

The Potential Impact of the Fourth Industrial Revolution on Jobs in South Africa

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Overview

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Section I.
Research Question

Research Question

- What will be the potential impact on jobs in South Africa as a result of the Fourth Industrial Revolution?
- Important question to investigate given South Africa's high unemployment rate and that previous research on other countries has suggested a large proportion of jobs are at risk of automation

Section 2. Literature Review

Technology and Jobs: Empirical Overview

- Technological innovation has been identified as one of the primary drivers behind unemployment rates.
- Typists, cashiers and telephone operators are jobs that have already been partially replaced by technology
- Pace of technological innovation increasing rapidly, making redundancies more likely in the future.
- Tasks that were previously thought not to be codifiable (e.g. driving) have been successfully codified.

The Interplay Between Technology and Jobs

- Computers ideally suited to routine, manual tasks and can play an assistive role for non-routine, cognitive tasks (Autor et al., 2013)
- In the 1960s in the USA, significant shifts in labour demand from routine to non-routine jobs
- Frey and Osborne (2017) argue that the scope of automation has increased rapidly due developments in machine learning and mobile robotics.
- They find that 47% of US jobs are at risk of automation.

Section 3. Methodology and Data

Methodology

- Use the methodology adopted by Frey and Osbourne (2017)
- Frey and Osbourne state that with recent technological innovations, almost every task is (or will be) codifiable, except for what are termed ‘engineering bottlenecks’
- These bottlenecks **do not** have clearly identifiable rules and therefore it is difficult to develop a computer algorithm
- The three bottlenecks are
 - Perception and manipulation
 - Creative intelligence
 - Social intelligence

Methodology

Computerisation Bottleneck	O*Net Variable	O*Net Description
Perception and manipulation:	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
	Cramped Workspace, Awkward Positions.	Working in cramped work spaces that requires getting into awkward positions.
Creative Intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
	Fine Arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social intelligence	Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behaviour.
	Assisting and Caring For Others.	Providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers or patients.

Source: Frey and Osborne (2013: 31)

Methodology

- Frey and Osborne computed an automation probability for every occupation, however, this was applied to US occupational data. So we performed three steps:
- **First Step:** apply the US Standard Occupation (SOC) to International Standard Classification of Occupations (ISCO-08)
- **Second Step:** Map the ISCO-08 occupational codes to the 2012 South African Standard Classification of Occupation Codes
- **Third Step:** Apply the automation probabilities for each occupation in Frey and Osborne (2017) to South African occupational data.
- In instances where there was a many-to-one correspondence between codes, we used the arithmetic mean.
- As a result of the different classification systems and different level of detail on occupations by Statistics SA, the number of occupations that could be assigned a probability was 311, or 82% of the occupations included in the original dataset.

Methodology

- Frey and Osborne (2017) divide occupations into groups which are at 'low risk', 'medium risk' and 'high risk' of automation based on that occupations automation probability
- **Low Risk:** Automation probability of between 0.0 and 0.3
- **Medium Risk:** Automation probability of between 0.3 and 0.7
- **High Risk:** An automation probability of greater than 0.7
- This is the approach adopted in our paper.

Data

- Labour Market Dynamics Study (LMDS) 2015
- Compilation of surveys and combines four waves of the Quarterly Labour Force Survey, supplemented with earnings data.

Choosing the Sample

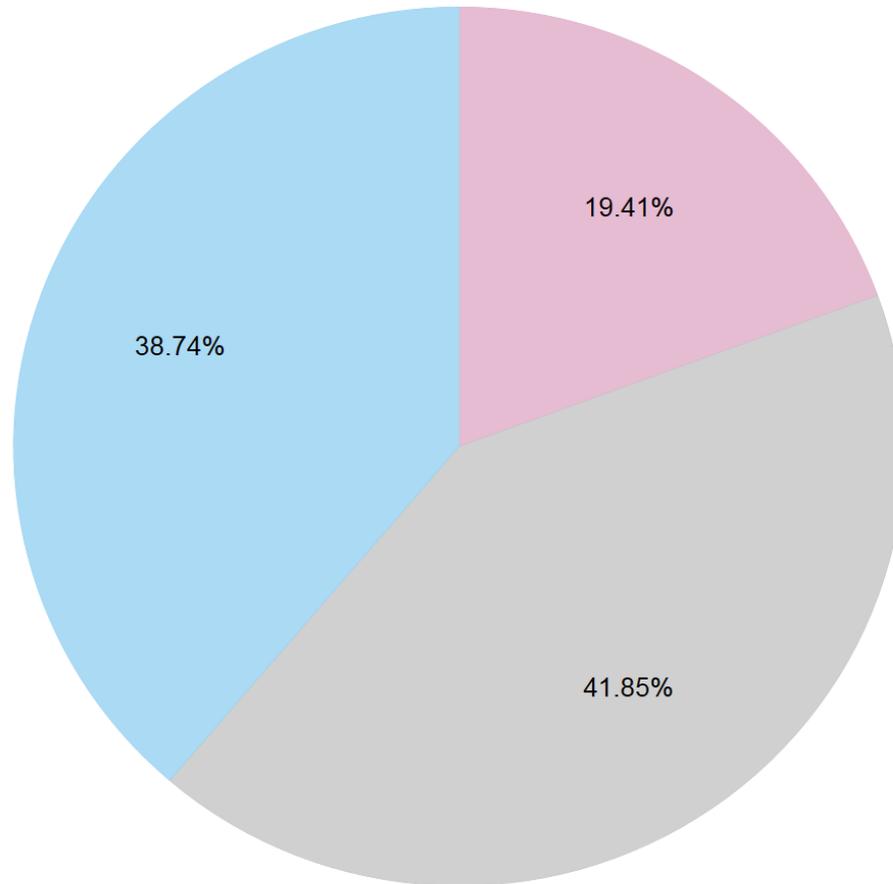
- **Criteria**

- Employee
- Formal Sector
- Matching occupational code between SASC0 and ISCO-08
- Associated probability with an occupation (one exception was for 'sweeper and manual labourers' due to the large number of individuals (865 000) in this role.)
- Total sample size was 10.2 million from the LMDS (from an original sample size of 11.1 million formal sector employees).

Section 4.

Descriptive Statistics

Distribution of Employment at Risk of Automation



low
medium
high

Employment Share of Each Risk Category

		Percent (%)		
		Low	Medium	High
Gender	Male	16.44	49.61	33.95
	Female	24.94	31.39	43.67
Race	African	15.68	45.98	38.35
	Coloured	17.19	37.85	44.95
	Indian	29.68	29.86	40.46
	White	41.77	27.39	30.83
Age	15-24 years	9.66	43.24	47.10
	25-34 years	15.22	44.10	40.67
	35-44 years	21.41	42.98	35.61
	45-54 years	27.27	38.07	34.65
	55-64 years	28.22	36.08	35.70
	65+ years	37.72	30.03	32.24
Education	No schooling	1.06	43.08	55.85
	Incomplete primary	1.78	47.44	50.78
	Incomplete secondary	3.85	54.27	41.88
	Matric	14.57	43.89	41.54
	Certificate / Diploma	38.66	30.01	31.33
	Degree	69.42	12.63	17.95
	Other / Unspecified	11.54	50.66	37.80
Province	Western Cape	20.66	39.63	39.71
	Eastern Cape	22.30	35.15	42.55
	Northern Cape	16.23	42.84	40.93
	Free State	17.62	42.68	39.70
	KwaZulu-Natal	19.04	41.31	39.65
	North West	13.50	52.78	33.72
	Gauteng	21.64	40.98	37.38
	Mpumalanga	17.90	46.37	35.73
	Limpopo	21.90	44.68	33.42

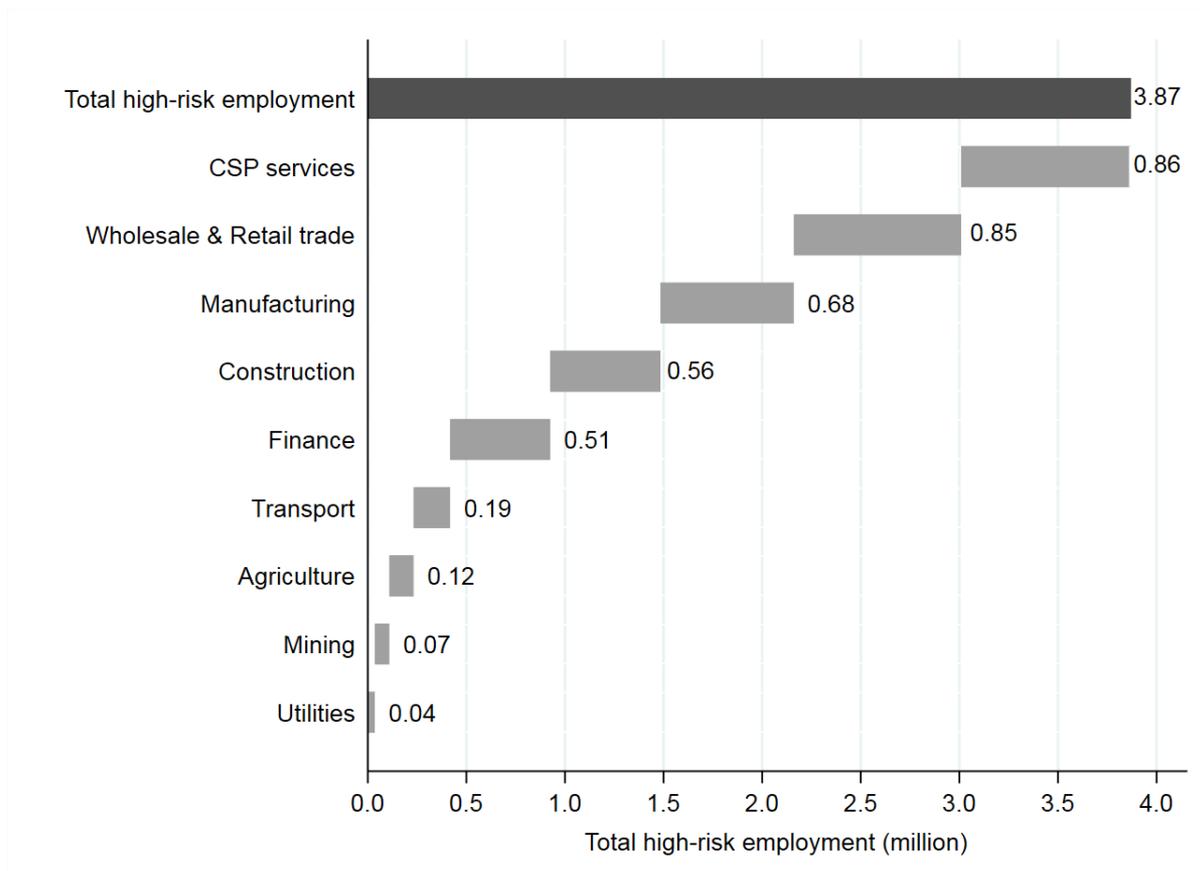
Source: Authors' own calculations using LMDS (2015).

Employment Share of Each Risk category (Industry)

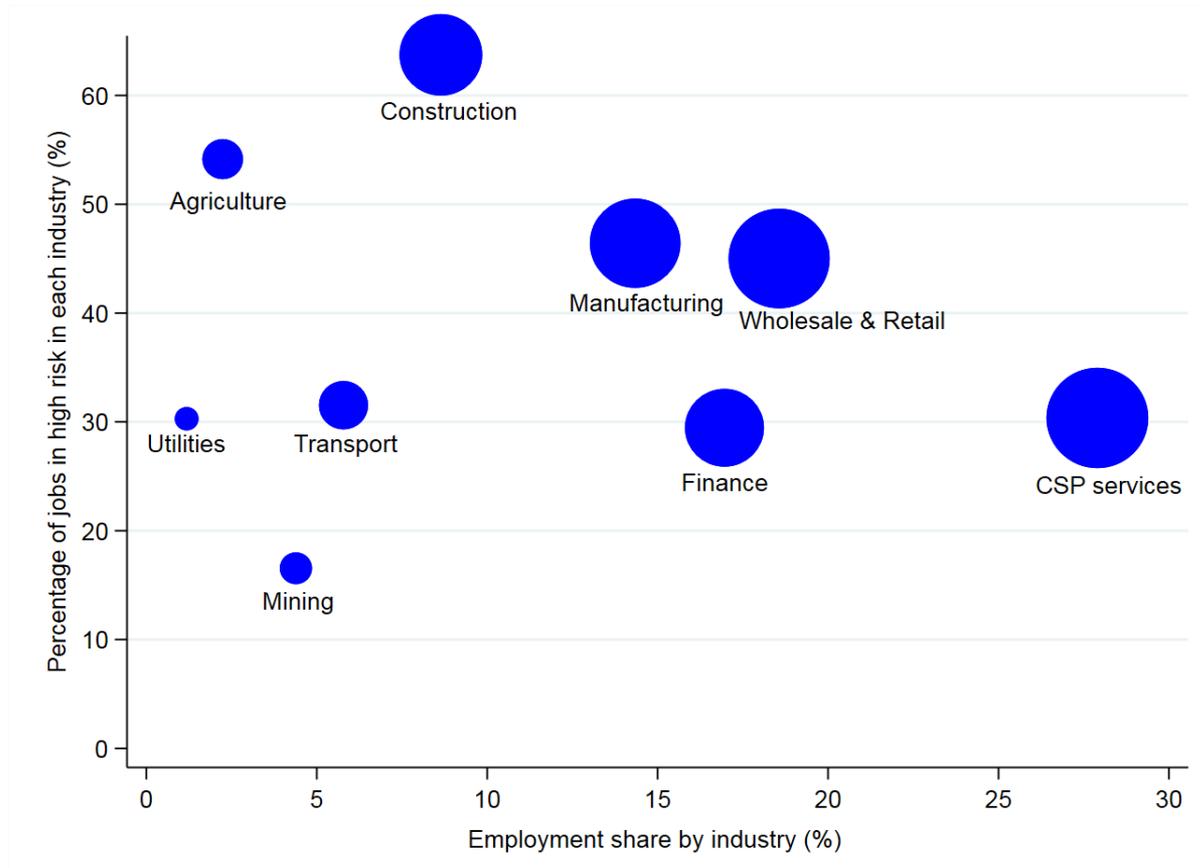
	Percent (%)		
	Low	Medium	High
Agriculture, forestry and fishing	8.47	37.38	54.15
Mining and quarrying	4.73	78.72	16.55
Manufacturing	8.33	45.25	46.42
Electricity, gas and water	14.51	55.20	30.29
Construction	5.86	30.41	63.73
Wholesale and retail trade	9.69	45.29	45.02
Transport, storage and communication	8.29	60.17	31.53
Financial and business services	17.75	52.79	29.46
Community, social and personal (CSP) services	44.84	24.80	30.36

Source: Authors' own calculations using LMDS (2015).

Potential Number of Jobs at High-Risk of Automation by Sector



Potential Impact of Automation by Sector



Summary

- 80% of jobs are at high or medium risk of being automated.
- Females, coloureds, young people (15 – 24) and those with no education are most at risk of seeing their jobs automated.
- **Absolute** job losses (total number of job losses) are likely to be highest in CSP services, wholesale and retail trade and construction
- **Relative** job losses (percentage of total employment) are likely to be highest in construction, agriculture and manufacturing

Section 5. Regression Results

Determinants of Automation: An Econometric Approach

- $Probability (High\ risk\ occupation = 1) = \theta (\beta_0 + \beta_1 (Female) + \beta_2 (Race) + \beta_3 (Age) + \beta_4 (Marital\ Status) + \beta_5 (Province) + \beta_6 (Education) + \beta_7 (Occupation) + \beta_8 (Industry) + \beta_9 (Tenure) + \beta_{10} (Contract\ Type) + \beta_{11} (Contract\ duration) + \beta_{12} (Union\ Membership) + \beta_{13} (Public\ Sector) + \beta_{14} (Firm\ Size))$
- The dependent variable is *Occupation* – if an individual is in a high risk occupation (automation probability of over 0.7), this variable is coded as a '1' else it is '0' otherwise.
- Only interesting results are shown.

Regression Results (Part I)

Independent variable	Reference Category	Regression [I]	
		Marginal effect	SE
Gender: Female	Male	0.0263***	0.0080
Education: Incomplete primary	No Schooling	-0.0606**	0.0263
Education: Incomplete secondary		-0.1371***	0.0244
Education: Matric		-0.1851***	0.0248
Education: Certificate or Diploma		-0.2046***	0.0251
Education: Degree		-0.1615***	0.0304
Education: Other or unspecified		-0.1549***	0.0392

Regression Results (Part 2)

Independent variable	Reference Category	Regression [I]	
		Marginal effect	SE
Union membership: Member	<i>Not a member</i>	-0.0909***	0.0093
Sector: Public	<i>Private</i>	0.1002***	0.0123
Firm size: 5-9 workers	<i>1 - 4</i>	0.0433	0.0277
Firm size: 10-19 workers		0.0699***	0.0269
Firm size: 20-49 workers		0.0688***	0.0269
Firm size: 50 workers or above		0.0757***	0.0263

Regression Results (Part 3)

Independent variable	Reference Category	Regression [I]	
		Marginal effect	SE
Real monthly earnings decile2	I	-0.1167***	0.0131
Real monthly earnings decile3		-0.0950***	0.0131
Real monthly earnings decile4		-0.1325***	0.0136
Real monthly earnings decile5		-0.1242***	0.0136
Real monthly earnings decile6		-0.1421***	0.0139
Real monthly earnings decile7		-0.1072***	0.0144
Real monthly earnings decile8		-0.1323***	0.0151
Real monthly earnings decile9		-0.1378***	0.0166
Real monthly earnings decile10		-0.0546***	0.0196

Key Results (Part I)

- Females are 3% more likely to be involved in a high risk occupation than males.
- Obtaining any sort of education reduces the probability of being in a job at high risk of automation
- Employees who belong to trade unions are 10% less likely to be in a high risk job.
- Public sector employees are 10% more likely to be in a high risk job than those in the private sector
- The bigger the firm size, the more likely an individual is to be in a job at high risk of automation

Key Results (Part 2)

- Individuals who were earning in all other deciles (with the notable exception of decile 10) were between 9 – 14% less likely to be in an occupation considered at high risk of automation compared to those in decile 1. Earners in decile 10, are only 5% less likely to be in a high risk job compared to low earners

Constraints to Automation

- **Economic Constraint**
 - Cost of purchasing robots
 - Abundance of relatively cheap labour in South Africa
- **Regulatory Constraint**
 - Lobby group (e.g. taxi drivers) can push for regulatory constraints against new technology e.g. Uber
 - Legal issues: who is responsible for an accident if a self-driving car crashes?

Opportunities from Automation

- New job types can arise from the introduction of new technology
- Productivity boost => could result in higher wages for people who use their technology in **assisting** them with their jobs

Section 6. Conclusion

Conclusion and Policy Recommendations

- Around 39% of formal employees in South Africa are at high risk of losing their jobs due to automation, with a further 42% at medium risk of losing their jobs
- Automation is likely to widen inequalities over time, as the highly skilled reap the benefits
- **Solutions**
 - Invest in education and training
 - Create an environment that is conducive to business, especially start-ups
 - Universal Basic Income (UBI)
 - Costs?
 - Removing incentive to work?

Thank You