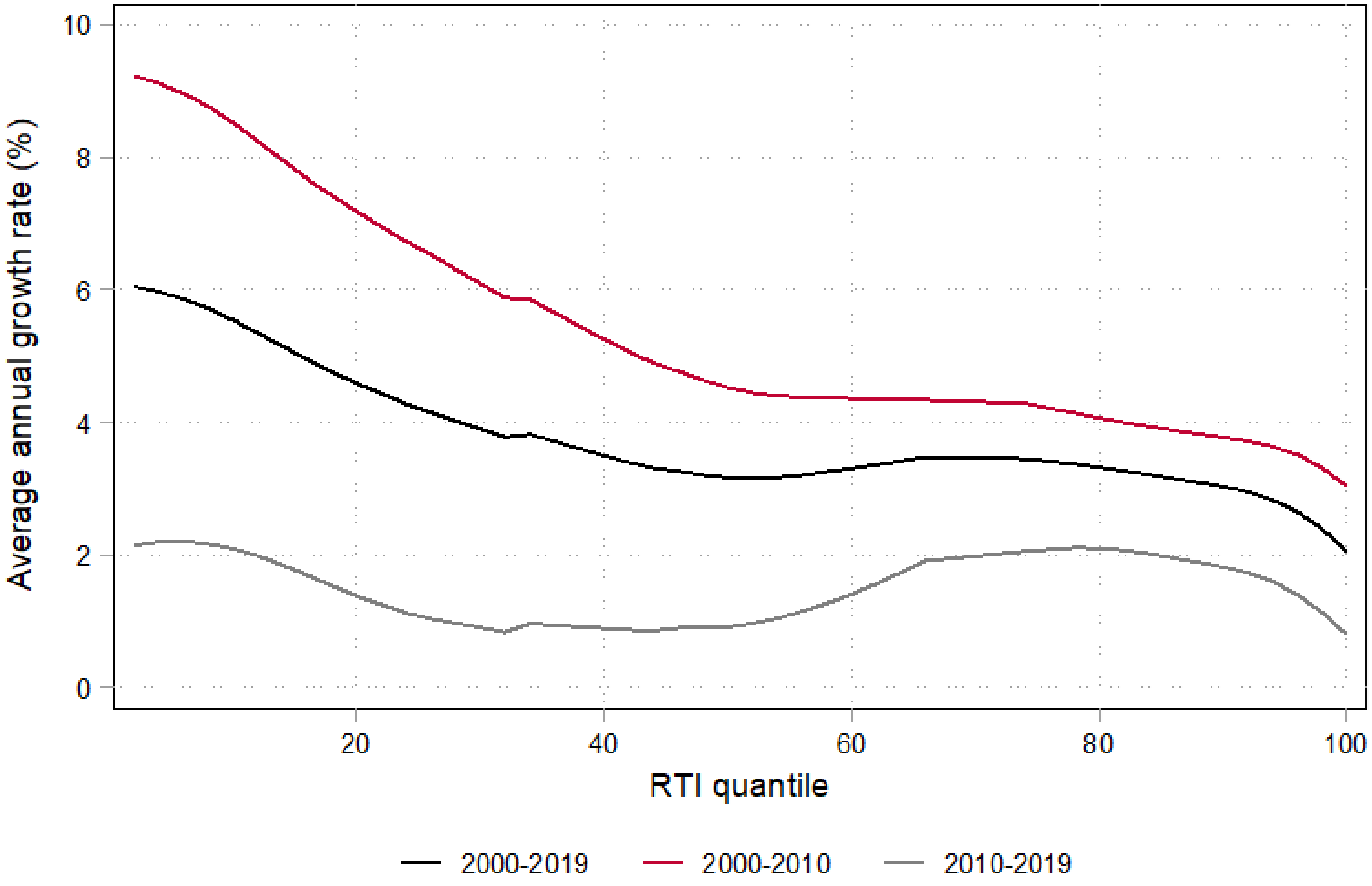
Authors' own calculations. Source: PALMS version 3.3 (Kerr et al., 2019) and O*NET.
Notes: Sample restricted working-aged (15-64 years) employees in the formal private sector. All estimates weighted using sampling weights and account for the complex survey design. Spikes represent 95 percent confidence intervals.

Relative de-routinisation evident when considering *employment shares*

- In Level terms:
  - Deterioration in share of routine manual employment from 48.3% in 2000 to 39.7% in 2019.
  - Growth in all other r_{hi} measures – with largest increase being non-routine cognitive 3.8% to 5.4% (44% increase)
- In Relative Share terms:
  - Clear erosion of share of routine manual jobs since 2000
  - Whilst share of non-routine cognitive jobs grew dramatically in the 2005-2015 period.

Trends in the task content of employment

Employment growth incidence curves across the RTI distribution, 2000 – 2019



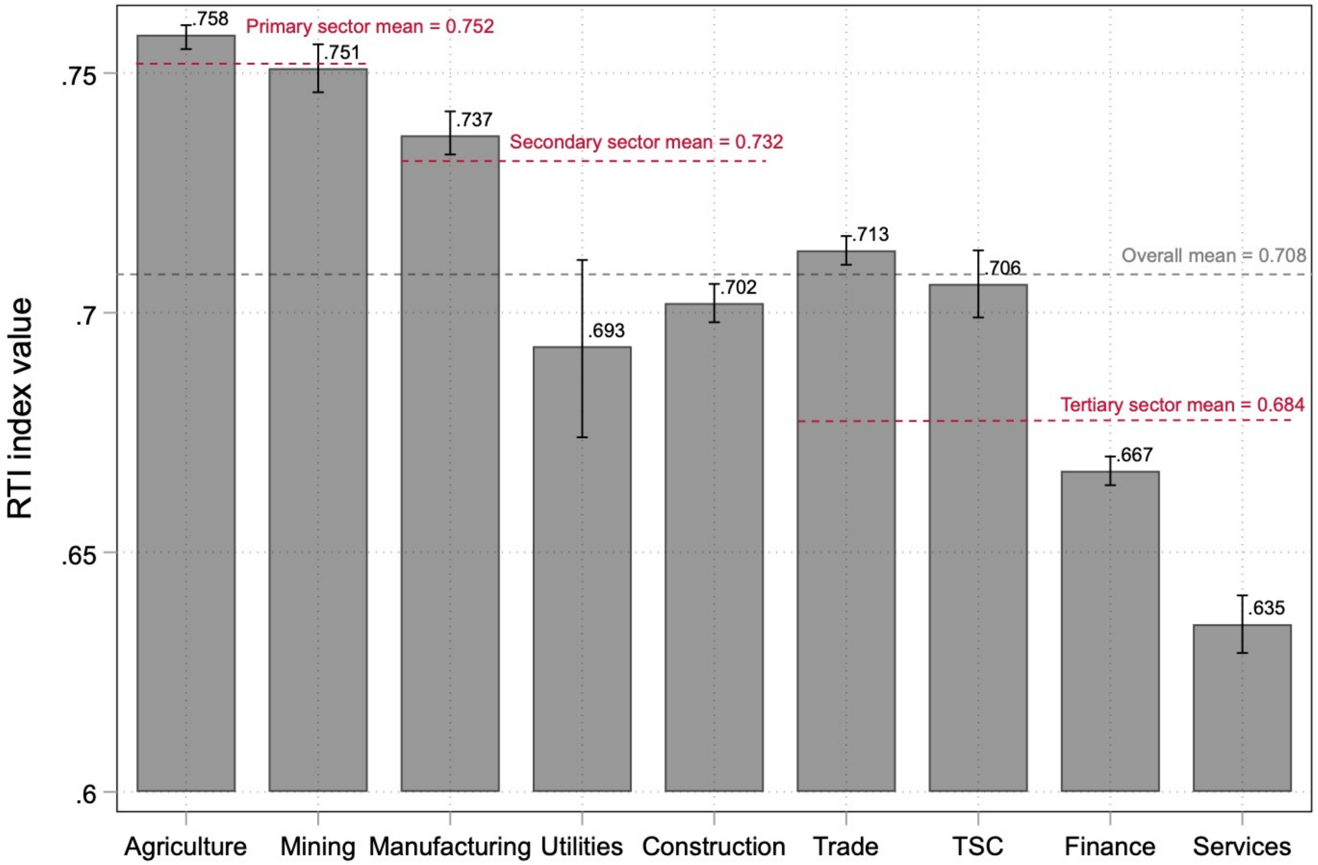
Authors' own calculations. Source: PALMS version 3.3 (Kerr et al., 2019) and O*NET.
Notes: Sample restricted working-aged (15-64 years) employees in the formal private sector. All estimates weighted using sampling weights and account for the complex survey design. Curves plotted using local linear smooth plots (lowess).

- Pattern of *relative de-routinisation* evident when looking at employment growth incidence curves – measuring growth of employment (2000-2019) across quantiles of RTI measure.
- 2000-2019: Employment grew across the entire RTI distribution but fastest for low RTI jobs, and slowest and relatively constant for those around the 40th percentile
  - Full period pattern driven by changes between 2000 and 2010 (similar GIC)
- 2010-2019: Sub-period exhibits mild-hollowing out of distribution
  - Suggestive of technology-induced employment polarisation
  - Positive, albeit sluggish emp growth rates over the latter sub-period. Higher at low RTI and high RTI, while lowest in middle RTI

Sectoral trends in the task content of employment

Sectoral trends in the task content of employment

Routine Task Intensity by sector and industry



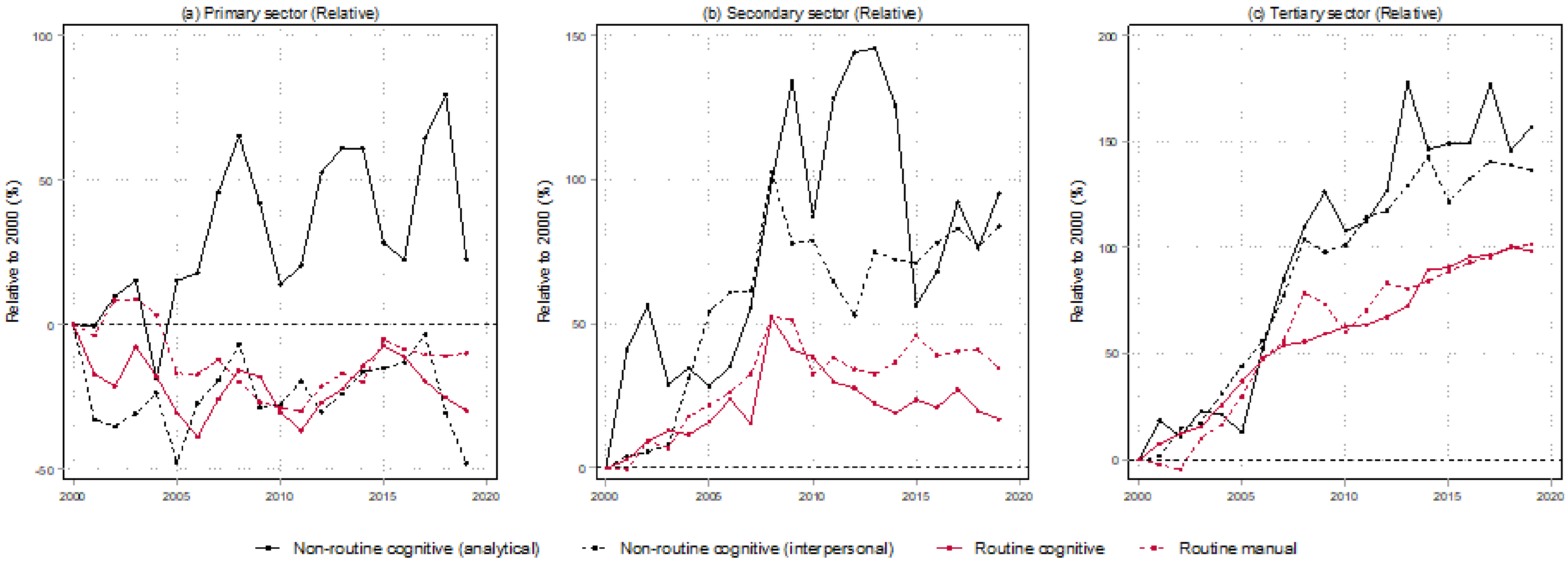
Authors' own calculations. Source: PALMS version 3.3 (Kerr et al., 2019) and O*NET.
Notes: Sample restricted working-aged (15-64 years) employees or wage workers in the formal private sector. Pooled sample for 2000 – 2019 used. All estimates weighted using sampling weights and account for the complex survey design. Capped spikes represent 95 percent confidence intervals. TSC = Transport, Storage, and Communication; Services = Community, Social, and Personal services.

- Evidence of cross sectoral and cross-industry variation in RTI
- Thus, task content of jobs (occupations) varies across industries/sectors
- Clear that Primary Sectors record highest RTI measures, followed by manufacturing.
- Finance and Services – yield lowest RTI.
- Consistent with RTI showing Primary > Secondary > Tertiary.

Sectoral trends in the task content of employment

Relative employment levels by task content component and sector, 2000 – 2019

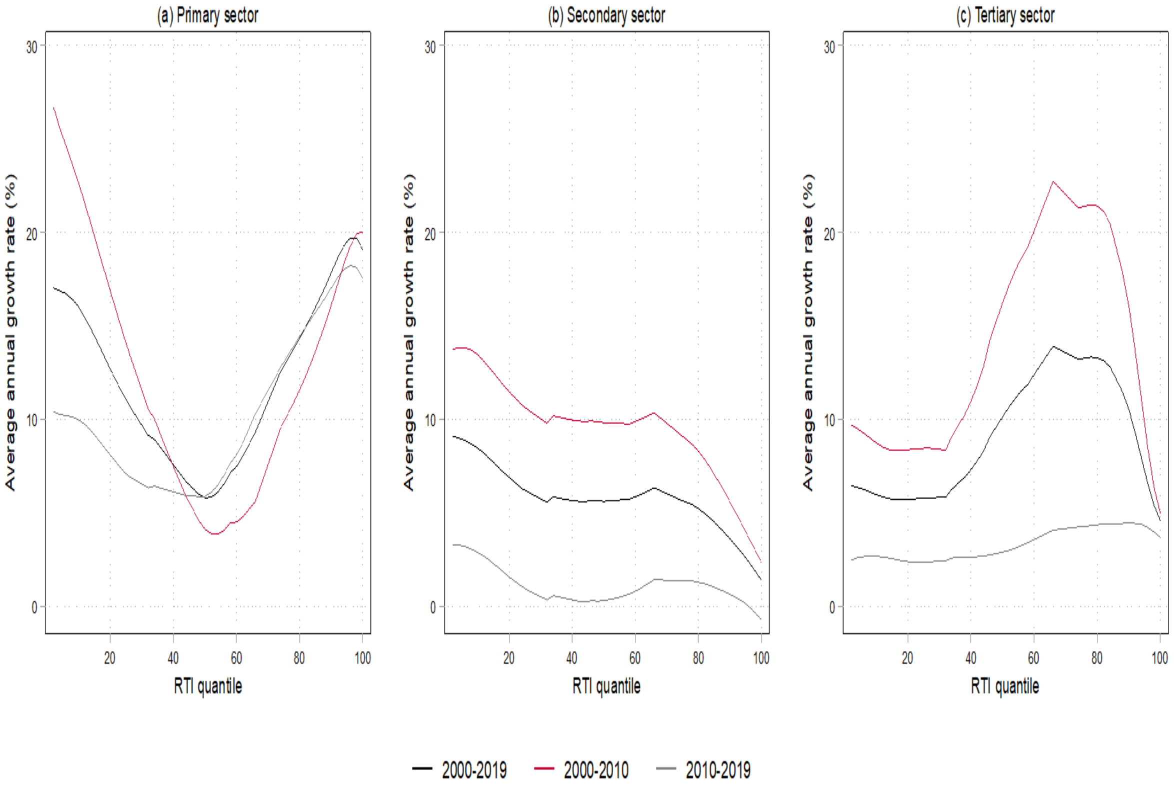
- Non-routine jobs grew fastest across all sectors
- Relative de-routinisation pattern seems to be driven by tertiary sector (2/3 of economy) (panel c)



Authors' own calculations. Source: PALMS version 3.3 (Kerr et al., 2019) and O*NET.
Notes: Sample restricted working-aged (15-64 years) employees in the formal private sector. All estimates weighted using sampling weights and account for the complex survey design.

Sectoral Trends In The Task Content Of Employment *(RTI_j)*

Main Sector RTI GICs: 2000 – 2019



- Sectoral RTI GICs show differential patterns of growth dependent on sector and time period.
- *Panel (a):* Distribution of jobs growth in the primary sector is U-shaped – indicative of job polarisation i.e. growth highest at bottom and top of the RTI distribution over 2000-2019
- *Panel (b):* Jobs growth favoured non-routine work in the secondary sector throughout period
- *Panel (c):* In the tertiary sector jobs growth varied across the RTI distribution but appears higher among more routine jobs.
  - May reflect growth of routine services jobs in temporary employment services sector – and overall sectoral shift to services economy in South Africa.
  - Rise of public sector employment incl. the PWP programme.

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al., 2019) and O*NET.
Notes: Sample restricted working-aged (15-64 years) employees in the formal private sector. All estimates weighted using sampling weights and account for the complex survey design.

Trends In The Task Content Of Employment (r_{hi}): Individual Characteristics

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

- Africans under-represented in non-routine cognitive analytical (0.63) and non-routine cognitive interpersonal (0.71) tasks, while Whites over-represented in these non-routine task content components (2.69 and 2.33)
- In turn African & Coloured workers over-represented in Routine Manual.
- Women under-rep. in Routine Manual but over-rep in routine cognitive.
- Over-representation in routine manual jobs of young workers and those with incomplete secondary schooling or less.

Trends In The Task Content Of Employment (r_{hi}): Individual Characteristics

DPRU DEVELOPMENT POLICY RESEARCH UNIT

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	
	Num. ('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

- Despite low union density levels (24.57%), disproportionate share of routine manual tasks →union members.
  - Non-union members relatively more dominant in non-routine analytical & cognitive jobs.
- Medium to large firms relatively larger employers of routine manual occupations.
  - Smaller firms larger employers of routine cognitive.

Authors' own calculations. Source: PALMS version 3.3 (Kerr et al., 2019) and O*NET.
Notes: Sample restricted working-aged (15-64 years) employees in the formal private sector. All estimates weighted using sampling weights and account for the complex survey design.

A Policy Pivot: Occupational Relatedness

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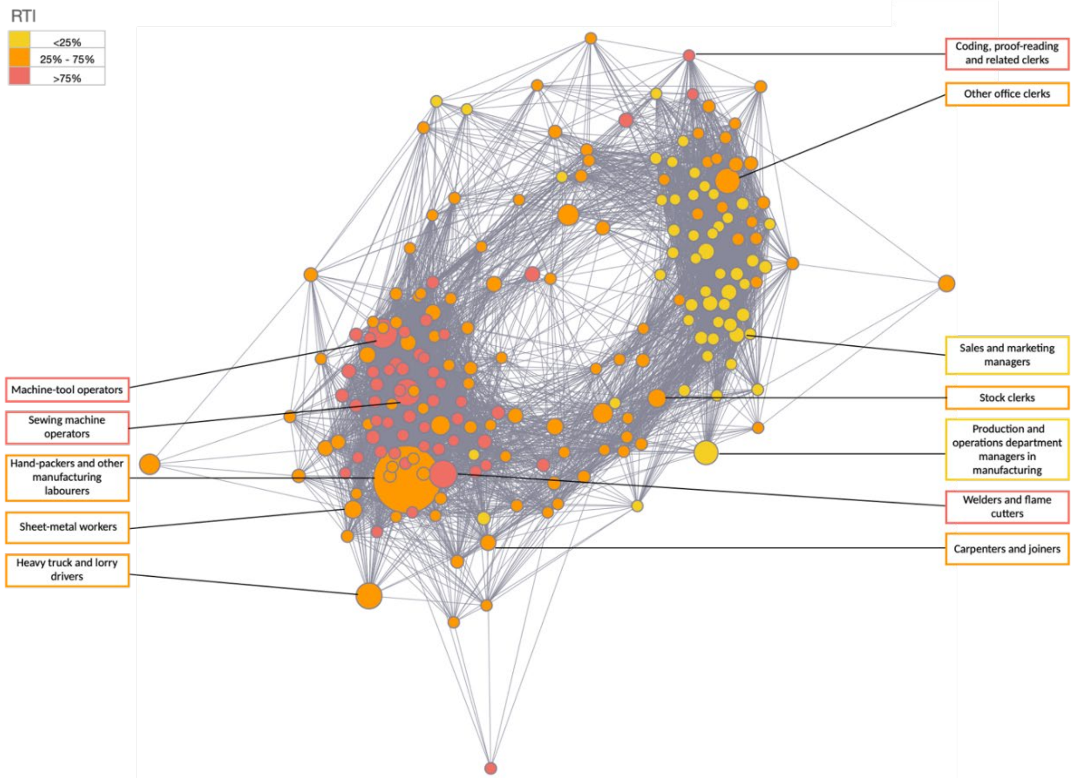
South African Manufacturing Sector Occupation Space - Shaded by RTI Score



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020) and taken from Allen-Whitehead, Bhorat, Hill and Kohler (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.

- Skills development interventions → Shift individuals out of routine task-intensive jobs into non-routine task-intensive jobs likely to require substantial educational and skill input
  - i.e. jump to new occupation is big. Can be visually depicted using *occupation space* for South African manufacturing sector – as developed by Allen-Whitehead, Bhorat, Hill, Kohler and Steenkamp (2021)
- Each node= an occupation, shaded according to RTI score, (*Red high RTI score, orange=medium RTI, yellow=Low RTI*).
- Edge (line connecting nodes) = Relatedness → similar tasks and skills, between pairs of occupations.
- If occupations (nodes) connected & close (short edges) → substantial overlap between skills & tasks required by each occupation → Shifts between such occupations require minor skills development interv.
- Conversely: Disconnected & far away nodes → shifts between such occupations require substantial skills development interventions.
- *Occupation space* network for South African manufacturing sector polarised: Cluster of predominantly non-routine task intensive occupations (yellow nodes) to right & cluster of predominantly routine task intensive occupations (red nodes) to the left.

Conclusion

- Implement routinisation methodology drawn from Autor & Acemoglu (2011) and others – to South African data.
  - First African study and one of a handful of developing country studies.
- In aggregate terms:
  - Non-routine jobs grew at faster rate: South African economy experienced *relative de-routinisation* through ***contraction of routine manual jobs*** & ***expansion of non-routine cognitive analytical jobs*** over time.
- Sectoral patterns more mixed, suggesting primary and secondary sectors yield to strong relative growth of non-routine jobs, whilst tertiary sector shows growth of high RTI jobs
  - Latter reflects patterns of ST in South Africa towards services sectors and growth of TES & Public sector employment.
  - Not sufficient to overturn the aggregate result of de-routinisation.
- Individual characteristics: Young, male, unionised, African & Coloured and workers with less completed high school and working in larger firms – bear brunt of being in routine manual jobs.
- Clear need for policy interventions focused on narrowing the skills gaps in a carefully targeted manner – possibly using occupational mapping as an adjacent tool.

Thank-you

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The paper and the accompanying policy brief can be accessed on the following links from the South African Chair in Industrial Development

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E.g. O*NET Work Activities Data

O*NET-SOC Code	Title	Element ID	Element Name	Scale ID	Scale Name	Data Value	N	Standard Error	Lower CI Bound	Upper CI Bound	Recommend Suppress	Not Relevant	Date	Domain Source
19-3011.00	Economists	4.A.2.a.4	Analyzing Data or Information	IM	Importance	4,78	23						08/2019	Occupational Expert
19-3011.00	Economists	4.A.2.a.4	Analyzing Data or Information	LV	Level	6,43	23					N	08/2019	Occupational Expert
19-3011.00	Economists	4.A.2.b.2	Thinking Creatively	IM	Importance	4,17	23						08/2019	Occupational Expert
19-3011.00	Economists	4.A.2.b.2	Thinking Creatively	LV	Level	5,61	23					N	08/2019	Occupational Expert
19-3011.00	Economists	4.A.3.a.3	Controlling Machines and Processes	IM	Importance	1,22	23						08/2019	Occupational Expert
19-3011.00	Economists	4.A.3.a.3	Controlling Machines and Processes	LV	Level	0,35	23					Y	08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.a.1	Interpreting the Meaning of Information for Others	IM	Importance	3,95	22						08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.a.1	Interpreting the Meaning of Information for Others	LV	Level	5,45	22					N	08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships	IM	Importance	3,36	22						08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships	LV	Level	4,55	22					N	08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.b.4	Guiding, Directing, and Motivating Subordinates	IM	Importance	2,45	22						08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.b.4	Guiding, Directing, and Motivating Subordinates	LV	Level	3,13	23					N	08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.b.5	Coaching and Developing Others	IM	Importance	2,91	22						08/2019	Occupational Expert
19-3011.00	Economists	4.A.4.b.5	Coaching and Developing Others	LV	Level	4,18	22					N	08/2019	Occupational Expert

E.g. O*NET Work Context Data

O*NET-SOC Code	Title	Element ID	Element Name	Scale ID	Scale Name	Category	Data Value	N	Standard Error	Lower CI Bound	Upper CI Bound	Recommend Suppress	Not Relevant	Date	Domain Source
19-3011.00	Economists	4.C.3.b.4	Importance of Being Exact or Accurate	CX	Context		4,35	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.4	Importance of Being Exact or Accurate	CXP	Context (Categories 1-5)	1	0	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.4	Importance of Being Exact or Accurate	CXP	Context (Categories 1-5)	2	4,35	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.4	Importance of Being Exact or Accurate	CXP	Context (Categories 1-5)	3	8,7	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.4	Importance of Being Exact or Accurate	CXP	Context (Categories 1-5)	4	34,78	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.4	Importance of Being Exact or Accurate	CXP	Context (Categories 1-5)	5	52,17	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.7	Importance of Repeating Same Tasks	CX	Context		2,35	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.7	Importance of Repeating Same Tasks	CXP	Context (Categories 1-5)	1	21,74	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.7	Importance of Repeating Same Tasks	CXP	Context (Categories 1-5)	2	39,13	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.7	Importance of Repeating Same Tasks	CXP	Context (Categories 1-5)	3	30,43	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.7	Importance of Repeating Same Tasks	CXP	Context (Categories 1-5)	4	0	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.b.7	Importance of Repeating Same Tasks	CXP	Context (Categories 1-5)	5	8,7	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.d.3	Pace Determined by Speed of Equipment	CX	Context		1,17	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.d.3	Pace Determined by Speed of Equipment	CXP	Context (Categories 1-5)	1	91,3	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.d.3	Pace Determined by Speed of Equipment	CXP	Context (Categories 1-5)	2	4,35	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.d.3	Pace Determined by Speed of Equipment	CXP	Context (Categories 1-5)	3	0	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.d.3	Pace Determined by Speed of Equipment	CXP	Context (Categories 1-5)	4	4,35	23						08/2019	Occupational Expert
19-3011.00	Economists	4.C.3.d.3	Pace Determined by Speed of Equipment	CXP	Context (Categories 1-5)	5	0	23						08/2019	Occupational Expert

Top 10 Non-routine cognitive analytical occupations

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
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

Top 10 Non-routine cognitive interpersonal occupations

Occupation title	ISCO-88 code	Employment Share (%)	RTI Score
Non-routine cognitive interpersonal			
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
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

Tope 10 Routine cognitive occupations

Occupation title	ISCO-88 code	Employment Share (%)	RTI Score
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
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

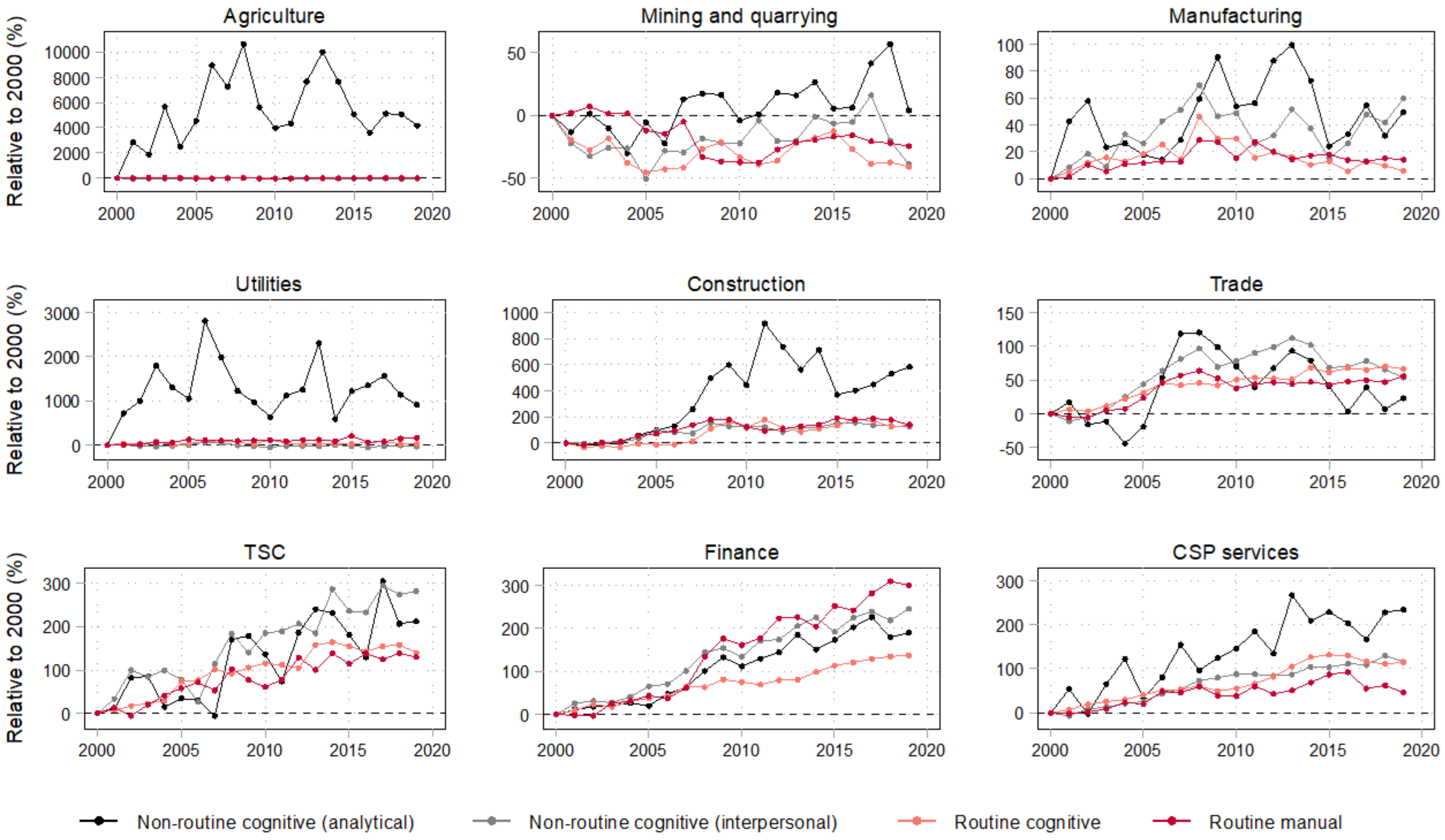
Tope 10 Routine manual occupations

Occupation title	ISCO-88 code	Employment Share (%)	RTI Score
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
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

Sectoral trends in the task content of employment

Relative employment levels by task content component and industry in South Africa, 2000 – 2019

- Evidence of *relative de-routinisation* in six industries: mining and quarrying, manufacturing, utilities, construction, transport, storage, and communication (TSC), and community, social, and personal (CSP) services.
  - Together, these industries accounted for approx. 2/3 of formal private wage employment in 2019.



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

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