The Potential Employment Implications of the Fourth Industrial Revolution Technologies:
The Case of the Manufacturing, Engineering and Related Services Sector

By Caitlin Allen Whitehead, Haroon Bhorat, Robert Hill, Timothy Köhler and François Steenkamp

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Abstract

In this paper we examine the potential employment displacement effects of technologies related to the Fourth Industrial Revolution (4IR) on the MER sector, by observing this risk through the lens of the task-content of occupations or the routinisation hypothesis. We use network analytics to develop a MER sector occupation space, which shows the occupational structure of the MER sector labour force. Given the occupational structure of the sector, we identify occupations at high risk of displacement – i.e. what tasks, and hence what occupations, are most at risk of being automatated, computerised or digitised. Drawing on household survey data, we explore the characteristics of workers who occupy these high risk occupations in an attempt at identifying a typology of individuals most likely to be deleteriously impacted on by 4IR technologies. Three implications emerge: Firstly, technology induced employment displacement is likely to jeopardise low- to medium-skill employment in the production cluster occupations, and correspondingly result in an increase in relative demand for semi- and high-skilled non-production cluster occupations. Second, the non-random distribution of high risk occupations across the two clusters of the occupation space suggests that the skill transition to shift workers from high to low risk occupations is long, and in the event of substantial uptake of employment displacing technologies across the sector, technological unemployment is that much harder to mitigate. Third, the relatively high employment share associated with high risk occupations in the production cluster indicates that the potential displacement effects resulting in technological unemployment are likely to be substantial.

JEL codes: O13; O14; O25

Keywords:
Automation; employment; manufacturing; fourth industrial revolution; task content of occupations; technology

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1 INTRODUCTION

At least since the industrialisation of weaving in the 1700s, the notion that "robots are coming to take our jobs" has raised fears of the displacement of workers and subsequent disruption in livelihoods (World Bank, 2019). However, while the notions of automation, and more recently computerisation and digitisation, and their potential impacts has not fundamentally changed, Autor (2015) notes that the cost and pace of uptake of these techoligies has. For instance, Nordhaus (2007) shows that between 1850 and 2006, the real cost of performing a standardized set of computational tasks is estimated to have fallen by at least 1.7 *trillion*-fold, with most of the cost reduction occurring in the last three decades. This rapid price decline creates substantial incentives for employers to substitute relatively expensive labour for computer capital to perform workplace tasks (Acemoglu & Autor, 2011; Frey & Osborne, 2017).

While the impacts of these evolving technologies are felt across the entire labour market, they are particularly acute in the manufacturing sector. Workers involved in routine tasks that are 'codifiable' – as is the case with many workers in the manufacturing sector – are most vulnerable to being displaced by technology (World Bank, 2019). For example, it is noted in the World Bank's *2019 World Development Report: The Changing Nature of Work*, that approximately two in every three robots are employed in the automotive, electronics, and metal and machinery industries (World Bank, 2019). [1] This is certainly worth noting given that these industries strongly overlap with the Manufacturing, Engineering, and Related Services (MER) sector.[2]

The disemployment effects of these technologies on manufacturing sector jobs exhibits a degree of cross-country heterogeneity, being notably more pronounced in developed, relative to developing, economies. The decline in industrial (or manufacturing) employment in many high-income economies over the last two decades is a well-established trend (World Bank, 2019). This pattern is consistent with a structural shift of these economies from manufacturing to services. Conversely, over the same period, the share of industrial employment in developing East Asian economies, such as Vietnam and Cambodia, has risen substantially, while the corresponding share in other developing economies has on aggregate, remained stable (World Bank, 2019). While finding labour displacing effects of automation in developed economies, a recent study by Maloney and Molina (2019) finds little evidence of this in developing economies.

Despite limited evidence of aggregate employment displacement effects among developing economies, these effects have played out at the country level. It is thus important to understand the potential risks associated with the automation, computerisation and digitisation of tasks in the South African manufacturing context. From a South African policy standpoint, the manufacturing sector is seen as an engine of growth and source of accelerated employment creation. However, the South African manufacturing sector has undergone premature deindustrialisation – evident in declining manufacturing employment shares – since the 1980s (Bhorat, Lilenstein, Oosthhuizen and Thornton, 2020a).

In this report we examine the potential employment displacement effects of technologies related to the fourth industrial revolution on the MER sector. Since the impact of Fourth Industrial Revolution (4IR) technologies on the labour market occurs at the occupation level, we examine this potential

[1] The World Bank's 2019 World Development Report provides some examples of technology impacting on manufacturing employment through displacement and reshoring. Foxconn Technology Group, the world's largest electronics assembler, based in China, displaced 30 percent of its workforce after introducing robots into its production process. Using 3-D printing technologies, Adidas shifted shoe production away from low-labour cost Vietnam – shedding 1000 jobs – and 'reshored' production to factories in Germany and the USA.

[2] It is important to note up front that advances in technology, while having potential adverse employment effects, also provide provide opportunities to create new jobs, increase labour productivity, and deliver effective public services (World Bank, 2019), since the technology generates new sectors and new tasks.

impact through the lens of the task-content of occupations. Firstly, through the application of network analytics to the task content of occupations, we examine the occupational structure of the MER sector. Secondly, given the occupational structure of the MER sector, we identify occupations at high risk of displacement – i.e. what tasks, and hence what occupations, are most at risk of being automatated, computerised or digitised. Thirdly, drawing on household survey data, we explore the characteristics of workers who occupy these high risk occupations in an attempt at identifying a typology of individuals most likely to be deleteriously impacted on by 4IR technologies.

Analysing the potential risk of employment displacement in the MER sector by focusing on the task-content of occupations is appropriate since this approach offers substantial explanatory power when assessing the evolution of labour markets in response to automation, digitisation, and similar such technologies. The routinisation hypothesis, which emerged from the seminal work by Autor, Levy and Murnane (2003), details how occupations are characterised by routine and non-routine tasks, within which there are cognitive and manual tasks. It contends that computer capital (or automation, computerisation and digitisation technology) substitutes for human labour in carrying out routine tasks (both manual and cognitive), complements non-routine cognitive tasks, and does not affect non-routine manual tasks. Consequently, as the price of computer capital falls, automation, computerisation and digitisation technologies becomes relatively cheaper, and labour markets consequently adjust with respect to composition and wage structure.[3]

Using this task based approach, Autor, Levy and Murnane (2003) and Goos and Manning (2007) amongst others, are able to show a pattern of job polarisation in developed country labour markets. They observe growth in the number of low paying service occupations characterised by non-routine manual task content ('lousy jobs'), growth in the number of high paying professional and managerial occupations in business and finance characterised by non-routine cognitive task content ('lovely jobs'), and a decline in the number of clerical and skilled routine jobs in manufacturing characterised by routine manual and routine cognitive task content ('middling jobs).[4] This pattern of job polarisation is mimicked by a corresponding wage polarisation where wages at the top of the wage distribution – i.e. 'lovely jobs' – experience high growth, wages in the middle – i.e. 'middling jobs' – experience declining wage growth, and wages at the bottom – i.e. 'lousy jobs' – experience marginal wage growth. Applying this task based approach, Bhorat, Lilenstein, Oosthuizen and Thornton (2020b) observe a similar pattern of wage and employment polarisation in the South African labour market.[5] They too observe a 'hollowing out of the middle' – where much of manufacturing employment resides – in terms of employment composition and wage growth.

The body of work built around the task-content of occupations approach and routinisation hypothesis is thus able to explain long-term trends in manufacturing employment and wages. As such, it is conceptually relevant for the analysis to follow.

[3] It is important to note that this method is not exhaustive in its coverage of what can be termed 'fourth industrial revolution' technologies. These technologies are constantly evolving at a rapid pace, and existing datasets that inform such analyses are not able to evolve at the same pace. The method covers technologies that automate, computerise and digitise tasks performed by workers.

[4] Acemoglu and Autor (2011) note that because core job tasks in manufacturing occupations follow well defined repetitive (or routine) procedures, they can easily be codified in computer software and thus performed by computers.

[5] As we detail in Section 2 below, this pattern of wage and employment polarisation is typically observed in developed economies, with less evidence emerging in the case of developing economies (Maloney & Molina, 2019).

2 LITERATURE REVIEW: TECHNOLOGICAL DEVELOPMENT AND THE LABOUR MARKET

2.1 Introduction

The evolving relationship between technological advancement and the nature of work has been a topic of great interest far beyond recent years. This is not unexpected, considering that the changing nature of the production process of goods and services serves as a central feature of economic development (Aedo et al., 2013). For several centuries, there has been continuous cautioning that automation would result in a substantial share of jobs becoming obsolete (Autor, 2015). At least since the industrialisation of weaving in the 1700s, the notion that "robots are coming to take our jobs" has raised fears of the displacement of workers and subsequent disruption in livelihoods (World Bank, 2019). Further back in 1589, William Lee – hoping that it would relieve workers of hand-knitting – sought patent protection for his stocking frame knitting machine invention. However, Queen Elizabeth I was more concerned with the employment impact of his invention and refused to grant him a patent (Frey & Osborne, 2017). In the early 1800s, the Luddite movement – a group of English textile artisans – protested the automation of textile production by attempting to destroy some of the machines (Autor, 2015). In fact, the word *robot* originates from the Slavic-language word for work – *robota*, created by Czech writer Karel Čapek in 1920 to make the purpose of these machines clear. In 1930, economist John Maynard Keynes even warned that technology will result in widespread *technological unemployment* (Keynes, 1930).

Such concerns have regained prominence in recent years. However, throughout modern history, the principle of automation – for a machine or computer to complete a task, a programmer must first fully understand how to perform the task, and then must write an appropriate program so the machine can simulate these steps precisely – has not fundamentally changed; but importantly, the cost has (Autor, 2015). Between 1850 and 2006, the real cost of performing a standardized set of computational tasks is estimated to has fallen by at least 1.7 *trillion*-fold, with most of this reduction occurring within the last 30 years (Nordhaus, 2007). This rapid price decline creates substantial incentives for employers to substitute relatively expensive labour for computer capital to perform workplace tasks (Acemoglu & Autor, 2011; Frey & Osborne, 2017). This is particularly concerning for manufacturing, considering globally more than two in every three robots are employed in the automotive, electronics, and metal and machinery industries (World Bank, 2019).

Although many jobs are at risk of being automated, these jobs do not face the same degree of risk. In this light, understanding the relationship between technology and employment requires thinking beyond just substitution (Autor, 2015). The consequences of automation are believed to be distributed unevenly across workers of various characteristics (Apella & Zunino, 2017). Skill-biased technological change (SBTC) – the idea that technology is biased in favour of high-skilled workers – serves as the dominant theory in the literature which investigates this. We explore this theory in more detail in Section 2.2. However, SBTC can only explain changes in the demand for high-skilled labour at the top of the wage distribution, whereas economists have found evidence from around the world that there have been increases in the demand for high-skilled, high-wage workers, *as well as* low-skilled, low-wage workers – at the expense of workers in the middle of the distribution. Such wage and job 'polarisation' is not in line with the SBTC hypothesis. However, a more nuanced theory – Autor et al.'s (2003) routinisation hypothesis – is a more plausible explanation. In short, and discussed in detail in Section 2.3, the routinisation hypothesis distinguishes between skills and tasks, and ultimately proposes that jobs that have more routine-intensive tasks (those that follow explicit rules, like booking, or repetitive production and monitoring jobs) face a higher risk of automation, whereas non-routine tasks (characteristic of problem-solving, analytical judgment, and situational adaptability) tend to actually be complemented, and not substituted, by technology (Autor, 2015). In Section 2.4, we document the growing body of empirical evidence of this hypothesis and its implications in both developed and developing countries.

The rapid pace of technological development today – big data, artificial intelligence, and robotics – have led to automation, computerisation and digitisation spreading to domains commonly defined as non-routine which have, until now, largely remained a human domain. This increases the possibility of job substitution on a scale not yet observed (Brynjolfsson & McAfee, 2011; Autor, 2015; Frey & Osborne, 2017). Ultimately, the impact of technology on the labour market has and will continue to be significant through job substitution, creation, and shifts in the demand for specific types of labour, skills, and tasks. However, many uncertainties remain. In the following sections, we discuss the dominant theories of the relationship between technology and the labour market mentioned above, as well as the empirical evidence found so far in both developed and developing countries, South Africa included.

It is worth emphasising that in this literature, the use of the term *automation* needs to be considered in its given context. Autor et al.'s (2003) routinisation hypothesis is concerned with the automation of tasks arising from technological change, particularly computerisation. Their analysis does not distinguish between the individual technologies that emerge over time, but instead aggregate these technologies under the term 'computerisation'. In this light, *automation* can encompass concepts such as digitisation, artificial intelligence, machine learning, robotics, and other emerging technologies – all of which can fall under the term '4IR technologies'. As such, applying such a lens provides useful insights into the effects of these technologies on the labour market.

2.2 Skill-biased technological change

Increases in the returns to skills, despite relative increases in the supply of tertiary educated workers, has motivated a large literature that investigates the relationship between technology and wages in both developed and developing countries (Acemoglu & Autor, 2011). The fact that the return to skills has risen in the context of a rising supply of skills suggests that the growing aggregate supply of skilled workers has been accompanied by even larger increases in the demand for such workers. This is likely linked to changes in technology.

Skill biased technological change (SBTC), the idea that technology is biased in favour of high-skilled workers and against low-skilled workers, has been emphasized by economists writing about the impact of technology on the labour market (Tinbergen, 1974, 1975; Goos & Manning, 2007). Acemoglu and Autor (2011) describe the SBTC perspective as the return to skills being determined by "a race between the increase in the supply of skills in the labour market and technical change". Importantly, from a wage inequality perspective, the demand for skilled jobs is rising relative to that for low-skilled jobs. Because of this, SBTC has been proposed as the primary cause of rising wage inequality in many countries (Autor & Dorn, 2013). However, the routinisation hypothesis, formalised by Autor et al. (2003) and discussed in Section 2.3 below, offers a more nuanced explanation for rising wage inequality.

Compared to investigating the effect of technology on job loss, it is analytically easier to consider how technology has affected the demand for skills. Technology is reshaping the skills needed for work across and within several industries and occupations, as well as how these skills are being remunerated (World Bank, 2019). Often attributed to SBTC, a large literature highlights a substantial shift of employment from low- and middle-skilled occupations towards high-skilled occupations across the world, including in developing countries (Hardy et al., 2016). In Bolivia, Ethiopia and South Africa, the share of the employed in high-skill occupations increased by at least 8 percentage points from 2000 to 2014 (World Bank, 2019). In South Africa, Denmark, France, Germany, the Slovak Republic, Spain and Switzerland, there is evidence that individuals who exhibit one particular high skill – complex problem-solving – are associated with earning, on average, a 10-20 percent higher wage relative to those who do not (World Bank, 2019). Bhorat and Khan (2018) show that in the post-apartheid period (1995-2016), all the main sectors of the South African economy experienced a steady rise in skill-intensity.

However, this dominant view of the relationship between technological development and the labour market cannot explain all important changes observed across both developed and developing countries. Specifically, economists have found that there have been increases in the demand for high-skilled, high-wage workers, as well as low-skilled, low-wage workers, relative to workers in the middle of the income distribution (Goos & Manning, 2007). This is not in line with the predictions of the SBTC hypothesis. An increasingly broad literature has shown that such employment and wage 'polarisation' – that is, disproportionate wage gains to workers at the top and at the bottom of the income and skill distribution, but not to those in the middle – is linked to variation in the task content of occupations.[6] This has important implications for manufacturing in South Africa, considering that as of 2017, for a given hour of work, the average worker in the industry earns a wage in the middle of the wage distribution (Bhorat et al., 2020b). Goos and Manning (2007) note that SBTC can only explain what is happening in the top half of the wage distribution, but not the bottom. On the other hand, Autor et al.'s (2003) more nuanced 'routinisation' hypothesis can help explain the observed polarisation of wages and employment by looking at tasks in more detail. It is this that we turn to next.

2.3 The routinisation hypothesis and the task content of occupations

As opposed to suggesting that technological development increases the demand for high-skilled workers at the expense of low-skilled workers, as per the SBTC hypothesis, Autor et al.'s (2003) routinisation hypothesis considers the observed increase in demand for both high- and low-skilled workers at the expense of workers in the middle of the distribution. In contrast to the SBTC hypothesis, the routinisation hypothesis can then plausibly explain the observed wage and employment polarisation in many countries around the world. The theory does so by first distinguishing between skills and tasks. A task can be regarded as a unit of work activity that produces output (goods and services), whereas a skill is a worker's endowment of capabilities for performing tasks (Acemoglu & Autor, 2011). Workers apply their skills to tasks in exchange for wages, and skills applied to tasks produce output. Autor et al. (2003) and the subsequent literature further distinguish between manual (related to physical labour) and cognitive (related to knowledge work) tasks on the one hand, and routine and non-routine tasks on the other. Routine tasks are those that follow explicit rules that can be accomplished by machines, while non-routine tasks are not sufficiently well understood to be specified in computer code.

For a task to be regarded as routine, the task can be fully specified as a series of instructions to be executed by a machine – i.e. 'codifiable'. Routine tasks include the mathematical calculations involved in simple bookkeeping, or the retrieving and storing of information typical of clerical work, as well as repetitive production and monitoring jobs (Autor, 2015). The tasks of these jobs follow well-understood, codifiable steps and can thus be performed by machines, or alternatively outsourced to foreign worksites (Acemoglu & Autor, 2011). This process of automating routine tasks raises the demand for workers who can perform non-routine tasks that are yet to be subjected to automation and are thus complementary to technology.

Non-routine tasks can be disaggregated into two distinct groups. Manual non-routine jobs are characteristic of situational adaptability, visual and language recognition, and in-person interactions (for instance, driving a truck through traffic, meal preparation, mowing a lawn, cleaning and janitorial work), while cognitive or abstract non-routine jobs are characteristic of problem-solving, analytical judgment, and intuition (for instance, professional and managerial occupations, such as law, medicine, science, engineering, and design to name a few) (Acemoglu & Autor, 2011; Autor, 2015). Cognitive non-routine tasks are complementary to technology because they typically rely on information as an input – the price of which (accessing, organizing, and manipulating information) has fallen over time (Acemoglu & Autor, 2011). Manual non-routine tasks are not directly affected by technology (Goos & Manning, 2007), and are difficult to automate because they require a degree of flexibility and responsiveness to unscripted interactions (Acemoglu & Autor, 2011; Autor, 2015). Further, Autor

[6] As initially proposed by Autor et al (2003).

(2015) notes that these tasks are minimally reliant on information and data processing and thus offer minimal opportunities for direct complementarity or substitution.[7]

The routinisation hypothesis posits that technological development has resulted in, firstly, an increase in the demand for workers whose job's task content is regarded as non-routine, and secondly, a decrease in the demand for workers whose job's task content is regarded as routine. Whereas jobs marked by non-routine tasks tend to be complemented by technology, jobs marked by routine tasks are more at risk of being automated and thus replaced. This difference in the risk of automation by the 'routine task intensity' (RTI) of jobs – a summary measure that combines routine cognitive and non-routine cognitive tasks, which we employ later – is reflected by two observations. First, in a number of countries (mainly advanced economies) in recent decades, routine-intensive employment has seen a gradual decline. Second, this decline has been coupled by an increase in non-routine employment (Autor et al., 2003; Frey & Osborne, 2017). Autor et al. (2003) provide evidence that the adoption of computer capital has been concentrated in industries which have higher shares of routine-intensive employment. Since the onset of the century, the global share of employment in non-routine jobs has increased from 33 to 44 percent in advanced economies, and 19 to 23 percent in emerging economies (World Bank, 2019).

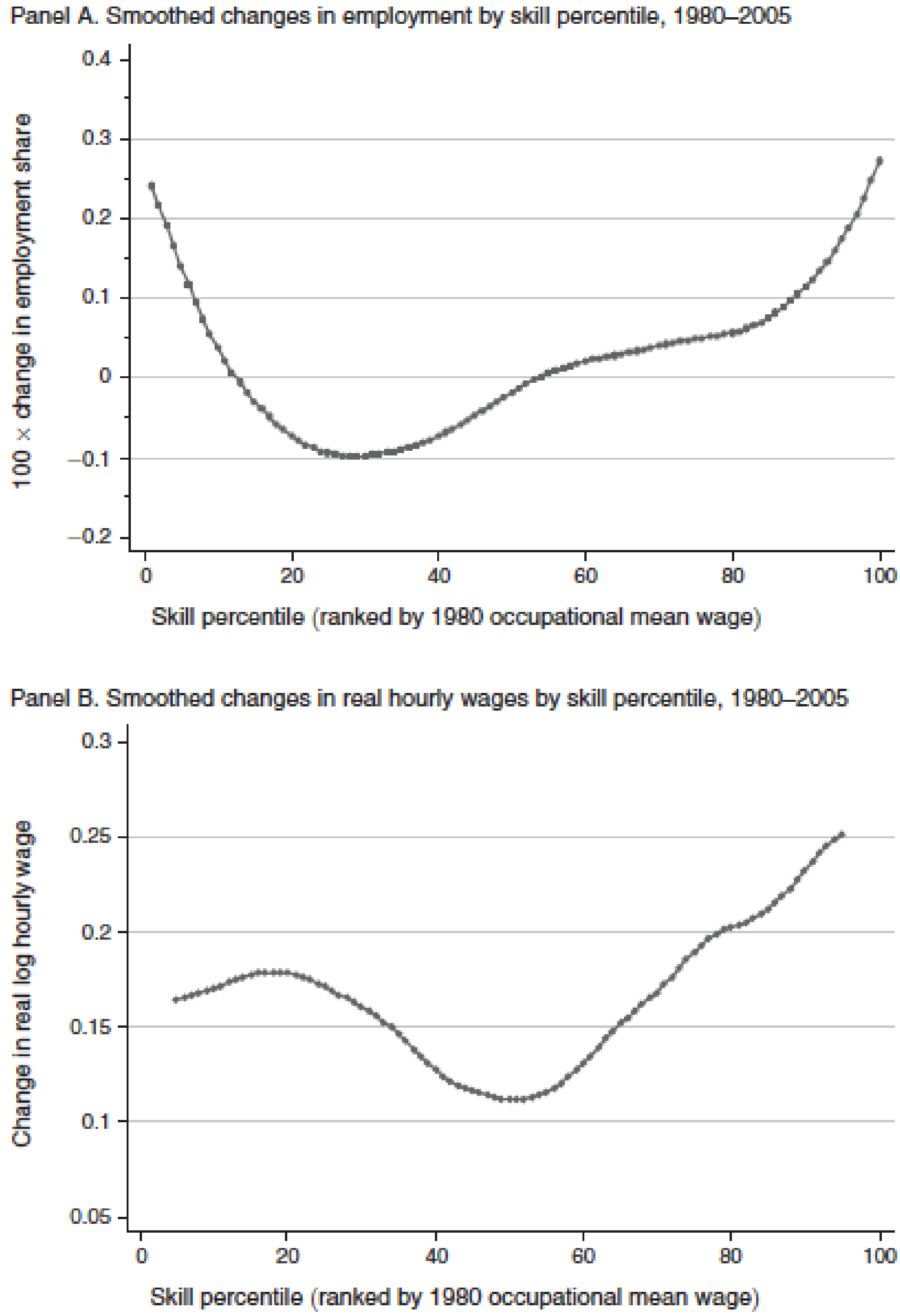
The routinisation hypothesis is regarded as a plausible explanation of both employment and wage polarization within countries. This is because jobs that are routine-intensive are not evenly distributed across the skills and wage distribution. Whereas routine jobs tend to be concentrated in the middle, non-routine jobs tend to be concentrated on either tail of the distribution: non-routine manual jobs at the lower tail, and non-routine cognitive jobs at the upper tail (Goos & Manning, 2007; Acemoglu & Autor, 2011; Autor, 2015). Considering these distributions, technological development is understood to increase the demand of high-wage, high-skilled jobs (that tend to entail cognitive non-routine tasks) as well as low-wage, low-skilled jobs (that tend to entail manual non-routine tasks), while 'middling' jobs (that tend to entail both manual and cognitive routine tasks) are subject to automation risk and consequently experience a reduction in demand – i.e. employment polarisation. Aptly, Goos and Manning (2007) refer to this as "employment growth in lovely and lousy jobs and employment falls in middling jobs".

In Figure 1 we draw on Autor and Dorn (2013) and provide a graphical depiction of employment and wage polarisation in the US labour market. The top panel of Figure 1 shows the change in employment share between 1980 and 2005 for 318 occupations encompassing nonfarm employment ordered by increasing skill level.[8] Autor and Dorn (2013) note that employment changes during the period were strongly u-shaped in skill level, with relative employment gains at the 'lousy job' and 'lovely job' tails of the distribution, and relative employment decline in the middle of the distribution. Correspondingly, the bottom panel, showing wage growth by skill percentile, also exhibits a u-shaped pattern, with the greatest gains in the high skill upper tail, modest gains in the low skill lower tail, and substantially lower gains in the middle (Autor & Dorn, 2013). This pattern of job polarisation is further evident in other advanced economies, such as the United Kingdom (Goos & Manning, 2007) and sixteen European Union economies (Autor, 2015).

[7] Autor (2014) notes that there are exceptions to this: For example, GPS and scheduling software allow truckers to minimise wasted milage, calendar and contact software allow home health workers to more effectively manage time and bill hours, and computerised ordering systems allow food service workers to rapidly tally customers' tabs. However, in the case of these exceptions, the information-intensive tasks are largely secondary to the occupations' core tasks.

[8] Skill level is approximated by the mean log of wages of workers in each occupation in 1980.

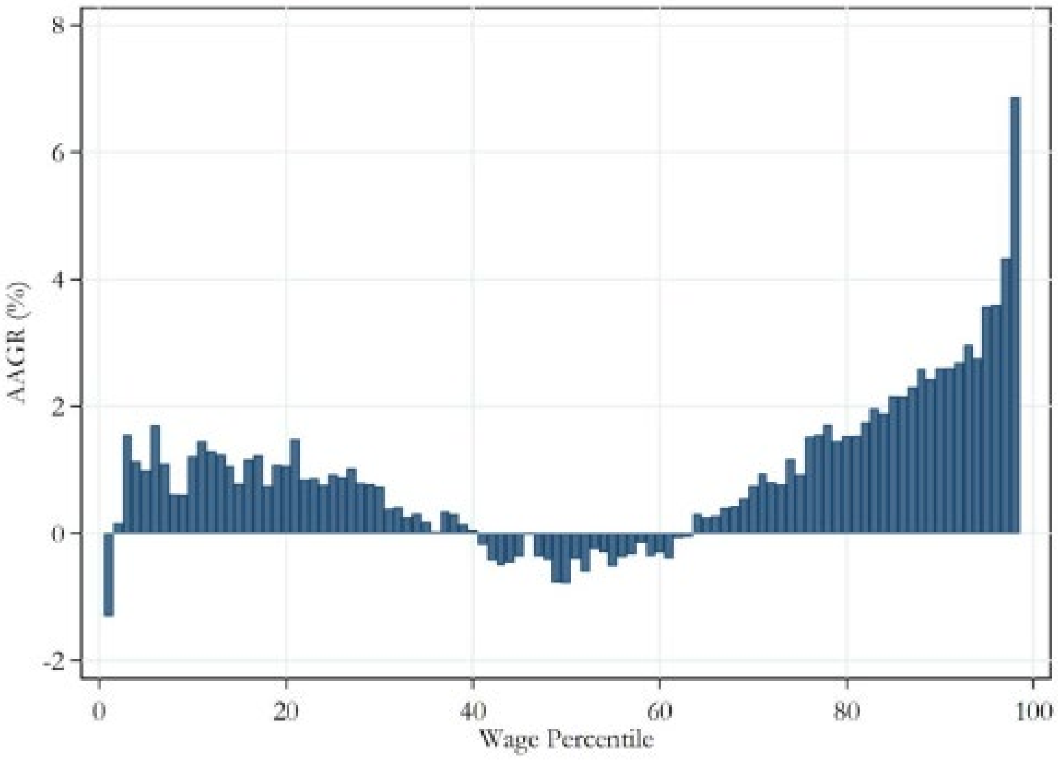
Figure 1: Smoothed Changes in Employment and Hourly Wages, 1980-2005



Source: Autor and Dorn (2013, Figure 1).

While labour market polarisation in advanced economies is well-established in the empirical literature, Maloney and Molina (2016) observe that polarisation is, for the most part, not evident in developing country labour markets. However, recent work by Bhorat et al. (2020b) shows a pattern of wage polarisation in the South African labour market, where they provide evidence of a U-shaped wage growth pattern across the distribution. This is evident in Figure 2, which shows the average annual growth rate of real monthly earnings, for every year over the period 2000 to 2015, plotted across wage percentiles for all employees in South Africa. The authors note specifically that wages in the middle were undermined "not only by a decline in mining and manufacturing, but also because increasing automation undermined returns to routine work", whereas "increasing returns to the highly educated performing non-routine tasks continue to reinforce growth at the top" (Bhorat et al., 2020b).

Figure 2: Annual Average Growth Rate of Real Earnings for Employees in South Africa, 2000-2015



Source: Bhorat, Lilenstein, Oosthuizen and Thornton (2020b, Figure 1).

However, Autor (2015) notes that wage polarisation need not always occur, but may only occur in certain labour markets. This is because several relevant forces (such as complementarity forces, demand elasticity, and labour supply – not discussed here) affect cognitive and manual tasks differently in different economies, partially because of variation in labour force characteristics. This leads us into our next discussion on empirical evidence in both the developed and developing world.

2.4 Routinisation in the developed and developing world

As alluded to above, one of the primary findings of the literature is that across the world, the relative share of routine-intensive jobs has decreased (presumably because such jobs are subject to automation and outsourcing), while the relative share of non-routine jobs has increased (Lo Bello et al., 2019; Lewandowski et al., 2019; Lewandowski et al., 2020). Such a finding is associated with several negative outcomes including rising wage inequality, and lower earnings and opportunities for low-wage, routine-intensive workers (Lo Bello et al., 2019), reflected in a significant growth in employment and wage polarisation in developed economies over the last 30 years (Acemoglu & Autor, 2011; Hardy et al., 2016). For these countries in particular, the empirical literature is rich with findings.

As previously discussed, the literature shows that employment is shifting from routine-intensive to non-routine-intensive occupations which are currently difficult to automate. The types of skills used across these occupations of course varies. In the UK, Goos and Manning (2007) find evidence of significant growth in the 'lousy' (manual, non-routine) as well as 'lovely' (cognitive, non-routine) jobs, with a significant decline or hollowing-out amongst 'middling' jobs, particularly in manufacturing.

Dicarlo et al. (2016) show that high-skilled occupations such as managers and professionals tend to engage in higher analytical and interpersonal tasks, whereas plant operators and craft workers tend to engage in higher routine tasks. Importantly, they show that these patterns are similar in several developed economies.

However, Acemoglu and Autor (2011) highlight that employment polarisation does not only reflect changes in the composition of skills available, but also changes in how different skill groups are allocated across occupations. In this light, Autor and Dorn (2013) find that a significant share of employment and wage polarisation in the US over the last few decades is attributable to rising employment and wages in service occupations. That is, in line with Autor et al.'s (2003) routinisation hypothesis, they show that as the real cost of technology has declined, the demand for low-skill workers to be engaged in routine tasks has decreased, reducing their wages, leading to these workers reallocating their labour supply from middle-income manufacturing to low-income service occupations which tend to be manual and non-routine in nature and are thus difficult to automate. This is substantiated by Autor and Dorn (2013) who observe substantial growth in the demand for low skill service occupations in the US – for example, child care, food preparation and serving, cleaning, janitorial and maintenance work, and in-person health assistance. Autor (2015) notes that the demand for manual non-routine work appears to be relatively income elastic, and thus rising aggregate incomes, which are concentrated in the upper tail of the income distribution marked by those working in cognitive non-routine task intensive occupations, tends to increase the demand for these activities. Thus, he contends that technology-driven productivity growth in other parts of the economy may indirectly increase the demand for manual non-routine work activities by increasing aggregate societal income.

Within- and between-occupation transitions have received considerably more attention in the literature. Mealy et al. (2018) use a novel approach to measure the similarity between jobs in terms of the tasks they have in common. Intuitively, they find that workers in the US are significantly more likely to shift into jobs with similar tasks relative to their current job. However, they emphasise that this explains just 9 percent of variation in the probability of transitioning between jobs, which highlights that there are other important factors at play.

Although the majority of studies have tended to focus on developed countries, there is a growing body of work on developing countries. Evidence on changes in the nature of work in developing and emerging economies is, however, mixed (Lewandowski et al., 2019). This is not necessarily unexpected. The effects of automation may be different in developing countries for several reasons, such as different occupational compositions and the net effect of offshored jobs from developed countries (Maloney & Molina, 2016). Moreover, the labour force in developing countries tends to be relatively less formally educated which could affect the allocation of routine and non-routine work (Lewandowski et al., 2019). Importantly, Lewandowski et al. (2020) suggest one should expect different skillsets and tasks to be used differently across occupations between low-, middle-, and high-income countries. Indeed, there is evidence that routine-intensive jobs as a share of national employment are negatively associated with GDP per capita, whereas the opposite holds for non-routine-intensive jobs (Aedo et al., 2013; Lo Bello et al., 2019; Lewandowski et al., 2020). This implies that more jobs in developing countries tend to be more routine-intensive relative to developed countries. Indeed, Apella and Zunino (2017) found that the task content of jobs in Argentina and Uruguay are more similar to jobs in Central and Eastern European (CEE) countries, relative to richer countries.

In line with trends in developed countries, however, there is some evidence of job de-routinisation in developing countries (World Bank, 2016). Hardy et al. (2016) document that all CEE 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. In another study in which South Africa was included, Lewandowski et al. (2020) find that the average RTI 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. Moreover, it seems that the relationship between economic development and RTI may vary by occupation group. Lewandowski et al. (2019) show that (i) high-skilled occupations are more routine-intensive in poorer countries, but (ii) the routine-intensity of middle-skill occupations (like clerical workers) and low-skill occupations (like plant and machine operators and assemblers) is not systematically related to countries' levels of development. It seems that analyses which use more detailed data paint a more nuanced picture.

2.5 Automation and the future of work

It is not disputed that automation has substituted a significant number of routine-intensive tasks, and will continue to replace many workers' jobs in both developed and developing countries. Fears of automation-induced technological unemployment continue to dominate debates around the future of work, especially in relation to industrial sectors (World Bank, 2019). The rapid pace of technological development today – greatly improved computing power, big data, artificial intelligence, and robotics – have led to automation spreading to domains commonly defined as non-routine which have, until now, largely remained a human domain. This increases the possibility of job substitution on a scale not yet observed (Brynjolfsson & McAfee, 2011; Autor, 2015; Frey & Osborne, 2017). Arguably, the scope for such substitution may however be bounded because of the many tasks that people, and not machines, can understand tacitly and accomplish effortlessly – a constraint Autor (2015) refers to as "Polanyi's paradox" after the economist, philosopher, and chemist who in 1966 observed "We know more than we can tell". The question is whether such a constraint will be overcome.

The expanding capabilities and declining costs of technology today, such as artificial intelligence and machine learning, will generate entirely new possible uses for robots, allowing them to substitute an increasing number of routine tasks. However, although robots are still not able to sufficiently substitute for the depth of human perception, the boundary that is non-routine tasks may soon be overcome. Indeed, many technological innovations in recent years are largely attributable to efforts to turn non-routine tasks into well-defined problems (Frey & Osborne, 2017), suggesting that Autor et al.'s (2003) routinisation hypothesis may not continue to hold. What are then the implications of these changes on wage and employment polarisation? Autor (2015) suggests that while many middle-skill jobs are at risk of automation, employment polarization need not continue indefinitely. As history suggests, the extent of automation risk will likely vary over time. There is some evidence that manufacturing technologies were skill-complementary in the early 1900s, but not prior (Goldin & Katz, 2008), and that in the 1800s, technical change often "replaced – rather than complemented – skilled artisans" (Acemoglu & Autor, 2011).

Of course, the distribution of future automation within countries will likely vary by sector. It is estimated that currently, more than two in every three robots in the world are employed in the automotive, electronics, and metal and machinery industries (World Bank, 2019). Advances in robotics technologies in particular since the 1980s have allowed manufacturing firms to automate a wide range of production tasks, such as machining, welding, and assembling (Acemoglu & Restrepo, 2018). Typically, low-income countries of the past have gradually shifted employment from agriculture to manufacturing. However, given the concentration of automation within the industry, manufacturing in developing countries might be expected to generate fewer jobs relative to the past. In this light, many developing countries may need to search for alternative growth models and upskill workforces in response to new technologies. One important policy response may be to help workers gain the skills which new technologies complement, and not those which it replaces (Millington, 2017). Whether the labour market effects of these technologies are fundamentally different to those in the past, however, remains an open-ended question (Atack et al., 2019).

While the potential risk of automation affecting the emergence and growth of manufacturing industries in developing countries is real, Kucera and de Mattos (2020) contend that this risk may be overstated, and that a more nuanced perspective is required. A key concern for developing economies looking to industrialise, is the prospect of firms in advanced economies using automation technology to ‘re-shore’ manufacturing production back to their home markets. Further, this sense of risk is more apparent in developing countries. Studies applying the method of Frey and Osborne (2017) report very high levels of routine work in developing countries, since employment shares in these high risk routine task intensive occupations are relatively high in developing countries. However, Kucera and de Mattos (2020) note that a distinction needs to be made between whether a job *could be* automated and whether a job *will be* automated. The former refers to technological feasibility – whether a robot can perform a task – while the latter is an economic consideration that is based on the relative cost of labour, and whether investing in automation is at least as profitable as prevailing production processes. Adopting a case study approach – focusing on the apparel and electronics industries – they find that analyses pointing to the high risk of automation facing developing countries is overstated. The measures used in these studies do not take into account technological bottlenecks involved in automation (e.g. tasks that may appear routine for humans may in fact be very difficult for machines), and they underscore the skills involved in certain tasks and simply equate low skill with low pay.

Despite substantial disruptions, technology is at the same time creating opportunities to create new jobs encompassing new tasks in new sectors (World Bank, 2019). In some existing sectors, jobs are being replaced, but in others, robots are complementing the productivity of workers and creating jobs as it alters the demand for goods and services. It is intuitive that this cluster of effects will likely vary across countries of varying levels of economic development. It is widely documented that in the South African context, the minority of workers who are well-paid and highly skilled easily obtain jobs that are secure and well-regulated, whereas the majority of workers face much more insecure conditions (Bhorat et al., 2020). Such labour market outcomes are largely determined by educational outcomes. To ensure labour supply keeps up with demand, one apparent approach is to prioritise policy that aims to improve educational attainment and quality (Lo Bello et al., 2019). However, the appropriateness of country responses likely depends on a wide variety of factors.

2.6 Concluding Comments

While the automation of production, and the substitution of labour, has been a pattern of industrial progress since the industrial revolution, it is clear that the sustained decline in the price of computer capital in recent decades is driving a new wave of automation, computerisation and digitisation. With respect to the manufacturing sector, the impact of these technologies is evident in employment and wage polarisation with the ‘hollowing out of the middle’, which is characterised by a predominance of manufacturing sector occupations. More specifically, the empirical literature points to both declining employment shares and stagnant wage growth in the middle of the skill distribution, within which many routine task-intensive manufacturing occupations reside. These labour market trends are best observed through the lens of the routinisation hypothesis, and consequently, this report applies a methodological approach that has emerged from the empirical literature on the routinisation hypothesis. As such, we use the task content of occupations to provide insight into the potential employment displacement effects of 4IR technologies on the MER sector. It is worth noting that while the impacts of automation, computerisation and digitisation – the de-routinisation of the labour market – are evident in advanced economies, the evidence is mixed, and thus less clear, in the case of developing economies. This can be partly explained by, amongst other things, the labour force in developing countries tending to be relatively less formally educated, which could affect the allocation of routine and non-routine work (Lewandowski et al., 2019), and the distinction between technological feasibility and economic considerations (Kucera and de Mattos, 2020).

3 DATA AND METHODOLOGY

This report is focused on estimating the effects of technologies related to the fourth industrial revolution on labour market outcomes in the MER sector at the occupational level. This research objective is achieved using the following method: Firstly, the concept of occupational relatedness based on occupations' task content is used to illustrate the occupational structure of the MER sector labour market. Second, given this occupational structure, additional measures of task content are used to identify which MER sector occupations are at high risk of employment displacement effects. These measures of task content include measures of, amongst others, the importance of conducting repetitive tasks; thinking creatively; establishing and maintaining personal relationships; controlling machines and processes; coaching and developing others; and the like.[9] Generally speaking, these measures provide insight into fourth industrial revolution technologies including, for example, mechanisation of labour; artificial intelligence; interaction of labour with digital processes – specifically as regards data analysis; and the ability of labour to interact with technologies that are subject to further digitisation and development in the future. Third, labour market survey data is used to analyse the characteristics of MER sector workers who are employed in these high-risk-of-displacement occupations.

Two datasets are used in the analysis: Firstly, the Occupational Information Network (O*NET) database (detailed in Section 3.1), and secondly, the Post-Apartheid Labour Market Series (PALMS) database (detailed in Section 3.2). The O*NET dataset provides occupation level task content information required to, firstly, compute a measure of relatedness between occupations, which is used to inform the occupational structure of the MER sector labour market (detailed in Section 3.5), and secondly, compute a routine task intensity index, which is used to measure the potential risk of employment displacement at the occupation level (detailed in Section 3.6). The South African labour force survey data, contained in PALMS, allows one to focus the analysis on the MER sector labour market. Further, PALMS contains individual-level characteristics, which allows one to assess the characteristics of workers in occupations at high risk of displacement as a result of fourth industrial revolution technologies. The mapping of the O*NET task data to PALMS labour market data is relatively complex due to differences in the nomenclature used, and is detailed Section 3.3 below. These data are then aggregated at the occupational level, with the resultant dataset containing all of the task content and individual characteristics required to perform the analysis outlined above (detailed in Section 3.4).

3.1 Occupational Information Network (O*NET) Dataset: Task Data at the Occupation Level

The Occupational Information Network (O*NET) is a dataset drawn from a United States survey of a comprehensive set of occupational descriptors based on labour market demands such as work activities, abilities, and work context (O*NET, 2020). Almost 1 000 standardised occupations are included in the database, which is compiled based on input from a wide range of employees in each occupation, and moderated by a set of occupational analysts. The usefulness of these data lies in the extent of the descriptors available, as well as the fact that these data are reported so as to allow quantitative comparisons across occupations for each descriptor. These data are freely available to the public and are updated on an annual basis in the 3rd quarter of each year. The latest version is O*NET 25.0 Database from August 2020, which is used in this report.

The O*NET occupation descriptors used in this analysis include Work Activities, Abilities, and Work Context modules, with the Work Activities module containing data on tasks performed at the occupation level. While all three modules are used to compute the RTI, only Work Activities are used to measure occupational relatedness.

Work activities are generalised statements based on the aggregation of a set of 19 450 detailed task statements. The aggregation method is qualitative in nature and involves the grouping of tasks into

[9] A full list of the skills included in this calculation are listed in Table A1 in the appendix.

clusters based on similarities in activity, objects, purpose, context, and technology (Hansen et al., 2014). Thereafter, precise activity statements are formed to reflect these shared characteristics and differentiate between activity statements. There are three levels of activity statement contained in the O*NET database – detailed, intermediate, and generalised – and this report makes use of generalised work activities. There are 41 unique work activities in the data, which include activities such as: handling and moving objects; inspecting equipment, structures, or material; and thinking creatively. The abilities database consists of 20 different abilities, which include elements such as oral comprehension, written comprehension, and deductive reasoning. The O*NET data has occupation level information on both the `level' and `importance' for each of the work activities and abilities. 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.

There are also 20 alternative types of work context and for each of these a set of values (or context categories). 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 that reported that value. These frequencies sum to 100.

One obvious concern with using O*NET data is the applicability of the descriptors to developing country labour markets, such as South Africa. While these labour market data are drawn from the US economy, work by Hardy, Lewandowski, Park and Yang (2018) has shown that they are acceptable for use in the developing country context. Of course, a drawback remains when using the O*NET data to assess the impact of the fourth industrial revolution in South Africa: As much as the data may be broadly appropriate for skill analysis in a developing country, it will be impossible to extract South African-specific information regarding the advent of fourth industrial revolution technologies without further input from industry. For example, it will be impossible to determine whether the list of occupations listed as being at risk of employment displacement is truly reflective of the South African situation without input from industry stakeholders and experts. As a result, the reader is advised to further interrogate the results presented below within the context of the South African labour market.

3.2 Post-Apartheid Labour Market Series database: Labour Force Survey Data

The PALMS dataset, developed by Kerr, Lam & Wittenberg (2020), covers a harmonised series of South African labour force survey data for the years 1995 through 2019. The original data for the series are based on nationally representative cross-sectional labour force surveys conducted by Statistics South Africa. These include: the October Household Surveys (1995-1999), Labour Force Surveys (2000-2007), and Quarterly Labour Force Surveys (2008-present). The harmonised nature of the variable definitions contained in the PALMS dataset makes it particularly useful for studies of the South African labour market over time.

The analysis in this report is restricted to the period corresponding with the use of the Quarterly Labour Force Survey, which has a sample size of approximately 30 000 dwellings and 70 000 individuals. To deal with issues of seasonality and unexpected shocks, we average the data across the four quarters of 2018. The use of the 2018 data is motivated by the fact that the 2018 data is the most recent in which all four quarters of the QLFS are present in PALMS. This allows us to average over a much larger set of observations, thus improving the accuracy of the estimates. This is especially important when dealing with disaggregated occupation level data.

In order to align the analysis with the MER sector labour market, we restrict the sample to wage earners in the formal sector aged between 15 and 64. We map the manufacturing element of the MER sector to the PALMS dataset, and thus further restrict our sample to this subset of the broader South African manufacturing sector. This mapping is informed by merSETA's 2020 Sector Skills Plan, which lists the three-digit Standard Industrial Classification Codes (SIC) that fall within the MER sector (merSETA, 2020).[10]

3.3 Linking Datasets – Crosswalks

The dataset used in this report is compiled by combining the O*NET database of scores for work activities, abilities, and work context with the PALMS database. This process is undertaken by making use of a set of `crosswalks' that bridge the gap between the two different occupation nomenclatures, namely, the 8-digit Standard Occupational Classifications 2010 (O*NET-SOC10) used in the O*NET data, and the 4-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 (IBS, 2016; O*NET, 2020). The merging of O*NET and PALMS datasets was successful with a 94 percent match when considering ISCO-88 occupations codes at the 4-digit level. Occupations are dropped where O*NET data is missing, resulting in a list of 339 occupations. An adjustment is made to some of the occupation labels to account for differences in PALMS ISCO-88 4-digit occupation labels and those used in the crosswalks, however, this makes no material difference to the analysis.

3.4 Aggregating data to the occupation level

The final dataset, combining O*NET and PALMS data, is aggregated to the occupation level, since this is required to compute a measure of occupational relatedness, and develop the occupational structure of the labour market as described in Section 3.5. In addition, the RTI is calculated at the occupation level as per Section 3.6. The resultant dataset contains information about task content and labour market characteristics at the occupation level. It should be noted that a disaggregated version of the O*NET-PALMS data is used when analysing the characteristics of individuals employed in certain occupations at high risk of automation.

The aggregation process with respect to the O*NET task content variables is to use the mean values for importance, level, and frequency. These are later combined to create measures of occupational relatedness and the RTI. The mean of the gender variable (1 = female and 2 = male) for each individual in a given occupation is also used. Given the fact that the MER Sector is, on aggregate, male-dominated, a more meaningful relative value, indicating relative abundance of males or females in a given occupation, is used. Simply put, the MER Sector is made up of approximately 71.2 percent male employment, which means that the majority of occupations would employ more than 50 percent men. Taking this into account, the relative measure indicates whether a particular occupation is relatively more female-dominated, more male-dominated, or approximately on par with the MER Sector average gender distribution.

The age characteristic is aggregated by dividing individuals into two groups – youth (15 to 34 years) and non-youth (35 to 64 years) – and taking the mode of the two groups for each occupation. Level of education is treated similarly, with each occupation being assigned an education level based on the modal value for all individuals employed in that occupation. At the conclusion of this process, the occupation level dataset consists of 142 occupations, each with aggregate labour market characteristic and occupational descriptor information.

3.5 Occupational Relatedness and the Occupation Space

The occupational relatedness method applied in this report closely follows that applied in Mealy, Rio-Chanona and Farmer (2018).[11] Using task content data from the O*NET database, which provides

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[10] There are Standard Industrial Classification codes that fall within the retail and construction industries. Since the focus of the analysis is on the manufacturing sector, these are excluded from the sample.

[11] Similar approaches have been applied by Alabdulkareem, Frank, Sun, AlShebli, Hidalgo and Rahwan (2018) who explore how workplace skills drive job polarisation and wage inequality, and Nedelkoska, Diodato and Neffke (2018) who analyse whether the current wave of automation will result in technological unemployment.

information on work activities (aggregation of tasks) for specific occupations, we measure the relatedness between occupations. This approach deems occupations to be closely related if they have a large overlap in work activities (aggregation of tasks), whereas unrelated occupations have few work activities (aggregation of tasks) in common.[12] By calculating the degree of relatedness between occupations we are able to depict the occupational structure of the MER sector labour market using a network mapping called the occupational space. In this network mapping occupations are represented by nodes, and the edges, or lines, joining them together represent the degree of commonality in the work activities (aggregation of tasks) undertaken between the pair of occupations. Occupations which are highly related, or those with many work activities (aggregation of tasks) in common, are closely linked to one another in the network forming clusters of related occupations. For example, biochemists and material scientists conduct similar tasks, and are thus measured as related, while maintenance workers and human resource specialists conduct disparate tasks, and are thus measured as unrelated. We use this information to compute a set of occupational similarity measures.

The strength of this novel approach to viewing the occupational structure of the MER sector lies in its ability to depict the relationships between occupations in a single snapshot which enables one to clearly view the connections between occupations in a way that is intuitive. In identifying prominent clusters of occupations within these networks it is possible to gain insight into how work trends are spread amongst occupations in the MER sector, as well as how occupations relate to one another based on an overlap in the tasks that they perform. Further, we superimpose occupation level measures, including the routine task index (detailed below) and select labour market characteristics onto the occupation space, and thus provide a detailed occupation level graphical depiction of the MER sector labour market with respect to these labour market characteristics.

It is worth noting that we deviate marginally from Mealy et al. (2018) when generating a measure of relatedness between sets of occupations – i.e. the proximity measure. While the proximity measure used in Mealy et al. (2018) is based on a binary vector where elements = 1 if a work activity (aggregation of tasks) is undertaken by an occupation, and = 0 otherwise, this is not appropriate in our case. Instead of a binary measure capturing the presence of a work activity (aggregation of tasks) for a given occupation, we employ a continuous measure derived from data on both the `level' and `importance' of each work activity (aggregation of tasks) to each occupation – an average importance score. While we do not convert this continuous variable into a binary variable, as is recommended in Mealy et al. (2018), an adjustment is made to ensure that only work activity (aggregation of tasks) that are relatively important for a given occupation are used to calculate the similarity between occupations. In our case, this is achieved by using a modified version of what Mealy et al. (2018) call the Relative Importance Indicator (RII). This is formalised in Technical Box 1.

[12] As detailed in Section 4, we use the work activities data from O*NET as an occupation level measure of tasks. Work activity data represent an aggregate measure of tasks by occupation.

Technical Box 1: Calculating the Relative Importance Indicator

The Relative Importance Indicator used in this analysis is based on Balassa's (1965) definition of Revealed Comparative Advantage and the Relative Importance Indicator (RII) as defined by Mealy, del Río-Chanona and Farmer (2018).

The RII represents the ratio of two measures as follows:

Firstly, the importance rating for work activity (aggregation of tasks) $\boldsymbol{w}$ for a given occupation $\boldsymbol{i}$, represented by $\mathbf{X}_{\boldsymbol{w},\boldsymbol{i}}$, compared to the sum of the importance ratings for all work activities (aggregation of tasks) for occupation $\boldsymbol{i}$.

Secondly, the sum of the importance ratings of a work activity (aggregation of tasks) w for all occupations compared to the importance ratings across all occupations and work activities (aggregation of tasks).

The RII can be interpreted as the importance of a work activity (aggregation of tasks) for a given occupation relative to its overall importance for all occupations. The mathematical definition of the RII is as follows:

$$\mathbf{RII}_{\boldsymbol{wi}} = \frac{\mathbf{X}_{\boldsymbol{w},\boldsymbol{i}}}{\sum_w \mathbf{X}_{w,i}} \Big/ \frac{\sum_i \mathbf{X}_{w,\mathrm{i}}}{\sum_{w,\mathrm{i}} \mathbf{X}_{w,\mathrm{i}}} \tag{1}$$

where $\mathbf{X}_{w,i}$ is the importance rating given to a single work activity (aggregation of tasks) for occupation $\boldsymbol{i}$; $\sum_w \mathbf{X}_{w,\mathrm{i}}$ is the sum of the importance ratings for all work activities (aggregation of tasks) across a single occupation; $\sum_i \mathbf{X}_{w,\mathrm{i}}$ is the sum of the importance ratings for a single work activity (aggregation of tasks) across all occupations; and $\sum_{w,\mathrm{i}} \mathbf{X}_{w,\mathrm{i}}$ is the sum of the importance ratings assigned across all occupations for all work activities (aggregation of tasks).

Once the relative importance of each work activity (aggregation of tasks) for each occupation is determined using the RII, the occupational similarity measure is computed. This similarity between occupations is based on the proximity measure, which calculates the pairwise conditional probability of two occupations performing the same work activity (aggregation of tasks). Only work activities (aggregation of tasks) for which the RII is ≥ 1 are considered, as these are flagged as being relatively important for a given occupation. For example, as the `getting information' work activity (aggregation of tasks) is highly important for both biochemists and material scientists, it is highly probable that these occupations will be very similar. On the other hand, as the `repairing and maintaining mechanical equipment' work activity (aggregation of tasks) is not important for human resource specialists, but is very important for maintenance workers, there is a low probability that these occupations are related. It is with this information that proximity measures are calculated for each pair of occupations, and transformed into a proximity matrix as is detailed in Technical Box 2. This collection of all proximities forms the basis for building the MER sector occupational space – a network map showing the occupational structure of the MER sector.

Technical Box 2: Calculating the proximity between occupations

If two occupations are engaged in the same work activity (aggregation of tasks) where the relative importance of that activity (aggregation of tasks) is high (RII $\geq$ 1), then these occupations are said to be related. Conversely, if occupations do not share similar work activities (aggregation of tasks) then it is less probable that they are related.

Based on the conditional probability that work activity (aggregation of tasks) $\boldsymbol{w}$ is performed by occupation $\boldsymbol{i}$ and is relatively important, given that it is performed by occupation $\boldsymbol{j}$ and is relatively important, $\mathbf{P}\left(\mathbf{RII_i} \geq \mathbf{1} \middle| \mathbf{RII_j} \geq \mathbf{1}\right)$, and vice versa for $\mathbf{P}\left(\mathbf{RII_j} \geq \mathbf{1} \middle| \mathbf{RII_i} \geq \mathbf{1}\right)$, it is possible to calculate a measure of proximity between two occupations as follows[13]:

$$\boldsymbol{\phi}_{\mathbf{i,j}} = \mathbf{min}\ \{\mathbf{P}\left(\mathbf{RII_i} \geq \mathbf{1} | \mathbf{RII_j} \geq \mathbf{1}\right); \mathbf{P}\left(\mathbf{RII_j} \geq \mathbf{1} | \mathbf{RII_i} \geq \mathbf{1}\right)\} \tag{2}$$

All pairwise proximity values are then arranged in a symmetric proximity matrix, $\boldsymbol{\Phi}$, which is used to construct the occupational space.

Source: formula adapted from Hidalgo et al. (2007); Allen et al. (2019); and Allen and Bhorat (2020).

To build the occupational space, representing the occupational structure of the MER sector, network analysis is applied to the symmetric proximity matrix. The result is a set of x and y co-ordinates that are used to plot out the occupational space network map, a process which is expounded upon in Technical Box 3.

Technical Box 3: Building the occupational space

Based on work by Mealy, del Río-Chanona and Farmer (2018), a network map is developed to depict the occupational structure of the MER sector. The use of network analysis to generate the occupational space has its foundation in the product space method by Hidalgo et al. (2007), which was later adapted by, among others, Hausmann et al. (2014).

The occupational space is required to satisfy two conditions as described by Hausmann et al. (2014). Firstly, no occupations should be independent of the network. In other words, all nodes should be connected. This is achieved using a Maximum Spanning Tree (MST) of the proximity matrix which is calculated using Kruskal's algorithm. The MST serves the purpose of connecting all nodes in the occupational space using the least numbers of links, or edges, with the highest possible weights – in this case the proximity measures are used as weights.

The resultant network is not densely populated, including only those edges represented by the highest proximities. In order to achieve a less sparse occupational space, the links with a proximity measure above a selected proximity threshold are included in the network. This ensures that the links with the strongest proximities are included in the network to provide a more comprehensive representation of the MER sector occupational structure. The rule of thumb applied by Mealy, del Río-Chanona and Farmer (2018) is that the proximity threshold, $\boldsymbol{\alpha}$, should be approximately 1 standard deviation higher than the mean proximity measure $< \boldsymbol{\phi}_{\mathbf{i,j}} >$. In this case $\boldsymbol{\alpha}$ = 0.55 which is approximately equivalent to Mealy, del Río-Chanona and Farmer's (2018) measure, but is slightly adjusted downward to account for outliers. The links for which $\boldsymbol{\phi}_{\mathbf{i,j}} > \boldsymbol{\alpha}$ are included back in the occupational space.

Secondly, the network needs to be relatively sparse so as to be able to distinguish key relationships between occupations. This is achieved by using a Directed Force-Spring layout as per the method followed by Hausmann et al. (2014). This adjustment causes nodes of the occupational space to repel one another, with edges acting as springs pulling the nodes back together. The force at which nodes are pulled back is positively related to

[13] As the proximity measure is related to distance, and a distance function defined on any metric space must be symmetric (Khamsi & Kirk, 2001), the minimum of these two conditional probabilities must be used to meet this requirement. In other words, a valid distance function, d, as defined between points x and y should satisfy the property that $d(x, y) = d(y, x)$ (Allen et al. 2019; Allen & Bhorat, 2020).

the proximity between a pair of occupations. In other words, the greater the proximity between two occupations the closer they are within the occupational space, as the pulling force results in shorter edges.

The interpretation of the occupational space network map is as follows: each node represents an occupation, with the length of the lines connecting them, or edges, being a function of the proximity between adjoining occupations. Connected nodes share similar work activities (aggregation of tasks) and are thus related, hence, shorter lines indicate greater proximity in work activities (aggregation of tasks). The size of the nodes is derived from the employment share of each respective occupation within the MER sector. Further, we shade the nodes according to the degree of risk to automation specific to a given occupation – the measure for which is discussed in the next sub-section. To provide more insight into the labour market characteristics associated with these occupations that vary in terms of the risk to automation, we also shade the nodes according to aggregate measures of gender, age, 1-digit occupation code, and education.

3.6 The Routine Task Index – Measuring the Risk of Employment Displacement

We create an occupation level Routine Task Index (RTI) as a proxy for an occupation's risk of suffering employment displacement as a result of technologies related to the fourth industrial revolution. Based on the Routine Biased Technical Change (RBTC) hypothesis put forward by Goos, Manning and Salomons (2014), or just simply, the routinisation hypothesis, we assume that tasks that are more routine in nature are more likely to be able to be replicated by a machine, computerised or digitised. As a result, an occupation that is more routine in its task content is more at risk of employment displacement effects.

The final RTI is constructed from a variety of intermediate indicators regarding the task content of an occupation. These intermediate indicators are formed by grouping measures present in the O*NET database together according to definitions put forward by Acemoglu and Autor (2011). These measures range across a variety of tasks that could be impacted by a varieity of 4IR technologies, including, but not limited to mechanisation and automation.[14] For example, an occupation where the tasks of establishing and maintaining personal relationships and being creative are important, is less likely to be digitised by technologies such as artificial intelligence. We make use of four intermediate indicators, namely: routine cognitive tasks, routine manual tasks, non-routine cognitive analytical tasks, and non-routine cognitive personal tasks.

Elements comprising these intermediate indicators include data from the Work Activities and Work Context files in the O*NET database. Elements in the Work Activities file 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 where 'importance' is assigned a weight of two-thirds, and 'level' a weight of one-third.[15] Work Context measures are captured by multiplying the reported frequency by level. This can be summarised in the system of equations (3a) to (3d) as follows:

$$r_{h,i} = \sum_{k=1}^{A_h} WA_{k,h,i} + \sum_{l=1}^{C_h} WC_{l,h,i} \tag{3a}$$

with components defined as

[14] A full list of the O*NET components used to define each intermediate indicator, as per these definitions, is provided in Table A 1 in the Appendix.

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

$$WA_{k,h,i} = \frac{\overline{WA}_{k,h,i} - WA_{\min}}{\max\left(\overline{WA}_{k,h,i} - WA_{\min}\right)} \tag{3b}$$

and

$$WC_{l,h,i} = \frac{\sum_{V_{i,l}=1}^{5}(V_{i,l} \times F_{V_{i,l}}) - 100}{400} \tag{3c}$$

where

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

Note that $WA_{\min}$ is the minimum value of the $\overline{WA}_{k,h,i}$ distribution. The transformations described in equations (3b) and (3c) 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 intermediate indicator for occupation i, and h represents the category of task under consideration.[16] 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 is simply to assist in equalising the weight of intermediate indicators in the construction of the final RTI, as without normalisation, the ranges of each individual intermediate indicator can vary substantially. A numeric example detailing the calculation of an intermediate indicator is presented in the Appendix for the interested reader.

Our chosen RTI is based on the formulation put forward by Lewandowski et al. (2019) and Lewandowski, Park and Schotte (2020). However, this formulation of the RTI omits routine manual tasks due to the incomparability of tasks across multiple countries. We opt to reinsert them in the construction of our RTI. This decision is based on the fact that in the MER Sector, manual tasks are likely to make up a substantial proportion of tasks, particularly for some of the more physical occupations, and the exclusion of measures of manual tasks would have led to mischaracterisation of occupations' routineness in the MER Sector. As a result, we opt to include a measure for routine manual tasks as defined by Acemoglu and Autor (2011), and we define our RTI in the following way in equation (4):

$$RTI_i = \ln\left(\frac{r_{cognitive,i} + r_{manual,i}}{2}\right) - \ln\left(\frac{nr_{analytical,i} + nr_{personal,i}}{2}\right) \tag{4}$$

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

This formulation of the RTI was then 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.

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

Following the method suggested by Lewandowski, Park and Schotte (2020), we subdivide our RTI into three mutually exclusive categories in order to categorise an occupation's risk of displacement. The RTI is divided as follows: occupations with a value of the RTI equal to or lower than the 25th percentile of the RTI distribution are classified as "non-routine". Occupations with an RTI between the 25th and 75th percentile (exclusive) of the RTI distribution, are classified as "intermediate". Occupations with an RTI above the 75th percentile of the RTI distribution are classified as "routine". Based on the routinisation hypothesis, we can think of so-called routine occupations as being at risk of displacement, while those that are non-routine are at low risk of displacement. Those occupations classified as intermediate in their routineness are classified as intermediate in their risk of displacement. The nodes (occupations) in the network map in Figure 7 below are shaded according to this categorization.

4 TECHNOLOGY AND LABOUR MARKET CHANGE: THE CASE OF THE MER SECTOR

In this section, we present the results of our empirical strategy for identifying occupations at risk of displacement according to the Routine Task Index (RTI) indicator described in Section 3. The main analysis in this section can be divided along three lines: Firstly, through the use of network analytics, we present the MER sector "occupation space" that graphically maps the structure of occupations within the sector. Secondly, we integrate a measure of routineness into our analysis to identify those occupations most at risk of employment displacement as a result of 4IR technologies. This section presents both a descriptive overview of displacement risk in the MER sector in general, as well as an analysis of the relatedness of routine and non-routine occupations through the MER sector occupation space. Finally, we present results that detail the characteristics of workers employed in at-risk occupations in order to better understand the types of workers who are likely to be disadvantaged by 4IR technologies. We conclude by presenting a conditional probability regression model that quantifies the risk of an individual finding themselves employed in an at-risk occupation, conditional on demographic and firm-level characteristics, as well as broader sectoral factors.[17]

4.1 The Occupational Structure of the MER Sector Labour Market

The MER sector occupation space, developed using network analytics discussed on Section 3.1, depicts the occupational structure of the MER sector labour market. The task content of occupations and the relatedness between tasks performed across all sets of occupations determines the structure of the occupation space. The MER sector occupation space, shown in Figure 3, depicts MER sector occupations as nodes. Occupations (nodes) are connected by an edge (line joining nodes) the length of which is a function of the similarity of the work activities (aggregation of tasks) performed by the two connected occupations. The size of each node represents the share of MER sector employment within each respective occupation. The nodes are shaded according to the 1-digit occupation code within which each occupation falls.[18]

The MER sector occupation space shown in Figure 3 exhibits a polarised MER sector labour market, which emphasises a clear dichotomy between production and non-production jobs.[19] The left-hand side of the occupation space shows a cluster of production occupations falling within the following 1-digit occupation categories: Craft and related trades (light green nodes); Plant machine operators and assemblers (purple nodes); and Elementary occupations (dark blue nodes). The right-hand side of the occupations space shows a cluster of non-production occupations falling within the following 1-digit occupation code categories: Legislators, senior officials and managers (yellow nodes); Professionals

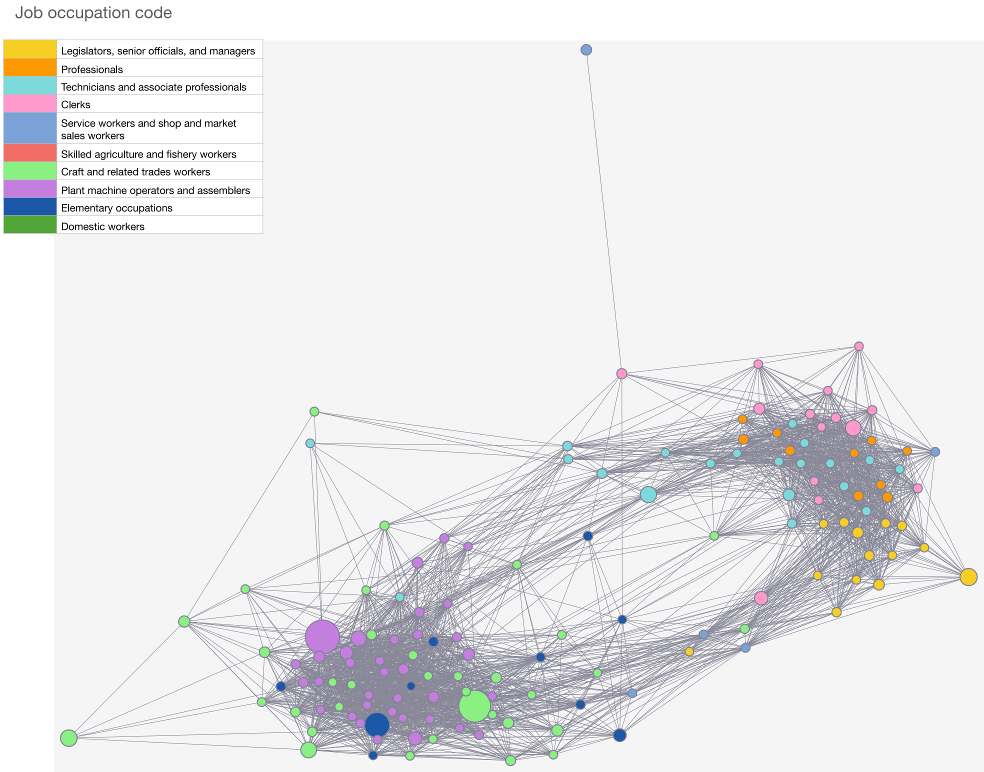
[17] Although this is the preferred specification for interpretive ease, a set of regressions with varying specifications are run to act as robustness checks.

[18] In the occupation spaces shown in the following sections, nodes are shaded according to worker characteristics, such as age, gender, routine task intensity and education.

[19] The structure of the MER sector occupation space is consistent with that of the Job Space developed by Mealy et al. (2018). This is expected since this paper adopted the same methodology.

(orange nodes); Technicians and associate professionals (light blue nodes); and Clerks (pink nodes). It is important to emphasise that it is the task content of occupations that is driving this dichotomy between production and non-production jobs

Figure 3: The MER Sector Occupation Space



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: 1. The 4-digit occupation, represented by a node in the map, falls within a 1-digit occupation grouping based on the mode value of 1-digit occupation categories within a 3-digit occupation.

One can draw a number of implications from the polarised occupational structure of the MER sector labour market: First, the two distinct occupation clusters suggest that shifts of the labour force within clusters is feasible but shifts across clusters is much harder. There is a growing literature that shows that workers are more likely to transition into new occupations that share similar work activities (aggregation of tasks) to that of their current occupation (Mealy et al., 2018; Alabdulkareem et al., 2018). This suggests that shifts within clusters of connected occupations is easier because the skill transition, to enable a worker to perform a relatively small number of new tasks specific to the new occupation, is short. Conversely, the jump across disconnected and distant clusters, and hence dissimilar tasks, is harder because the skill transition is longer (Nedelkoska, Diodato and Neffke, 2018). Second, if the risk of displacement is not randomly distributed across occupations, and instead high-risk occupations fall predominantly within one of the clusters, the ability of those workers to avoid technology-induced unemployment is much more difficult, since there is no short skill transition available to them. In the next section, we explore the risk of displacement expressed at the occupation level, and graphically represent this risk using the MER sector occupation space.

4.2 MER Sector Occupations at Risk

The polarised structure of the MER sector occupation space clearly indicates that there are two intrinsically different groupings of occupations present within the MER Sector – production and non-production occupations. The way these occupations cluster within the standard skill-classification of occupations is also of interest: low-skilled occupations (comprising elementary workers) are located on the production orientated left-hand side of the occupation space, while high-skilled occupations (comprising legislators, senior officials and managers, and professionals) are located on the non-production orientated right-hand side of the occupation space. Occupations that are classified as semi-skilled, however, span the entirety of the occupation space, but cluster according to the nature of the work done: production focused occupations, such as craft workers and machine operators, are located on the left side of the space, while non-production focused occupations, such as clerks, associate professionals and service workers, are clustered on the right of the space. This polarisation of the occupation space allows one to distinguish clearly between a set of production-centric occupations on the left side of the occupation space and a set of non-production occupations on the right side of the space.

Acemoglu and Restrepo (2018) point out that the type of automation that occurs in a market – whether among high- or low-skilled occupations – can have differential impacts on wage inequality, and as a result, inequality as a whole. Given the nature of South Africa's economy as one in which inequality is high, it is critical to consider where the risk of technology-induced displacement may be greatest, so that policy to combat wage inequality can be rolled out should the need arise.

The point of entry for this discussion concerning the risk of displacement, is the Routine Task Index (RTI) described in Section 3.6. In particular, the use of the Lewandowski, Park and Schotte (2020) classification of occupations into "routine", "intermediate", and "non-routine", allows us to conduct a high-level analysis of the displacement risk of the MER sector in general. In the interests of contextualising the discussion to follow, Table 1 presents a brief overview of both total and at-risk employment levels for each of the MER Sector chambers estimated from the PALMS data.

The estimates in Table 1 show that between 2010 and 2018, the MER sector has seen a decline in overall employment levels, with approximately 80 500 jobs being lost over this period.[20] The largest absolute decline in employment occurred in the Metal chamber, which accounted for approximately half of all jobs lost over the period. However, given that the Metal chamber is by far the largest of the MER sector chambers, it is unsurprising that the majority of jobs lost would originate here. Relatively speaking (in percentage terms), the Auto components chamber has experienced the greatest loss of employment between 2010 and 2018, with job losses of approximately 33.82 percent – 2.3 times higher than the chamber with the second highest relative job loss, Plastics.

[20] For the interested reader, estimates of actual employment numbers by chamber for all years between 2010 and 2018 are presented in Table A 5, in the Appendix.

Table 1: Total and at-risk employment by MER Sector chamber, 2010 and 2018

	Total employment				At-risk employment			
	2010	2018	Absolute change	Percentage change	2010	2018	Absolute change	Percentage change
Automotive	50,321	43,660	-6,661	-13.24	13,253	10,147	-3,105	-23.43
Auto components	58,850	38,947	-19,903	-33.82	30,075	17,042	-13,033	-43.34
Metal	408,250	368,846	-39,405	-9.65	154,645	157,997	3,352	2.17
New Tyre	16,344	16,154	-190	-1.16	9,443	8,401	-1,041	-11.03
Plastics	100,086	85,650	-14,436	-14.42	55,778	44,509	-11,270	-20.20
Other	2,226	2,313	87	3.91	520	1,340	820	157.65
Total	636,077	555,570	-80,507	-12.66	263,714	239,436	-24,278	-9.21

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Note: 1. Figures may not add exactly to totals in final column due to rounding. 2. "Other" chamber represents employees in sectors that, according to SIC classifications, would fall into multiple MER Sector chambers. 3. At-risk employment defined to be those individuals employed in an occupation with an RTI above the 75th percentile of the RTI distribution.

Coupled with the decreasing level of overall employment in the MER sector, the absolute number of employees at risk of displacement has also decreased between 2010 and 2018. Although there is a general trend of at-risk employment decreasing for the MER sector, this is not the case for the Metal chamber, where levels of at-risk employment increased by approximately 3 300 employees (or 2.17 percent of 2010 employment levels). This result is a clear anomaly in the general trend, as all other chambers have experienced decreases in the relative levels of at-risk employment over the period in excess of 10 percent. Declining levels of at-risk employment, in the context of declining aggregate employment, is consistent with a narrative of employers laying off workers who are at risk of replacement by machines, as this would simultaneously decrease overall employment and decrease the number of workers employed in at-risk occupations. Thus, the Metal sector showing increased levels of at-risk employment, in the context of declining aggregate employment levels, could suggest that the process of adopting employment-displacing technology within this chamber has been slower than for the MER Sector in general. While this may have saved jobs in the short run, it is possible that the resultant 4IR technology adoption path for the Metal chamber in the future will be accelerated, potentially placing employees in this chamber at greater risk of displacement in the future.

Although interesting, absolute employment numbers for the MER sector, as estimated from the PALMS dataset, may not be entirely accurate, and thus must be treated with caution. The PALMS dataset is designed to be nationally representative (Kerr & Wittenberg, 2019), and as such, it is not immediately clear that employment estimates at the MER sector chamber-level will be precise. As a result, we opt to continue the analysis in this report considering shares of employment, as they represent more robust interpretations of results.

Simply by ranking the RTI from highest to lowest, it is possible to create a list of MER sector occupations ranked from most to least at risk of displacement.[21] Table 2 presents the top 10 most at risk or high-risk occupations in the MER sector for 2018, along with their relative share of employment both by chamber and total. The bottom line of Table 2 provides the relative employment share of each chamber in the MER sector as a comparator for the share of at-risk employment accounted for by each chamber (this figure is reported in the second-last line of Table 2). For the interested reader, Table A 4 in the Appendix presents results for the full list of 146 occupations in order of risk.

The New Tyre and Plastics chambers show disproportionately more risk of employment displacement than other chambers when considering the top 10 at-risk occupations. While the New Tyre chamber accounts for only approximately 2.89 percent of all MER sector manufacturing employment, it accounts for approximately 44.29 percent of the employment amongst the top 10 most at-risk occupations. Similarly, the Plastics chamber accounts for 26.41 percent of at-risk employment even though it only accounts for a total of 15.64 percent of all employment in MER sector manufacturing. Interestingly, although the Metals chamber employs workers in the highest absolute number of top 10 at-risk occupations (6), it seems to be disproportionately less at risk of displacing workers, accounting for only 20.72 percent of total at-risk employment amongst the top 10 occupations, compared to an approximate 66 percent share of total MER sector manufacturing employment. It is however worth noting that in level terms, the number of at-risk jobs in the metals chamber is substantial given the large size of the chamber (see Table A 5 in the Appendix).

[21] It must be noted that some occupations in the top 10 at risk list, and the broader list in the dataset, appear to be occupations that don't easily link with what one would expect in the MER sector. For example, Sewing-machine operators is an occupation one would expect to find in the apparel sector, not the MER sector. However, firms do not always fit neatly within industry classifications, but rather spread across multiple industries, and this in turn affects the occupations that spread across these industries. For example, an auto components manufacturer producing car seats, would need a sewing-machine operator to perform tasks that involve working with the seat upholstery.

Table 2: Top 10 occupations at risk of displacement in the MER sector, 2018

Rank	Occupation description	Share of total MER sector manufacturing employment per occupation by chamber (%)					
		Auto	Auto components	Metals	New Tyre	Plastics	All chambers
1	Textile-, fur- and leather-products machine operators not elsewhere classified	0.00	0.00	0.13	0.00	0.00	0.13
2	Woodworking-machine setters and setter-operators	0.00	0.00	0.05	0.00	0.00	0.05
3	Wood-processing-plant operators	0.00	0.00	0.09	0.00	0.00	0.09
4	Sewing-machine operators	0.00	0.05	0.00	0.00	0.14	0.19
5	Shoe-makers and related workers	0.00	0.02	0.00	0.00	0.00	0.02
6	Cement and other mineral products machine operators	0.00	0.00	0.04	0.00	0.00	0.04
7	Wood-products machine operators	0.00	0.00	0.05	0.00	0.00	0.05
8	Sewers, embroiderers and related workers	0.00	0.06	0.03	0.00	0.00	0.08
9	Rubber-products machine operators	0.00	0.03	0.00	0.83	0.31	1.16
10	Chemical-processing-plant operators not elsewhere classified	0.00	0.00	0.00	0.00	0.05	0.05
Share of total MER sector manufacturing employment accounted for by top 10 at-risk occupations (%)		0.00	0.16	0.39	0.83	0.50	1.87
Top 10 employment share as a proportion of total MER Sector top 10 employment share (%)		0.00	8.57	20.72	44.29	26.41	100.00
Total chamber employment as a share of total merSETA manufacturing		7.88	6.97	66.20	2.89	15.64	100.00

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).

Note: 1. Figures in body of table indicate the share of employment relative to total MER Sector manufacturing employment. Figures may not add exactly to totals in final column due to rounding. 2. Figures in the final column indicate the share of total MER Sector employment accounted for by a given occupation in percentages. 3. Numbers in the 3rd last row of the table indicate the proportion of total MER Sector manufacturing employment accounted for by the top 10 at-risk occupations, by chamber. Numbers in the 2nd last row are calculated as the share of total top-10 occupation employment (i.e. 1.93) accounted for by chamber. Figures in the last row indicate the relative employment share of chambers in the MER Sector, irrespective of risk category.

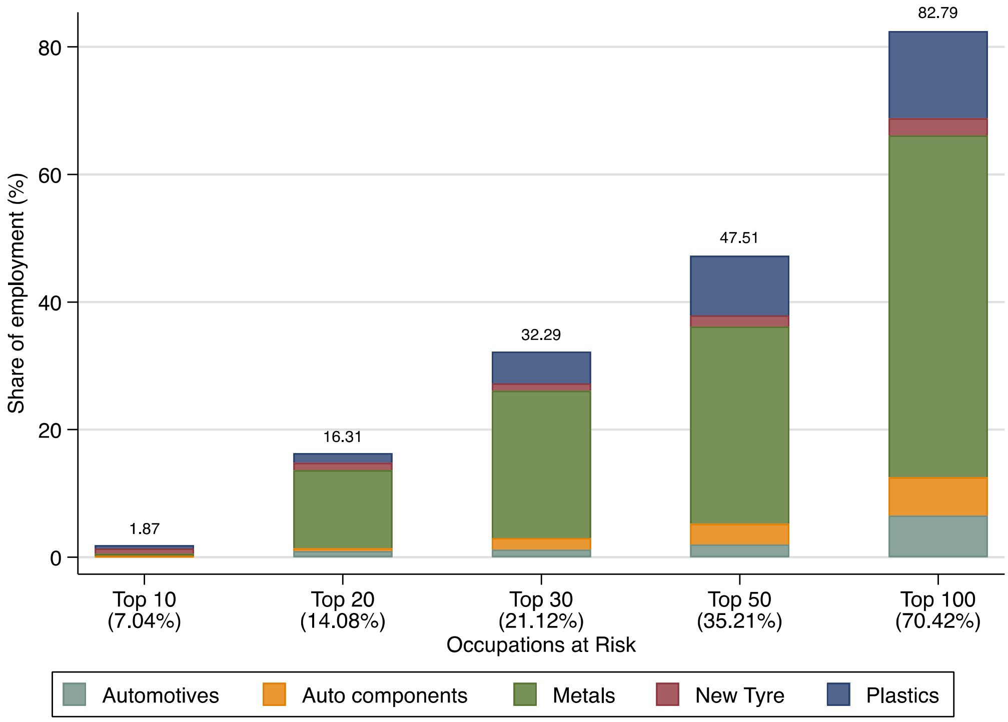
Although we can identify the chambers with the most jobs at risk of displacement within the MER sector, it is not immediately clear what the impact of 4IR technologies on employment in the MER sector is likely to be. The top 10 most at-risk occupations make up less than their proportional share of total MER sector employment, meaning that the employment displacement effects of 4IR technologies may be more modest than expected. To expand on this: the MER sector comprises a total of 142 disparate occupations, meaning that the top 10 occupations represent approximately 7.04 percent of this list. However, these top 10 at-risk occupations make up only 1.87 percent of total MER sector employment, with workers in the ninth most at-risk occupation (Rubber-products machine operators) making up approximately 62 percent of the total top 10 employment share. Put differently, if the top 7.04 percent of at-risk occupations were to be automated (i.e. the top 10 occupations shown in Table 2), the MER sector would only lose approximately 1.87 percent of all employment. This indicates, perhaps, that the impact of 4IR technologies on the MER sector is unlikely to have large negative employment displacement effects – at least not in the short run.[22]

When the list of most at-risk occupations is expanded as in Figure 4, an interesting result emerges: namely, that the largest proportion of high-risk employment is clustered in occupations that rank between 10th and 20th, and 20th and 30th, in terms of displacement risk as measured by the RTI. The share of total MER sector employment accounted for by the top 10 occupations remains relatively low, as discussed above. However, employment share in MER sector occupations increased by a factor of approximately 8.07 between the top 10 and top 20 most high-risk occupations, indicating that the adoption of 4IR technologies that impact these occupations would likely result in large employment displacement effects. Similarly, the employment share in MER Sector occupations increased by a factor of approximately 2 between the top 20 and top 30 most high-risk occupations.[23]

[22] Of course, these figures are relative shares only, and as a result could represent large numbers of jobs. In fact, 1.87 percent of total MER sector employment in 2018 is equivalent to approximately 10 389 jobs.

[23] Referring to Appendix Table A 4, these occupations include: Metal finishing-, plating- and coating-machine operators; Metal moulders and coremakers; Welders and flamecutters; Metal wheel-grinders, polishers and tool sharpeners; Plastic-products machine operators; Ammunition- and explosive-products machine operators; Machine-tool operators; Other machine operators and assemblers.

Figure 4: Share of employment in MER Sector occupations ordered by risk of displacement, 2018.

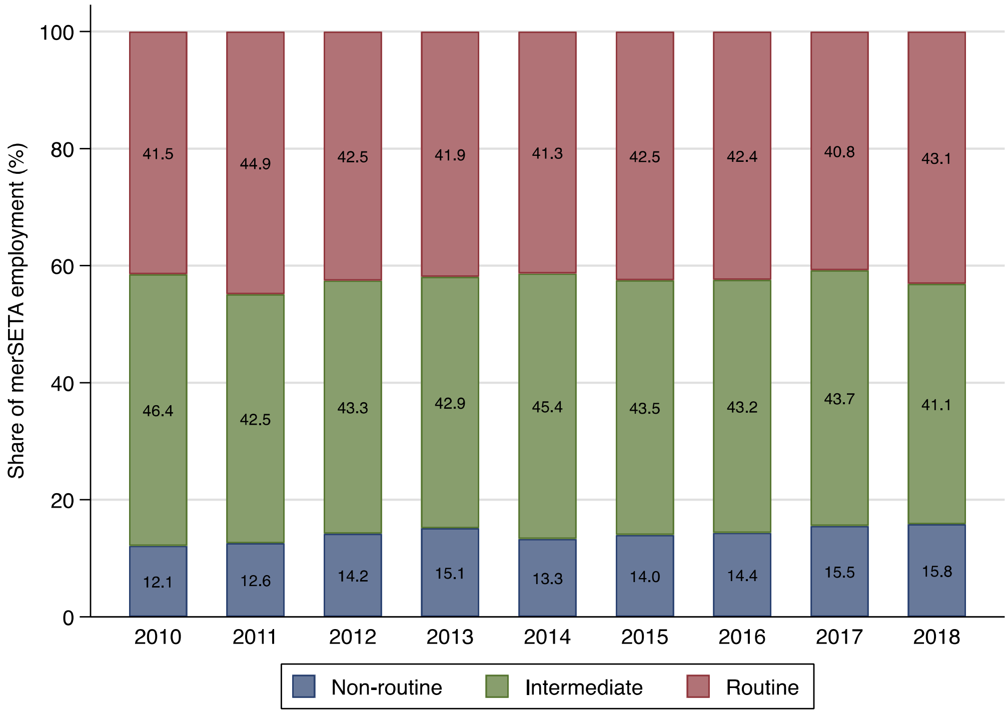


Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Note: 1. Figures in parentheses represent the proportion of the total 146 occupations represented in the MER Sector. 2. The figures above each bar represent the share of employment falling within each grouping.

Although the results above are only presented for 2018, there is little evidence to suggest that the proportion of workers employed in occupations with high risk of displacement has changed substantially over the past decade. In fact, Figure 5 shows the proportion of workers in the MER sector that are employed in occupations that would be classified as non-routine (low risk), intermediate (medium risk), or routine (high risk).[24] Those workers employed in routine occupations would be considered those most at risk of displacement according to the assumptions of the Routine-Biased Technical Change (RBTC) hypothesis put forward by Goos, Manning and Salomons (2014), or just simply, the routinisation hypothesis. Based on this assumption, we conclude that just more than 40 percent of workers employed in the MER sector work in occupations that are at a high risk of displacement, and that this proportion has been relatively constant since 2010.

[24] As discussed in Section 3.6, an occupation is classified as routine if it has an RTI value in excess of the 75th percentile of the RTI distribution in a given year; as intermediate if it has an RTI value between the 25th and 75th percentile of the RTI distribution; and as non-routine if it has an RTI value below the 25th percentile of the RTI distribution.

Figure 5: Employment shares at risk of displacement in the manufacturing MER Sector, 2010-2018



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Note: Occupations with an RTI below the 25th percentile of the RTI distribution are classified as non-routine, those above the 75th percentile as routine, and those in between as intermediate.

On the other hand, however, there seems to be a slow but steady increase in the proportion of workers who are employed in non-routine low risk occupations. This proportion has grown by approximately 31 percent from 12.1 percent of MER sector employment in 2010, to 15.8 percent in 2018.

These employment shares should be interpreted with caution, however, as the changes in employment shares are coupled with changes in the overall number of workers employed in the manufacturing MER sector. Employment in the manufacturing MER sector has shrunk by approximately 1.5 percent per annum, leading to a total decline in employment of approximately 80 500 individuals (see Table 1).[25] As a result, the relatively constant share of high-risk employees translates to a shrinking absolute number of employees at high risk of displacement over the past decade. Indeed, over the period 2010 to 2018, the absolute number of high-risk employees has shrunk by approximately 24 000 employees (see Table 1). Simultaneously, the number of employees employed in non-routine occupations has grown by approximately 10 700 over the period.

One possible explanation for these shifts in employment is that employees who have historically been employed in routine occupations at high risk of displacement could have been retrained and employed in occupations that are less routine, and thus less at risk of displacement. This is, however, purely conjecture as there is no evidence to support this claim. In fact, it is as yet unclear whether these changes in employment figures have been the result of routinisation pushing more vulnerable workers

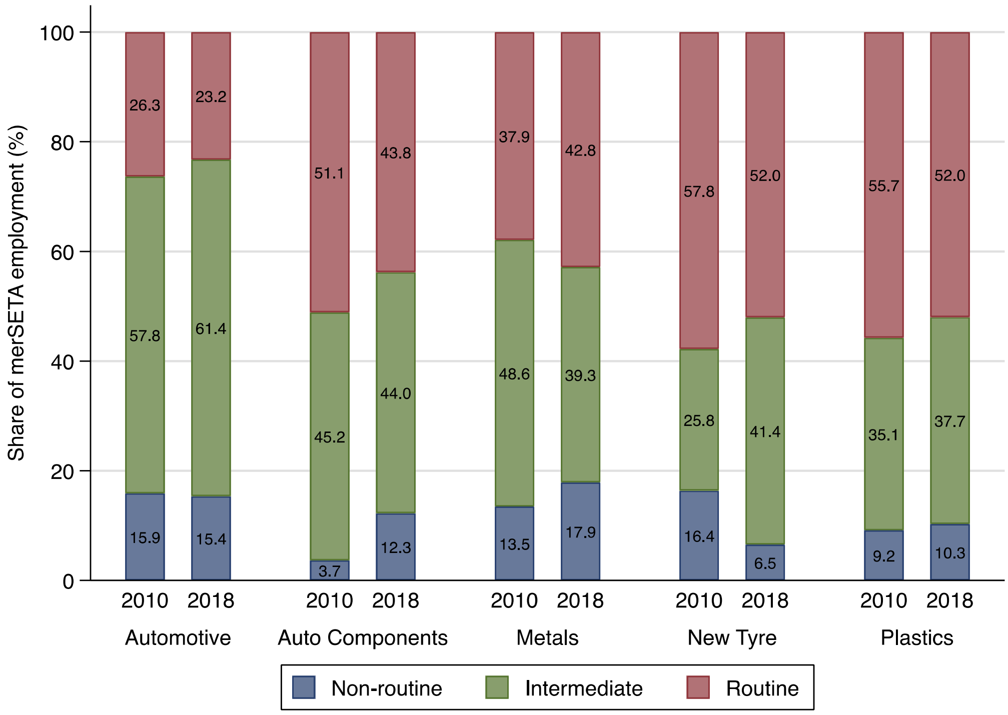
[25] See Appendix Table A 5 for estimates. It is important to note that these figures are derived from mapping the MER sector, using SIC codes that constitute the sector, to labour force survey data contained in the PALMS dataset. The estimates are thus subject to the sampling of the labour force survey and the survey weights.

into unemployment, vulnerable workers shifting into similar jobs outside of the MER Sector, or the retraining of vulnerable workers.

Analysing patterns of employment in high-risk occupations by chamber – depicted in Figure 6 – once again reveals that the New Tyre and Plastics chambers constitute the greatest share of high-risk employment in the MER sector. However, in both cases, the proportion of employment in high-risk occupations has decreased between 2010 and 2018 – by 10 percent and 6.6 percent of the New Tyre and Plastics employment shares in 2010, respectively. This translates to a decrease in high-risk employment of 1 041 and 11 270 individuals for the New Tyre and Plastics chambers, respectively (see Table 1).[26]

Combined with the fact that the Plastics and New Tyre chambers are both disproportionately represented in the top 10 at-risk occupations, these results may indicate a strong and persistent worker displacement process taking place in these chambers. In particular, if the Plastics and New Tyre chambers have seen the greatest decrease in at-risk employment share, but still feature heavily amongst the top 10 most at-risk occupations, one can conclude that the decrease in at-risk employment could be the result of shedding jobs in these high-risk occupations.[27]

Figure 6: Employment shares at risk of displacement in the manufacturing MER Sector by chamber, 2010-2018



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Note: Occupations with an RTI below the 25th percentile of the RTI distribution are classified as non-routine, those above the 75th percentile as routine, and those in between as intermediate.

Looking at the Metal chamber, the absolute number of high-risk employees actually increased over the period (see Table 1), and this is reflected in a rising share of high-risk employment in the Chamber,

[26] Again, the reader is reminded that these estimates of absolute employment changes may not be exactly accurate due to representativity concerns in the data, however, they provide a rough first look at the magnitude of employment effects.

[27] It is worth noting that analysis of such trends is best achieved using longitudinal panel data at the firm-occupation level. However, such data is scarce in the South African context.

shown in Figure 6. This result is interesting as it suggests that in the midst of declining employment levels, the Metals chamber has effectively protected jobs amongst those individuals who are employed in high-risk occupations. International evidence suggests that the metal processing industry has historically been well-suited to worker displacement through automation (Jämsä-Jounela, 2001). In light of this, the fact that routine workers have been spared job losses over the past decade in the South African context may indicate a lag in the adoption of 4IR technologies in the Metals chamber in the manufacturing MER Sector, or even the presence of strong trade unions who have negotiated with employers to save jobs at high risk of displacement.

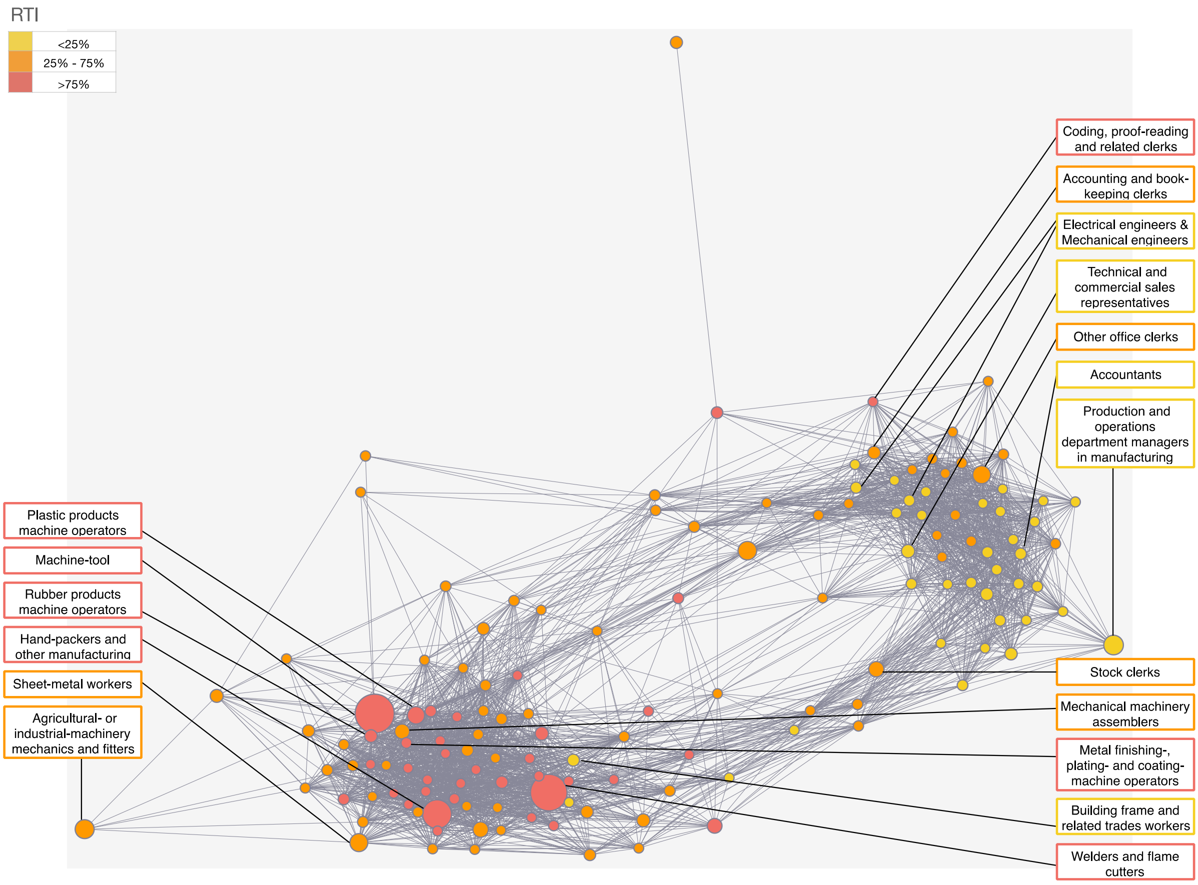
Coupled with the low levels of employment in Metal chamber occupations amongst the list of occupations most at risk of displacement, it does not seem that this slow adoption of 4IR technologies in the Metals sector is likely to be a precursor to accelerated worker displacement in the immediate future. However, the possibility exists that market competition will drive down the relative price of 4IR technologies for firms within this chamber, and thus lead to greater risk of displacement in the future – i.e. as Kucera and de Mattos (2020) contend, the economic conditions change, so as to incentivise adoption of 4IR technologies.

Considering the distribution of occupations across the MER sector occupation space, it is evident that jobs exposed to the effects of 4IR technologies are not distributed randomly across the space. In Figure 7, a clear dichotomy is evident across the aforementioned occupation clusters in the occupation space: occupations located in the left-hand production orientated cluster of the occupation space are decidedly more routine – and thus, at risk of displacement – than are occupations located in the right-hand non-production orientated cluster. This distribution of routine and non-routine tasks aligns strongly with the distribution of occupations by task content. Routine occupations are most commonly found amongst low- and semi-skilled occupations that focus on production processes, such as elementary workers, crafts workers and machine operators. In contrast, non-routine occupations are predominantly non-production related occupations, such as high-skilled management and professional occupations, as well as semi-skilled technical and associate professional occupations.[28] This suggests that 4IR technologies are likely to jeopardise low- to medium-skill employment in the production side of the MER sector, and correspondingly result in an increase in relative demand for high-skill non-production occupations – a result consistent with that predicted by Nokelainen, Nevalainen and Niemi (2018).

Furthermore, nodes (representing occupations) in the occupational space are sized according to the proportion of total MER Sector employment represented by a given occupation. It is thus of concern that the largest nodes in the occupational space are located in the high-risk left-hand production orientated side of the occupational space. Although results above have shown that the risk of displacement as a result of 4IR technology adoption in the MER sector is not necessarily immediate, this finding suggests that there is a significant proportion of individuals who could potentially be impacted by the routinisation of certain key occupations. These occupations, annotated in the graph below, are: Machine tool operators; Welders and flamecutters, and Hand packers and other manufacturing labourers. Together, these three occupations account for approximately 29.5 percent of total MER sector employment, and rank from 20th most at-risk to 33rd most at-risk of automation, and are all predominantly found in the Metal chamber. This result supports the finding that the Metal chamber could potentially experience accelerated displacement processes in the medium-term, and policy should be enacted in order to support potentially retraining these workers for related, less at-risk occupations.

[28] Low risk occupations located in the right-hand non-production orientated side of the occupation space include: Mechanical engineers; Personnel and industrial relations department managers; Technical and commercial sales representatives; Supply and distribution department managers; Accountants; Production and operations department managers in business services; and Electrical engineers.

Figure 7: The MER Sector Occupation Space - Routine Task Intensity



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
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.

Overall, when considering the propensity of the MER Sector towards employment displacement due to 4IR technologies, a few key results emerge: Firstly, the proportion of at-risk employment in the MER Sector has remained relatively constant at around 40 percent between 2010 and 2018. Given that this period was characterised by an aggregate decrease in MER Sector employment of approximately 80 500 jobs, it implies that the number of employees at risk of displacement has been decreasing, too.

However, the second key finding shows that this aggregate trend is not replicated when disaggregating by chamber. In fact, the Metal chamber has seen an overall increase in the number and share of at-risk employment, which could be the result of delayed adoption of 4IR technologies or labour market structures that protect workers from job loss in this chamber. This is of concern insofar as delaying technology adoption into the future may result in more significant displacement effects when the adoption processes start, particularly since the Metal chamber has been identified as being particularly well-suited to 4IR technology-induced automation in the past (Jämsä-Jounela, 2001).

It is not clear that this concern over accelerated employment displacement in the Metal chamber will have any short-run effects, however: When analysing the incidence of at-risk occupations in the MER sector, the Plastics and New Tyre chambers surface as being the most at-risk chambers in terms of displacement. These two chambers account for a cumulative 70.7 percent of employment amongst the top-10 at-risk occupations. Given that these two chambers cumulatively only account for 18.53

percent of total MER sector employment, this is indicative of a high relative risk of 4IR-driven worker displacement in these chambers.

Further, when considering the occupation space shaded by RTI value, it becomes clear that polarisation of the occupational space according to risk of displacement aligns closely with the polarisation of occupations according to task content. In particular, occupations that are classified as production orientated on the left-hand side of the space (including low- and semi-skilled production-focussed occupations) show greater propensity towards being at risk of displacement. On the other hand, however, non-production-orientated occupations (such as high-skilled occupations and some semi-skilled occupations, such as clerks and associate professionals) seem to be at lower risk of displacement when measured by RTI value.

Finally, the occupation space also provides an insight into the relative displacement risk faced by the MER Sector as a whole. Given that nodes in the occupation space are sized according to share of total MER Sector employment, the occupation space shows that there are a number of relatively large occupations that are at risk of displacement as a result of 4IR technologies. Although other results have indicated that displacement risk is modest in the short run, this result suggests that when the adoption of 4IR technologies in the MER Sector scales up, it is likely to have relatively large employment displacement effects. This would support greater intervention in the immediate future in order to assist in streamlining technology adoption processes in the future and mitigate disemployment effects.

4.3 Characteristics of MER Sector Occupations at Risk of Fourth Industrial Revolution Technologies – Descriptive analysis

The previous section focussed on identifying the occupations most at risk of employment displacement due to the adoption of 4IR technologies, as well as their relative share of employment and relative skill-level within the MER Sector. While this is useful for being able to identify specific occupations to target with skill interventions, it doesn't provide much insight into the demographic characteristics of the workers who are most likely to be affected. The adoption of 4IR technologies can have strong impacts on wage inequality amongst workers, and as a result, it can have large impacts on inequality more broadly (Acemoglu & Restrepo, 2018). In South Africa, inequality is particularly pronounced across certain demographic characteristics, such as race, gender, and age, to name a few. As a result, understanding the demographics of workers employed in high risk occupations – relative to low risk – allows for a greater understanding of how the fourth industrial revolution can impact on South African inequality as a whole.

The MER sector labour force is predominantly male. It is evident in Table 3 that, on average, approximately 70 percent of the MER sector manufacturing workforce is male. Further, this disproportionately male workforce has remained relatively unchanged over the period 2010 to 2018. It is also evident in Table 3 that, on average, employees in MER sector occupations are aged between 37 and 38 years – just above the age group defined as youth (15-34).

Table 3: Demographic characteristics of MER Sector occupations by risk of displacement, 2010-2018

	Non-Routine Low risk			Intermediate Medium risk			Routine High risk		Ratio (Routine to Non-Routine)	
	2010	2018		2010	2018		2010	2018	2010	2018
Age	37.84	38.49		37.14	38.01		37.80	38.69	1.00	1.01
Male	0.72	0.69		0.71	0.73		0.74	0.73	1.03	1.07
African	0.38	0.48	**	0.61	0.70	**	0.74	0.80	1.97***	1.68***
Coloured	0.14	0.09		0.15	0.12		0.15	0.14	1.04	1.57**
Indian	0.10	0.08		0.04	0.04		0.06	0.03	0.60**	0.39***
White	0.38	0.36		0.20	0.14	**	0.05	0.03	0.14***	0.09***
Years of education	12.67	13.39	**	10.73	11.44	***	10.10	10.32	0.80***	0.77***
Hours per week	41.73	42.61		42.53	42.26		42.69	43.18	1.02	1.01
Union	0.35	0.32		0.37	0.44	*	0.44	0.49	1.27*	1.51***

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).

Notes: 1. Occupations with an RTI below the 25th percentile of the RTI distribution are classified as non-routine (low risk), those above the 75th percentile as routine (high, and those in between as intermediate. 2. *** p<0.01, ** p<0.05, * p<0.1 3. Stars in the first three panels of the table denote the significance of a t-test on the equality of mean descriptive statistics between 2010 and 2018 within a given category of occupation (Non-routine, Intermediate, or Routine). Stars in the final panel of the table (Ratio panel) represent whether the value of the chosen descriptive statistic for individuals in routine occupations is statistically significantly different from the value of the descriptive statistic for individuals in non-routine occupations – equivalently, whether the ratio is statistically significantly different from 1.

Regarding the racial make-up of the MER sector workforce, a number of patterns emerge: First, the average proportion of African individuals employed in MER Sector occupations, particularly in non-routine and intermediate occupations, has increased. Given the negative correlation between increased risk of displacement and increased skill level, as described above, this result may suggest an upskilling of African workers in the MER Sector. Second, even with an increased prevalence of African workers employed in non-routine occupations, there is still a relative overemployment of White individuals in these roles compared to the distribution of individuals in the population. Third, it is clear that the share of African workers in routine tasks is consistently and significantly higher than the share employed in non-routine tasks, while the opposite is true for White workers. This speaks to African individuals facing a significantly greater risk of displacement due to 4IR technologies than White individuals, who are relatively sheltered from this same displacement effect, given their employment patterns. In 2018, for example, the share of African individuals employed in routine occupations was approximately 1.68 the share of African individuals in non-routine occupations. Put differently, this means that for every 100 African individuals employed in non-routine occupations, 168 are employed in routine occupations. Conversely, for White individuals, for every 100 White individuals employed in non-routine occupations in 2018, approximately 9 are employed in routine occupations.

For those occupations with relatively low risk of technological displacement, average education levels have risen significantly over time, while average education levels for employees in routine occupations has remained largely unchanged. Between 2010 and 2018, non-routine and intermediate occupations in the MER Sector have seen a significant increase in the average years of education – almost a full year more of education – of employees. Strikingly, irrespective of the year under analysis, the average education level across routine occupations in the MER Sector is approximately 80 percent of the level in non-routine occupations, and this difference is highly significant. This suggests that policies promoting the upskilling of workers across the MER Sector may assist in protecting workers against displacement in the future.

Over the past decade, there has been a trend of increased unionisation amongst workers employed in routine occupations in the MER Sector. The ratio of average proportion of unionisation amongst employees in routine occupations relative to that of non-routine occupations increased from 1.27 to 1.51 between 2010 and 2018, although this ratio is only significantly different from unity in the latter year. This pattern of increased unionisation of employees in routine occupations may partially explain the absolute increase in employment of workers in high risk occupations in the metal sector (discussed in the previous sub-section).

On the whole, according to the bivariate analysis presented in Table 3, we can conclude that an individual in 2018 is most likely to be at risk of technology-led displacement in the South African MER Sector if they are African or Coloured, unionised and with low levels of education. Employees with these characteristics are statistically significantly more likely to find themselves in routine occupations. There is also a marginally greater chance of being at risk of displacement if an employee is male; this finding is not, however, statistically significant. On the other hand, employees who are least likely to find themselves in occupations at risk of automation are White, more highly educated and non-unionised.

Decomposing demographic characteristics of routine and non-routine occupations by chamber reveal how the profile of workers at high risk of displacement differs across the various MER Sector chambers. Table 4 presents the ratio of demographic characteristics in routine occupations relative to non-routine occupations by chamber for 2018.[29] Values in Table 4 represent the ratio of the descriptive statistic of interest in a routine occupation relative to a non-routine occupation. In other words, if the value in the table is greater (smaller) than 1, then an individual with the characteristic in question is more (less)

[29] Exact values for each demographic characteristic by risk category are presented in Table A 6 in the Appendix.

likely to find themselves in a routine occupation at risk of displacement due to the adoption of 4IR technologies.

Certain results apply across all five chambers of the manufacturing MER Sector: African individuals are relatively more highly represented in routine occupations relative to non-routine ones, while the opposite is true for White individuals. Furthermore, all chambers are subject to a significant gap in average years of education required by individuals in routine relative to non-routine occupations. These results are relatively consistent in size and significance to the results presented for the aggregate MER sector, meaning that no one chamber stands out as particularly unequal in any of these aspects. Furthermore, the general trends in the demographics of individuals in occupations most at risk of displacement are broadly consistent across chambers.

However, individuals with certain characteristics stand out as being more at risk of displacement in certain chambers than others. For example: in the Metals, Plastics and New Tyre chambers, men are statistically significantly more likely to find themselves in occupations at risk of displacement than women, while in the Auto components chamber, the opposite is true. Broadly speaking, then, this suggests that African and Coloured men with lower educational attainment and who are members of a trade union are most at risk of being displaced by 4IR technology in the Metals, New Tyre and Plastics chambers. In the Auto components chamber, on the other hand, individuals most likely to be at risk of displacement are African and Coloured women with lower educational attainment and who are members of a trade union. Analogously, in the Auto chamber, there is no real gender or union effect, and we instead find that African and Coloured individuals of any gender, with lower educational attainment, are more likely to be in occupations at risk of displacement.

Table 4: Ratio of demographic characteristics for routine to non-routine occupations by chamber, 2018

	Auto	Auto Components	Metals	New Tyre	Plastics
Age	0.96**	1.00	0.99	0.94**	0.98
Male	0.98	0.81***	1.08***	1.25***	1.08*
African	1.75***	1.86***	1.92***	2.10***	1.79***
Coloured	2.00***	1.59***	1.29***	0.88	1.61***
Indian	0.27***	0.43***	0.31***	0.13***	0.41***
White	0.08***	0.09***	0.11***	0.14***	0.11***
Years of education	0.76***	0.76***	0.78***	0.78***	0.79***
Hours per week	0.99	1.00	1.02**	1.02	1.04***
Union	1.01	1.49***	1.59***	1.29**	1.53***

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: 1. Occupations with an RTI below the 25th percentile of the RTI distribution are classified as non-routine, those above the 75th percentile as routine, and those in between as intermediate. 2. *** p<0.01, ** p<0.05, * p<0.1 3. Stars represent whether the value of the chosen descriptive statistic for individuals in routine occupations is statistically significantly different from the value of the descriptive statistic for individuals in non-routine occupations – equivalently, whether the ratio is statistically significantly different from 1.

There is marginal evidence of a tendency towards younger individuals being less likely to find themselves in occupations at risk of displacement. Although this finding is statistically significant in some cases, the ratios all range from 0.94 to 1.00, indicating a practically small difference in average ages. As a result, we do not believe the magnitude of this effect to be large enough to be concerned with.

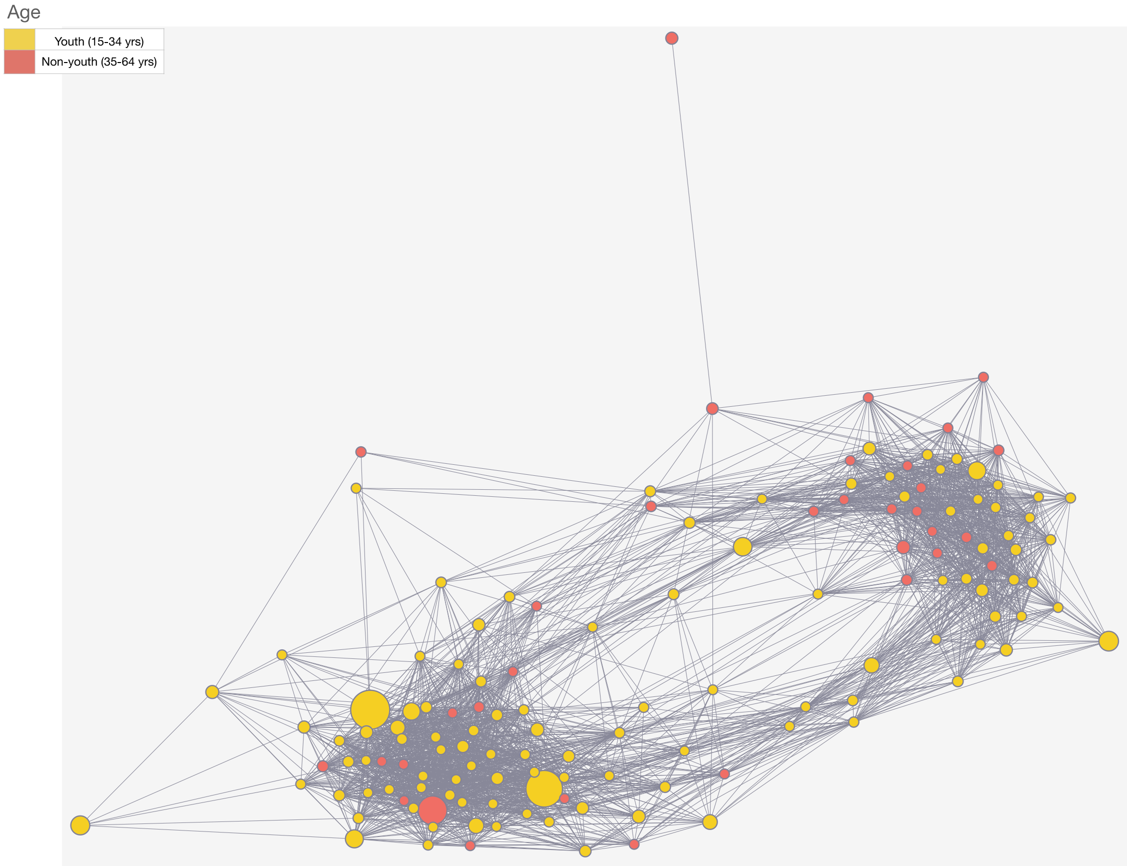
Finally, the ratio of employee unionisation in routine occupations compared to non-routine occupations differs substantially between chambers. The New Tyre and Metals industries have the greatest relative unionisation rates amongst routine occupations, at 1.59 and 1.53 times their non-routine occupation rates, respectively. Of particular interest here is the fact that the Metals chamber also showed a trend of protecting at-risk employment between 2010 and 2018. Evidence suggests that in the long run the presence of strong unions may actually expedite future displacement due to automation processes as a result of unions raising the relative cost of labour to capital (Parolin, 2020). These two facts in conjunction raise concerns about employment displacement effects in the Metals chamber moving forward, especially since the Metals chamber is the largest of the MER Sector's five manufacturing chambers. As a result, policy to protect workers from technology-led displacement in the Metals sector should be considered a priority in order to avoid a mass displacement due to automation of routine occupations in the future.

We now shift focus to how the demographic trends identified up to now fit into the occupation space mapping, starting with the distribution of employment by age group – youth and non-youth. In Figure 8, nodes in the occupation space are coloured based on the modal age category of individuals employed in a given occupation.[30] In other words, the shading of nodes corresponds to whether a particular occupation is youth-dominant or not.

Consistent with the results of there being no particular correlation between average age of employees in a given occupation and risk of displacement, the colouring of nodes by age category is not showing any particular patterns of clustering. There is a slightly greater proportion of youth-dominant occupations with greater overall employment shares on the left-hand production-orientated side of the occupation space, which corresponds to those occupations more at risk of displacement. This would speak to the chamber-specific results of youth being more at risk of dispalcement in the Metals, Automotive, and New Tyre chambers, but once again, it is not immediately clear that there is any aggregate employment displacement being faced by youth in the MER Sector.

[30] Employed individuals within each occupation are sorted into two age categories – youth and non-youth – and then the occupation node is shaded according to the modal age category. An occupation is shaded as youth if most of the employed within that occupation are categorised as youth. Youth and non-youth are defined as those aged 15 to 34, and 35-64 years of age, respectively.

Figure 8: The MER Sector Occupation Space – Age



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: 1. Occupations are shaded yellow (red) if the mode value of those employed favours youth (non-youth).

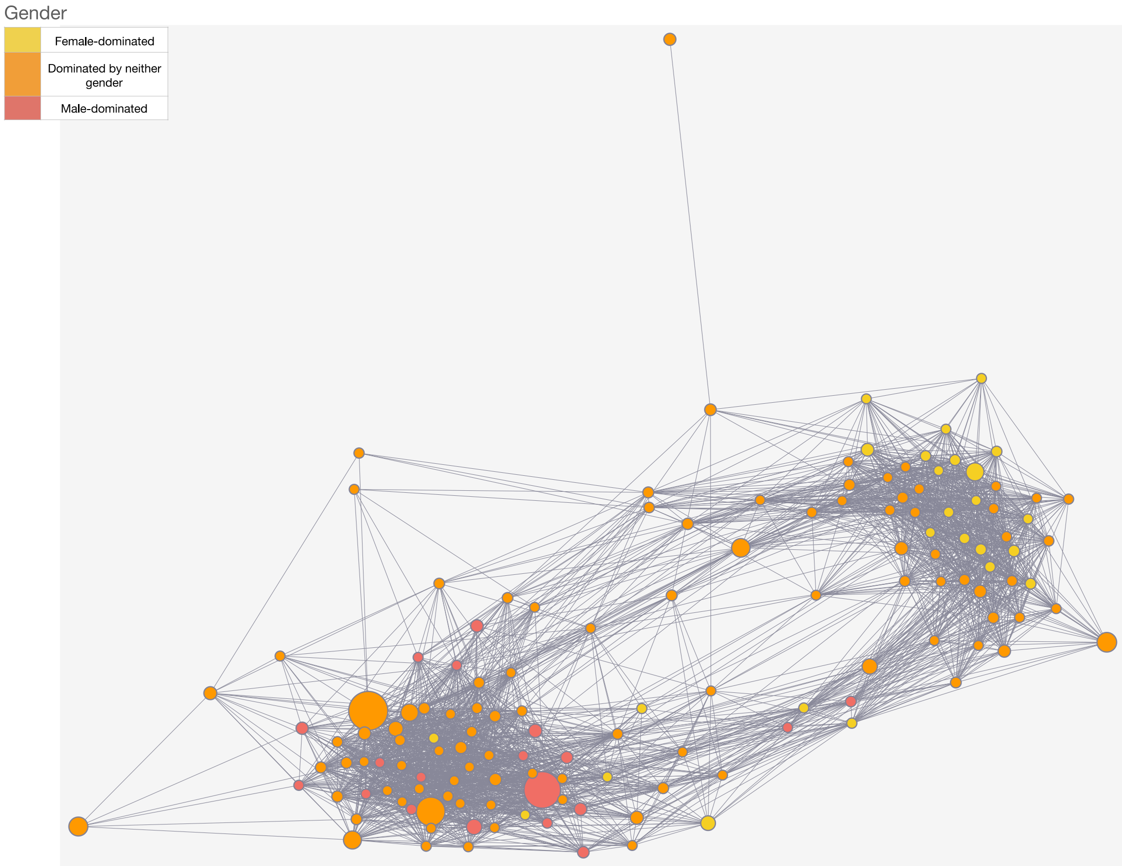
Figure 9 shows the occupation space with nodes coloured by the relative proportion of each gender employed in a given occupation. Note, however, that these nodes do not indicate whether a given occupation employs females *in the majority*. Rather, because of the fact that the MER Sector is, on aggregate, male-dominated, the nodes are coloured by the relative abundance of males or females in a given occupation. Simply put, the MER sector is made up of approximately 71.2 percent male employment, which means that the majority of occupations would employ more than 50 percent men. Taking this into account, the nodes of Figure 9 are instead coloured to represent whether a particular occupation is relatively more female-dominated, more male-dominated, or approximately on par with the MER Sector average gender distribution.[31]

When considering the occupation space coloured by gender, there is some evidence that occupations that are more female-dominated than the average occupation in the MER Sector are in general less likely to be at risk of displacement than occupations that are more male-dominated. This can be seen by the relative clustering of female-dominated nodes on the right-hand non-production orientated

[31] To ensure clarity on the shading of the nodes in this product space, we present the following numeric example. The average occupation in the MER Sector employs 71.2 percent men, and this has a standard deviation of approximately 26.0 percentage points. In practice what this means is that occupations that hire between 0 percent and 45.2 percent men are considered to be female-dominated compared to the average MER Sector occupation (and are thus shaded as female-dominated); occupations that hire between 45.2 and 97.2 percent men are considered to be generally on par with the average MER Sector occupation (and are thus shaded as equal); and occupations which employ between 97.2 and 100 percent men are considered to be relatively male-dominated compared to the average MER Sector occupation (and are thus shaded as male-dominated).

side of the occupation space, while the male-dominated occupations cluster more on the left-hand production orientated side of the occupational space. This result is corroborated when looking at the gender ratios of routine to non-routine occupations as reported in Table 3, however, the result was not found to be statistically significant. Although statistically insignificant, this result is still interesting as one can infer from it that men are more likely to be at risk of displacement due to the adoption of 4IR technologies than women.

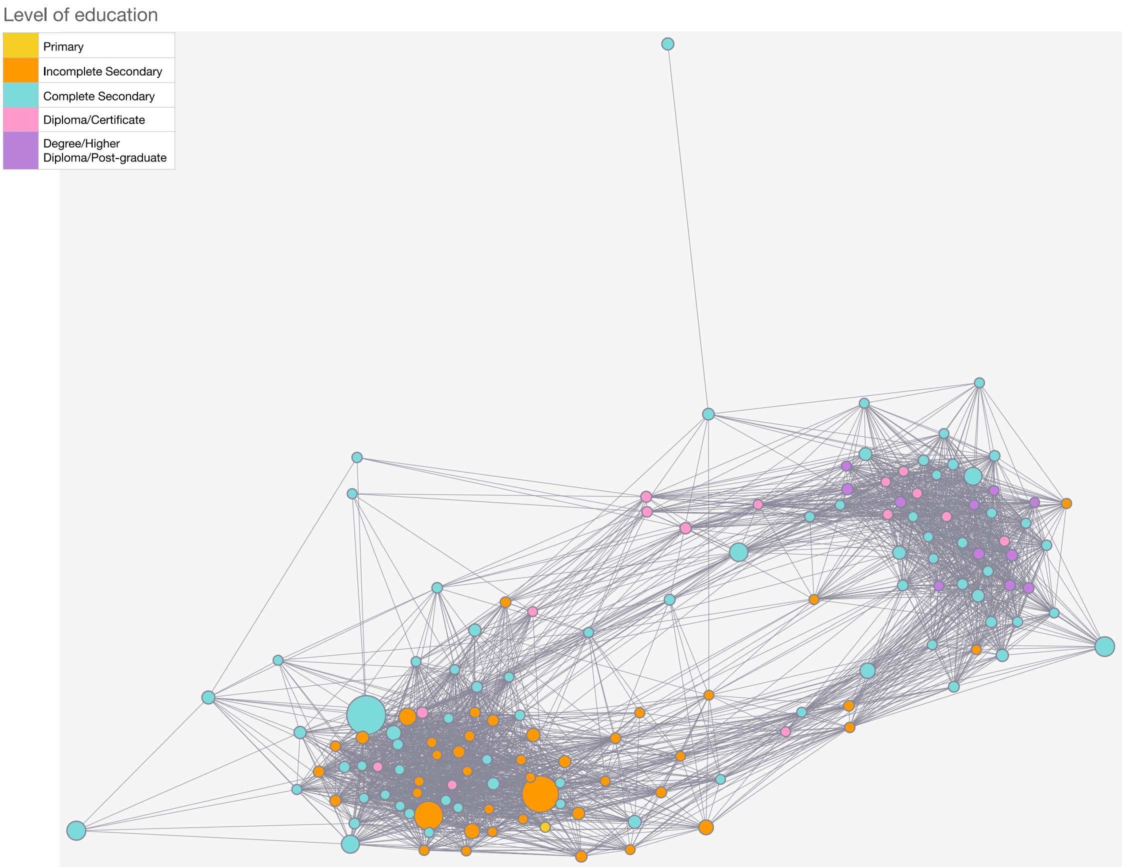
Figure 9: The MER Sector Occupation Space – Gender



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: The mean of the gender variable for each individual in a given occupation is also used. To make this value more meaningful, the mean and standard deviation of this aggregated gender variable is used to classify occupations as being male-dominated, female-dominated, or dominated by neither gender. 2. Occupations shaded in yellow are female dominated (<=mean(gender)-std(gender)), occupations shaded in orange are dominated by neither gender (>mean(gender)-std(gender) & <mean(gender)+std(gender)), and occupations shaded in red are male-dominated (> =mean(gender)+std(gender))

Finally, when modal education level in an occupation is considered, there is evidence to suggest that occupations characterised by workers with lower levels of education are more at risk of displacement than occupations characterised by workers with higher levels of education. This result is consistent with the findings above, which indicated that the average level of education amongst those employed in routine occupations was significantly lower than among those employed in non-routine occupations.

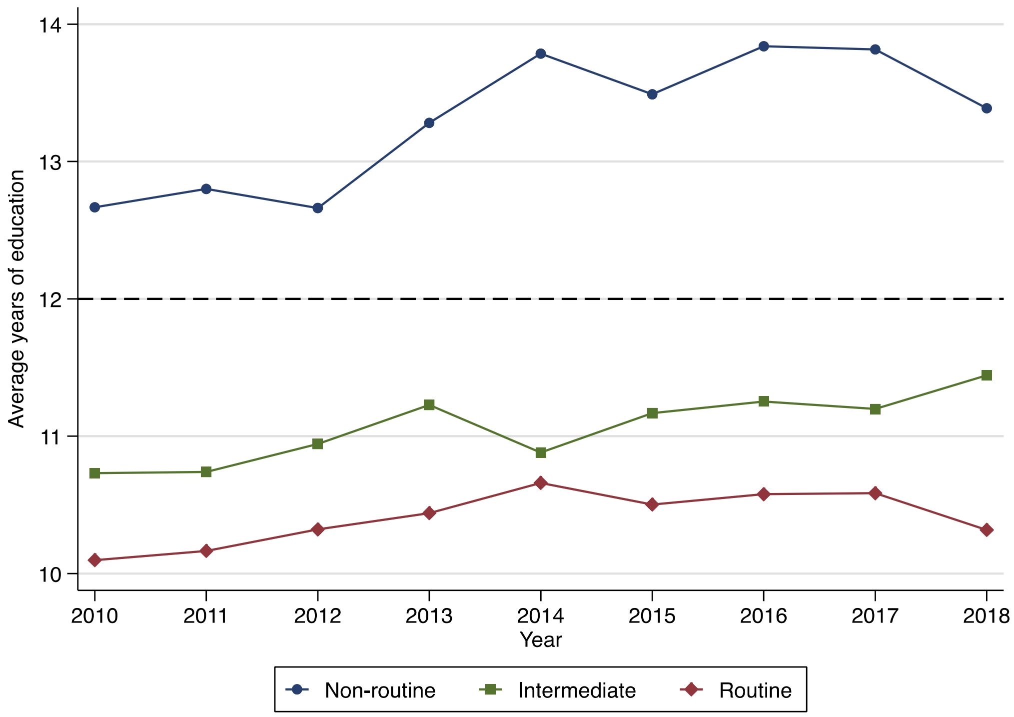
Figure 10: The MER Sector Occupation Space – Education



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: Each node is shaded according to the modal level of education taking into account all individuals employed in that occupation. Instead of using a continuous measure for education (such as years of schooling) this variable is represented by level of education as reported in PALMS and aggregated to form five main classifications.

Figure 10 presents these results graphically in the occupation space, and it is clear that the cluster of at-risk occupations on the left-hand side of the diagram, characterised by production jobs, has much greater incidence of individuals with incomplete secondary and primary education. In contrast, the less at-risk occupations on the right-hand side of the diagram, characterised by non-production jobs, show a higher incidence of diplomas and degrees. Although this is suggestive of the fact that individuals with higher education levels are less likely to be at risk of displacement, it does not follow that individuals need to be in possession of a degree or diploma in order to be safe from 4IR-driven displacement. In fact, the prevalence of nodes that indicate a completed secondary school-level education is high among occupations that are not at risk of displacement. This suggests that policy aiming to protect employees from automation may only have to ensure that workers have a completed secondary education rather than a tertiary education. Given South Africa's relatively fragile schooling system, and low levels of educational attainment, this provides hope that the MER Sector may be able to continue providing employment opportunities to less-educated workers in the future.

Figure 11: Average education level of employees by MER Sector occupation risk category, 2010-2018



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: 1. Occupations with an RTI below the 25th percentile of the RTI distribution are classified as non-routine, those above the 75th percentile as routine, and those in between as intermediate. 2. Dashed horizontal line indicates a completed secondary education.

Indeed, when looking at the average education level of employees in MER Sector occupations, as depicted in Figure 11, it is clear that the average education level of individuals across non-routine occupations is just above a completed secondary education (represented by the dashed horizontal line). Combined with heterogeneity across educational attainment at the occupational level, this result is indicative of a relatively high return to secondary education as far as safety from displacement due to 4IR technologies goes. Simply by completing a secondary education, an individual is immediately more aligned with the tasks and requirements for a non-routine occupation than a routine one, and as a result, they find themselves less likely to be in an occupation at risk of displacement when 4IR technologies are adopted. Further, a number of intermediate risk occupations positioned within the production cluster require, on average, a complete secondary education, which again suggests reaching this level of education may afford workers the opportunity to shift to occupations at less relative risk of displacement. From a policy perspective, adult school completion programmes may mitigate against the risk of job displacement. The education gap between individuals employed in routine and non-routine occupations has widened from approximately 2.5 years in 2010 to approximately 3 years in 2018. As identified above, the driving force behind this widening educational gap is increased education levels among individuals in non-routine tasks, while the average level of education among routine employees remained virtually unchanged.

4.4 Characteristics of MER Sector Occupations at Risk of Fourth Industrial Revolution Technologies – Multivariate analysis

Although useful, the above analysis has depended purely on unconditional estimates of differences in characteristics between occupations marked as at high risk of displacement and those marked as being at low risk. In this section, therefore, we present the results from a conditional regression estimation, which aims to provide estimates on the likelihood of a MER Sector employee finding themselves employed in an occupation at risk of 4IR-driven displacement, conditional on their individual- and firm-level characteristics. Time fixed effects are also included in the model specification. In order to do this, we make use of a probit regression specification and classify those occupations identified as routine to be at risk of displacement, while those identified as intermediate or non-routine are classified as not being at risk of displacement. We make use of the thresholds defined by Lewandowski, Park and Schotte (2020) in determining an occupation's risk status – namely, we classify those occupations with an RTI score greater than the 75th percentile of the RTI distribution as being routine, and as a result at risk of automation. All occupations with an RTI score below the 75th percentile of the RTI distribution are classified as being not at risk.

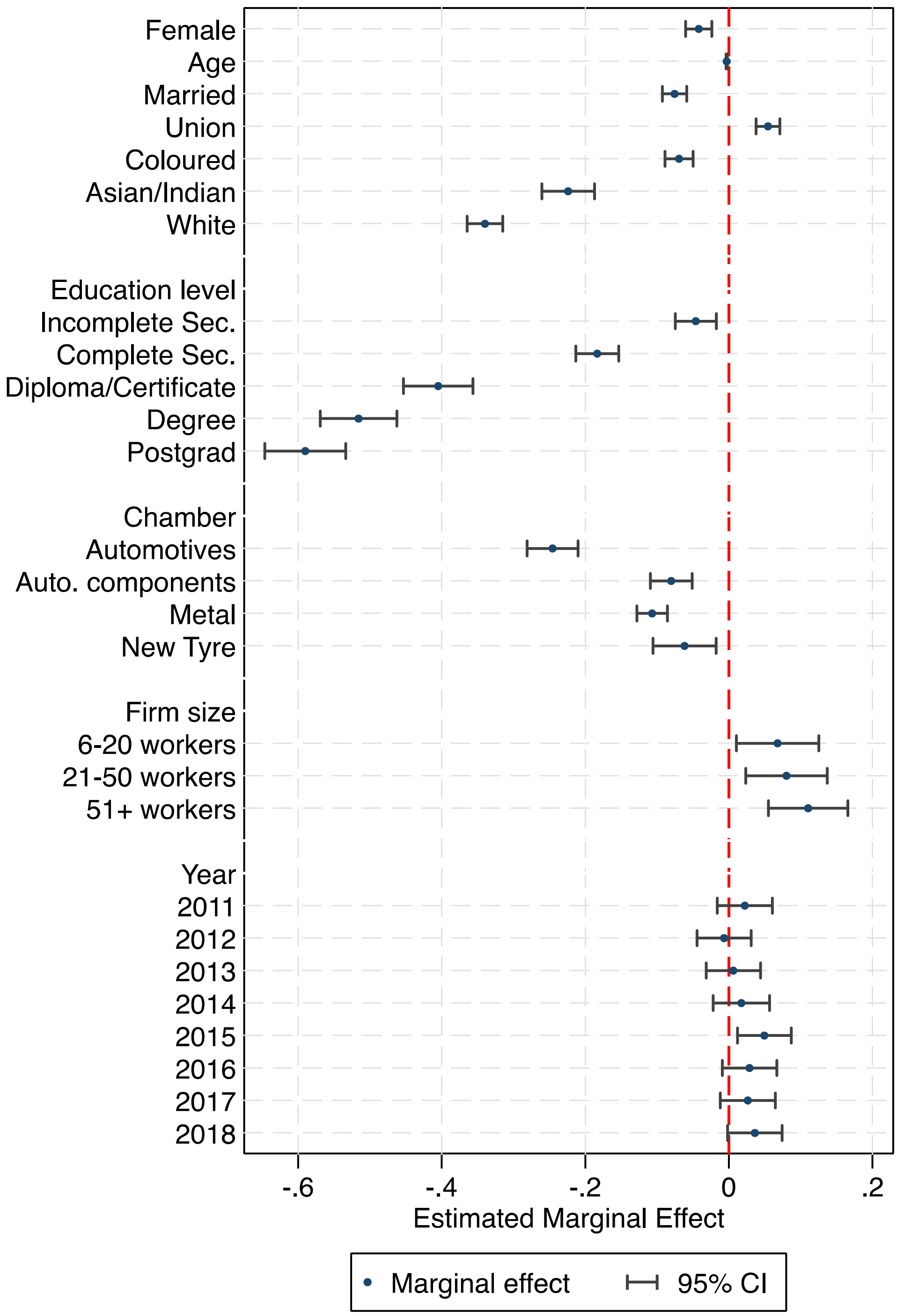
The average marginal effects from our probit regression estimation are presented graphically in Figure 12, and in full in column (1) of Table A 5 in the Appendix. The first key takeaway one obtains from the results is a broad overview of the characteristics that are likely to make an individual more likely to be employed in an occupation at risk of displacement. In particular, as expected from the above analysis, individuals who are most at risk of being employed in occupations at risk of displacement are single African men who are members of a trade union, with less than a completed secondary schooling, in larger firms within the Plastics chamber. As was alluded to above, the marginal impact of age on likelihood of displacement is minimal, and practically indistinguishable from 0.

As expected, given the bivariate analysis above, African individuals are most likely to find themselves employed in occupations at risk of displacement, while White individuals are least likely to be employed in occupations at risk of displacement. In particular, White individuals are approximately 34 percentage points less likely to be employed in an occupation at risk of displacement than African individuals, all else equal. Holding other factors constant, Coloured and Asian/Indian individuals are also less likely to be employed in at-risk employment than African individuals, but only by approximately 6.9 and 22.4 percentage points on average, indicating that White individuals are least at risk of finding themselves employed in occupations at risk of displacement.

Union membership, on the other hand seems to increase the likelihood that an individual will be employed in an at-risk occupation: specifically, employees who belong to a trade union are approximately 5.4 percentage points more likely to be employed in an occupation at risk of displacement than their non-unionised counterparts, all else equal. Research by Parolin (2020) suggests that this may be due to unionisation leading to increased wages for workers, ultimately leading to an increased relative cost of labour to capital for the firm. In this case, the firm may opt to substitute workers for labour-replacing technologies as it is cheaper to invest in the machinery required to automate a process than it is to continue paying workers the prevailing wage rate. For the MER Sector in particular, the trend of increasing unionisation between 2010 and 2018 is potentially of concern as this may drive firms to automate processes that would ultimately lead to job shedding in the future. However, this result is not causal – i.e. it does not imply that union membership causes increased likelihood of displacement. In fact, at this stage, this coefficient should simply be interpreted as a positive correlation between union membership and displacement risk, rather than causal in any way.

Higher education levels are correlated with a lower likelihood of an individual being employed in an at-risk occupation. Although those individuals with tertiary qualifications are least likely to be employed in occupations that are at risk of displacement, there are statistically significant negative effects on risk probability from a completed secondary education onwards. This is consistent with the results above, which suggested that individuals would be at less risk of displacement even if they managed to just achieve a completed secondary school education.

Figure 12: Average marginal effects on probability of being at risk of displacement



Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: 1. Average marginal effects estimated from a probit model. 2. Base categories are as follows: Gender – male; Race – African; Education level – Primary school; Chamber – Plastics; Firm size – 5 or fewer employees; Year – 2010. 3. Coefficients are statistically significant at the 95% level if confidence interval does not overlap vertical red line at 0. 4. Regression estimated at the individual level.

Analysing displacement risk by chamber, we see that the individuals in the Plastics chamber are more likely to be employed in occupations at risk of displacement than any other chamber, all else equal. Although results above showed that New Tyre and Plastics were both highly at risk of displacement effects, the Plastics chamber is approximately five times larger than the New Tyre chamber. The difference in chamber sizes would explain why the Plastics chamber stands out as the chamber most at risk of displacement in the regression output. All else equal, employees in the Automotive chamber are approximately 29 percentage points less likely than employees in the Plastic chamber to employed in an at-risk occupation, while the remaining chambers are between 6.2 and 10.7 percentage points less likely to be employed in an at-risk occupation than employees in Plastics. It is thus clear that employees in the automotive chamber are the least likely to be employed in at-risk occupations.

Furthermore, risk of displacement increases as firm size increases: As employees find themselves employed in larger firms, their likelihood of finding themselves employed in an occupation at risk of displacement increases. If individuals in larger firms are currently more likely to be employed in at-risk occupations, and larger firms are likely to have more resources available to begin the process of adopting 4IR technologies, this means that these jobs are likely the most precarious in terms of displacement effects. Upskilling of workers in these positions to fill new, related positions will be extremely important to ensure that they do not fall victim to the disemployment effects of 4IR technologies.

Finally, there is little evidence that individuals' risk of displacement has changed very much over time. Most time dummy estimates are statistically insignificant, and as such it is not clear that an individual's risk of displacement has changed substantially from 2010 through to 2018. This supports a hypothesis of little progress as pertains to adoption of 4IR technologies and their relative impact on employment over the past decade.

Given that the threshold used to define an occupation as at risk of displacement is essentially arbitrary, we undertook to run regressions with various specifications as robustness checks. These specifications are presented in columns (2) to (6) in Table A 5 in the Appendix. Regression (2) presents the average marginal effects of a probit regression where, following Frey and Osborne (2017), a RTI cutoff of 0.7 was used to classify occupations as at-risk, rather than the 75th percentile of the RTI distribution. Column (3) reports the results from a standard OLS regression with the RTI as a dependent variable, while columns (4) through (6) report quantile regressions run at the 25th, 50th and 75th quantiles of the RTI distribution, respectively.

In general, the coefficient estimates from the alternative specifications support the results found using the Lewandowski, Park and Schotte (2020) threshold of the 75th percentile of the RTI distribution. In the case of regression specification (2), the magnitudes of the marginal effects are also very similar to those found in our preferred specification, further supporting our findings. We can only compare our specification to Regression (3) insofar as the signs on the coefficients go, however, we see that these signs are generally consistent and support our findings above.

Finally, the coefficients from the quantile regressions indicate that the correlations we report above generally hold across the entirety of the RTI distribution, although the magnitude of the effect may change slightly. For example, women are likely to be employed in occupations with lower routineness scores than men across the entirety of the distribution, however, this is especially true at the top end of the RTI distribution.

One exception in the consistency of the reported results is the impact of chamber on routineness. In a number of cases, the impact of an employee being employed in the New Tyre chamber switches signs from negative to positive, indicating that it is unclear whether employees in the Plastics or New Tyre chamber are most at risk of automation. However, in the bivariate analysis, these two chambers were found to make up approximately 70 percent of the occupation share of the ten most at-risk occupations. Thus, given the disproportionate amount of risk apportioned to these two chambers, and depending on the exact distribution of employment share across the list of at-risk occupations, it is not wholly unexpected that there is some uncertainty about which of the two chambers is most at risk of displacement due to 4IR technologies.

In all, it is clear that the risk of employment displacement due to the adoption of 4IR technologies is concentrated particularly strongly amongst African men with an incomplete secondary education, who are members of a trade union, and who are employed in larger firms. Individuals in all other chambers show a relatively lower risk of displacement than those in the Plastics chamber, which is consistent with the univariate analysis of the RTI above. Moreover, the results are robust to model specification. While not causal, the results do provide an initial indication of the characteristics of individuals who are more likely to find themselves at risk of displacement in the future, as well as how strongly those characteristics influence displacement risk. Thus, while these results will not necessarily accurately predict an individual's risk of displacement in the MER Sector, they do provide a framework which can be used to target those individuals who are most at risk of displacement due to 4IR technologies and intervene to retrain or upskill such individuals before their jobs are lost.

5 Conclusion

In this report we examine the potential employment displacement effects of technologies related to the fourth industrial revolution on the MER sector, by observing this risk through the lens of the task-content of occupations or the routinisation hypothesis. Put simply, occupations characterized by a large proportion of routine and codifiable tasks are at greater risk of employment displacement due to the adoption of 4IR technologies. The Routine Task Index is used to measure the extent to which various MER sector occupations are at risk of displacement. We use network analytics to develop a MER sector occupation space, which shows the occupational structure of the MER sector labour force.

The MER sector labour market features a polarised occupational structure across which occupations at high risk of employment displacement are not randomly distributed. This polarised occupational structure features two distinct occupation clusters in the MER sector occupation space: Firstly, a set of production orientated occupations, comprising low-skilled elementary occupation workers, and semi-skilled craft workers and machine operators. Secondly, a set of non-production occupations, comprising high-skilled legislators, senior officials and managers, professionals, semi-skilled clerks, associate professionals and service workers. Occupations at high risk of employment displacement are not randomly distributed across the MER sector occupational space. A clear dichotomy is evident, with occupations located in the production orientated cluster being decidedly more at risk to employment displacement than occupations in the non-production orientated cluster. Further, a number of high risk occupations falling within the production orientated cluster represent substantial shares of the MER sector labour force – for example, Machine tool operators, Welders and flamecutters, Hand packers, and other manufacturing labourers, together, account for approximately 29.5 percent of total MER sector employment.

Three implications emerge: Firstly, technology induced employment displacement is likely to jeopardise low- to medium-skill employment in the production cluster occupations, and correspondingly result in an increase in relative demand for semi- and high-skilled non-production cluster occupations. Second, the non-random distribution of high risk occupations across the two clusters of the occupation space suggest that the skill transition to shift workers from high to low risk occupations is long, and in the event of substantial uptake of employment displacing technologies across the sector, technological unemployment is that much harder to mitigate. Third, the relatively high employment share associated with high risk occupations in the production cluster indicates that the displacement effects resulting in technological unemployment are likely to be substantial.

Approximately two in every five MER sector workers are positioned in high risk occupations, and this has remained relatively static over the past decade – 2010-2018. In a relative sense, the Plastics and New Tyre chambers exhibit the greatest shares of high risk occupations, while in an absolute sense, the Metal chamber accounts for the largest absolute number of workers positioned in high risk occupations. In the context of declining aggregate employment levels across the sector, the Metal sector has seen an overall increase in the number and share of high risk employment, which could be the result of delayed adoption of labour displacing 4IR technologies, or labour market structures that protect workers from job loss in this chamber. This is of concern insofar as delaying the adoption of labour displacing 4IR technologies into the future, may result in more significant displacement effects when automation processes start, particularly since the Metal chamber has been identified as being particularly well-suited to mechanisation and automation in the past (Jämsä-Jounela, 2001).

In terms of who is most likely to be impacted by these potential employment displacement effects: African and Coloured men with an incomplete secondary education, who are members of a trade union, employed in larger firms, and in the Plastics chamber, are most likely to find themselves in a high risk occupation. In contrast, we observe that workers who are white, who do not belong to a union, who work in the Automotive chamber, and who have at least a complete secondary education, are less likely to occupy occupations at high risk of employment displacement. Certainly, the level of formal education seems key to the positioning of workers across high and low risk occupations, and thus adult school completion programmes may have the potential to allow workers to shift out of high risk occupations – certainly to intermediate risk occupations – in the future.

It is worth noting that while 4IR technologies have the potential to displace workers from their jobs, this very same technology also has the potential to create new job opportunities, new tasks and thus new occupations. As such, Autor (2015) stresses the point that there is a tendency for analysts and commentators to emphasise employment displacement effects – the substitution of labour for computer capital – while ignoring the complementarities between technology and workers. Furthermore, these technologies increase aggregate productivity, which is a key driver of economic growth. The question is whether appropriate public policy can ameliorate the potential negative effects of these technologies. Further, as advanced by Kucera and de Mattos (2020), the risk to automation may be overstated. They note that it is important to be able to distinguish whether a job *could be* automated and whether a job *will be* automated. The former refers to technological feasibility – whether a robot can perform a task – while the latter is an economic consideration that is based on the relative cost of labour and whether investing in automation is at least as profitable as prevailing production processes.

The World Bank – in the report titled, *The Changing Nature of Work* – make a number of recommendations to ameliorate the potential employment displacement effects arising from the uptake of 4IR technologies, which include investment in infrastructure and creating fiscal space for social protection policy interventions. Pertinently, in the case of merSETA, they also advance the need for investing in human capital. Specifically, they point to three types of skills that are becoming increasingly important in labour markets (World Bank, 2019): First, advanced cognitive skills, such as problem solving. Second, sociobehavioral skills, such as teamwork. Third, skill combinations that are predictive of adaptability, such as reasoning and self-efficacy. These skills should feature as a part of future skill interventions within the sector.

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APPENDIX

Table A 1: Definition of intermediate indicators for RTI construction

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
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 personal	• 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).

A numeric example for calculating intermediate indicators

This appendix aims to expand on the method of calculating intermediate indicators as discussed in Section 3.6 of this report. As a reminder, the formula describing the method for calculating the intermediate indicator, $r_{h,i}$, related to indicator h for occupation i is given as follows:

$$r_{h,i} = \sum_{k=1}^{A_h} WA_{k,h,i} + \sum_{l=1}^{C_h} WC_{l,h,i} \quad \text{(B1)}$$

with components defined as

$$WA_{k,h,i} = \frac{\overline{WA}_{k,h,i} - WA_{\min}}{\max\,(\overline{WA}_{k,h,i} - WA_{\min})} \quad \text{(B2)}$$

and

$$WC_{l,h,i} = \frac{\sum_{V_{i,l}=1}^{5}(V_{i,l} \times F_{V_{i,l}}) \; - 100}{400} \quad \text{(B3)}$$

where

$$\overline{WA}_{k,h,i} = I_{i,k}^{\frac{2}{3}} L_{i,k}^{\frac{1}{3}} \quad \text{(B4)}$$

Note that $WA_{\min}$ is the minimum value of the $\overline{WA}_{k,h,i}$ distribution. The transformations described in equations (B2) and (B3) 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.

Now, for a numeric example of how to operationalise these formulae, consider Table B 1 and Table B 2. These tables provide an extract of the O*NET (2020) data specifically for the elements used in the calculation of the "routine manual" intermediate indicator for the occupation of "manufacturing engineer".

Table A 2: Extract of Work Activity data for manufacturing engineer

Occupation	Activity code	Work Activity	Importance	Level
Manufacturing engineer	4.A.3.a.3	Controlling machines and processes	3.23	4

Source: O*NET (2020)

Table A 3: Extract of Work Context data for manufacturing engineer

Occupation	Context code	Work Context	Value	Frequency
Manufacturing engineer	4.C.2.d.1.i	Spend time making repetitive motions	1	30.77
Manufacturing engineer	4.C.2.d.1.i	Spend time making repetitive motions	2	30.77
Manufacturing engineer	4.C.2.d.1.i	Spend time making repetitive motions	3	26.92
Manufacturing engineer	4.C.2.d.1.i	Spend time making repetitive motions	4	11.54
Manufacturing engineer	4.C.2.d.1.i	Spend time making repetitive motions	5	0
Manufacturing engineer	4.C.3.d.3	Pace determined by speed of equipment	1	53.85
Manufacturing engineer	4.C.3.d.3	Pace determined by speed of equipment	2	15.38
Manufacturing engineer	4.C.3.d.3	Pace determined by speed of equipment	3	0
Manufacturing engineer	4.C.3.d.3	Pace determined by speed of equipment	4	19.23
Manufacturing engineer	4.C.3.d.3	Pace determined by speed of equipment	5	11.54

Source: O*NET (2020)

If we were to calculate the value of the “routine manual” intermediate indicator for the occupation “manufacturing engineer”, then in the expression $r_{h,i}$ we have $h = manual$ to represent the routine manual intermediate indicator and $i = X$ to represent the occupation “manufacturing engineer”. In this case, given that the components of the routine manual intermediate indicator comprise one Work Activity and two Work Context variables, we can also infer that $A_{manual} = 1$ and $C_{manual} = 2$.

Step 1: Calculate the value for $\overline{WA}_{k,manual,X}$ (in general, this is repeated for each of $k = 1,2, \dots A_h$)

$$\overline{WA}_{1,manual,X} = I_{X,manual}^{\frac{2}{3}} L_{X,manual}^{\frac{1}{3}} = (3.23)^{\frac{2}{3}}(4)^{\frac{1}{3}} \approx 3.468606 \dots$$

Step 2: Normalise the value of $\overline{WA}_{k,manual,X}$ to obtain $WA_{k,manual,X}$ (in general, this is repeated for each of $k = 1,2, \dots A_h$)

$$WA_{1,manual,X} = \frac{\overline{WA}_{1,manual,X} - WA_{\min}}{WA_{\max}} = \frac{3.468606 - 0.401858}{4.91937} \approx 0.6234$$

Step 3: Calculate the value of $WC_{l,manual,X}$ for $l = 1$ and $l = 2$ (in general, this is repeated for each of $l = 1,2, \ldots C_h$)

$l = 1$ (Spend time making repetitive motions):

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

$$WC_{1,manual,X} = \frac{[(1 \times 0.3077) + (2 \times 0.3077) + (3 \times 0.2692) + (4 \times 0.1154) + (5 \times 0)] - 100}{400}$$
$$\approx 0.2981$$

$l = 2$ (Pace determined by speed of equipment):

$$WC_{2,manual,X} = \frac{\sum_{V_{i,l}=1}^{5}(V_{i,l} \times F_{i,l}) - 100}{400}$$

$$WC_{2,manual,X} = \frac{\big((1 \times 0.5385) + (2 \times 0.1538) + (3 \times 0) + (4 \times 0.1923) + (5 \times 0.1154) - 100\big)}{400}$$
$$\approx 0.2981$$

Step 4: Combine $WA_{k,manual,X}$ and $WC_{l,manual,X}$ to obtain a value for $r_{manual,X}$

$$r_{manual,X} = \sum_{k=1}^{A_h} WA_{k,h,i} + \sum_{l=1}^{C_h} WC_{l,h,i}$$
$$r_{manual,X} = WA_{1,rman,X} + WC_{1,rman,X} + WC_{2,rman,X}$$
$$r_{manual,X} = 0.6234 + 0.2981 + 0.2981$$
$$r_{manual,X} = 1.2196$$

Hereafter, the value of $r_{manual,X}$ is also rescaled to lie between 0 and 1 so as to ensure an equal weighting in the construction of the final RTI. This rescaling is achieved in a similar method to that expressed in equation (B2), which involves subtracting the minimum value of $r_{manual,i}$ across all occupations, and then dividing by the maximum value of this new transformed distribution.

Table A 4: MerSETA Occupations by displacement risk and chamber employment share, 2018

Rank	Occupation description	Share of merSETA employment (%)	Distribution of employment by chamber					Risk of automation
			Auto	Auto components	Metals	New Tyre	Plastics	
1	Textile-, fur- and leather-products machine operators not elsewhere classified	0.13	0.00	0.00	0.13	0.00	0.00	High
2	Woodworking-machine setters and setter-operators	0.05	0.00	0.00	0.05	0.00	0.00	High
3	Wood-processing-plant operators	0.09	0.00	0.00	0.09	0.00	0.00	High
4	Sewing-machine operators	0.19	0.00	0.05	0.00	0.00	0.14	High
5	Shoe-makers and related workers	0.02	0.00	0.02	0.00	0.00	0.00	High
6	Cement and other mineral products machine operators	0.04	0.00	0.00	0.04	0.00	0.00	High
7	Wood-products machine operators	0.05	0.00	0.00	0.05	0.00	0.00	High
8	Sewers, embroiderers and related workers	0.08	0.00	0.06	0.03	0.00	0.00	High
9	Rubber-products machine operators	1.16	0.00	0.03	0.00	0.83	0.31	High
10	Chemical-processing-plant operators not elsewhere classified	0.05	0.00	0.00	0.00	0.00	0.05	High
11	Metal finishing-, plating- and coating-machine operators	0.42	0.03	0.10	0.29	0.00	0.00	High
12	Mail carriers and sorting clerks	0.72	0.00	0.00	0.52	0.05	0.15	High
13	Bleaching-, dyeing- and cleaning-machine operators	0.01	0.00	0.00	0.01	0.00	0.00	High
14	Paper-products machine operators	0.09	0.00	0.00	0.00	0.00	0.09	High
15	Coding, proof-reading and related clerks	0.04	0.04	0.00	0.00	0.00	0.00	High
16	Messengers, package and luggage porters and deliverers	0.43	0.00	0.00	0.22	0.00	0.21	High
17	Metal moulders and coremakers	0.18	0.00	0.00	0.18	0.00	0.00	High
18	Stone splitters, cutters and carvers	0.10	0.00	0.02	0.00	0.00	0.08	High
19	Helpers and cleaners in offices, hotels and other establishments	1.93	0.37	0.07	1.02	0.17	0.30	High
20	Welders and flamecutters	10.52	0.52	0.10	9.61	0.10	0.19	High
21	Metal wheel-grinders, polishers and tool sharpeners	0.61	0.00	0.15	0.31	0.00	0.11	High

Rank	Occupation description	Share of merSETA employment (%)	Distribution of employment by chamber					Risk of automation
			Auto	Auto components	Metals	New Tyre	Plastics	
22	Ammunition- and explosive-products machine operators	0.04	0.00	0.00	0.04	0.00	0.00	High
23	Machine-tool operators	11.50	0.19	1.08	9.95	0.00	0.28	High
24	Other machine operators and assemblers	0.30	0.00	0.14	0.08	0.00	0.08	High
25	Pharmaceutical- and toiletry-products machine operators	0.12	0.00	0.00	0.12	0.00	0.00	High
26	Glass-makers, cutters, grinders and finishers	0.11	0.04	0.00	0.07	0.00	0.00	High
27	Plastic-products machine operators	3.01	0.00	0.00	0.02	0.00	2.98	High
28	Printing-machine operators	0.04	0.00	0.00	0.00	0.00	0.04	High
29	Metal drawers and extruders	0.21	0.00	0.00	0.21	0.00	0.00	High
30	Mining and quarrying labourers	0.04	0.00	0.00	0.04	0.00	0.00	High
31	Machine-tool setters and setter-operators	0.65	0.00	0.19	0.27	0.00	0.19	High
32	Mineral-ore- and stone-processing-plant operators	0.08	0.00	0.00	0.08	0.00	0.00	High
33	Hand packers and other manufacturing labourers	7.49	0.40	0.91	3.40	0.12	2.56	High
34	Lifting-truck operators	1.42	0.04	0.15	0.78	0.24	0.21	High
35	Jewellery and precious-metal workers	0.14	0.00	0.00	0.14	0.00	0.00	High
36	Metal-, rubber- and plastic-products assemblers	1.03	0.19	0.00	0.69	0.00	0.05	High
37	Crane, hoist and related plant operators	0.94	0.00	0.00	0.78	0.11	0.05	Intermediate
38	Metal melters, casters and rolling-mill operators	0.23	0.00	0.00	0.23	0.00	0.00	Intermediate
39	Glass and ceramics kiln and related machine operators	0.31	0.04	0.11	0.16	0.00	0.00	Intermediate
40	Ore and metal furnace operators	0.50	0.06	0.00	0.44	0.00	0.00	Intermediate
41	Telephone switchboard operators	0.06	0.00	0.00	0.03	0.03	0.00	Intermediate
42	Garbage collectors	0.67	0.00	0.00	0.00	0.00	0.67	Intermediate
43	Mining-plant operators	0.04	0.00	0.00	0.04	0.00	0.00	Intermediate
44	Miners and quarry workers	0.11	0.00	0.00	0.11	0.00	0.00	Intermediate

Rank	Occupation description	Share of merSETA employment (%)	Distribution of employment by chamber					Risk of automation
			Auto	Auto components	Metals	New Tyre	Plastics	
45	Cabinet-makers and related workers	0.05	0.00	0.00	0.00	0.00	0.05	Intermediate
46	Industrial robot controllers	0.08	0.04	0.04	0.00	0.00	0.00	Intermediate
47	Freight handlers	0.54	0.04	0.00	0.36	0.10	0.04	Intermediate
48	Riggers and cable splicers	0.05	0.00	0.00	0.05	0.00	0.00	Intermediate
49	Electrical-equipment assemblers	0.26	0.00	0.00	0.26	0.00	0.00	Intermediate
50	Crushing-, grinding- and chemical-mixing machinery operators	0.57	0.00	0.00	0.03	0.00	0.54	Intermediate
51	Plumbers and pipe fitters	0.35	0.00	0.00	0.35	0.00	0.00	Intermediate
52	Housekeepers and related workers	0.10	0.00	0.00	0.03	0.06	0.00	Intermediate
53	Farm-hands and labourers	0.34	0.00	0.00	0.15	0.00	0.19	Intermediate
54	Cashiers and ticket clerks	0.07	0.00	0.00	0.00	0.00	0.07	Intermediate
55	Mechanical-machinery assemblers	2.00	1.44	0.30	0.25	0.00	0.00	Intermediate
56	Building caretakers	0.04	0.04	0.00	0.00	0.00	0.00	Intermediate
57	Structural-metal preparers and erectors	1.09	0.00	0.00	1.09	0.00	0.00	Intermediate
58	Stock clerks	2.20	0.10	0.28	1.17	0.11	0.54	Intermediate
59	Wood and related products assemblers	0.39	0.00	0.00	0.16	0.00	0.23	Intermediate
60	Bookkeepers	0.22	0.08	0.04	0.07	0.00	0.03	Intermediate
61	Electronic-equipment assemblers	0.04	0.00	0.00	0.04	0.00	0.00	Intermediate
62	Accounting and bookkeeping clerks	1.18	0.06	0.00	1.06	0.00	0.07	Intermediate
63	Agricultural- or industrial-machinery mechanics and fitters	3.60	0.13	0.22	3.14	0.00	0.07	Intermediate
64	Heavy truck and lorry drivers	2.22	0.00	0.09	1.24	0.00	0.89	Intermediate
65	Earth-moving- and related plant operators	0.05	0.00	0.00	0.05	0.00	0.00	Intermediate
66	Data entry operators	0.03	0.00	0.03	0.00	0.00	0.00	Intermediate
67	Building construction labourers	0.14	0.00	0.00	0.06	0.00	0.08	Intermediate

Rank	Occupation description	Share of merSETA employment (%)	Distribution of employment by chamber					Risk of automation
			Auto	Auto components	Metals	New Tyre	Plastics	
68	Cooks	0.20	0.00	0.14	0.05	0.00	0.00	Intermediate
69	Tool-makers and related workers	0.44	0.00	0.06	0.26	0.00	0.11	Intermediate
70	Car, taxi and van drivers	1.05	0.07	0.14	0.71	0.14	0.00	Intermediate
71	Motor vehicle mechanics and fitters	0.95	0.27	0.07	0.34	0.24	0.00	Intermediate
72	Handicraft workers in wood and related materials	0.06	0.00	0.00	0.06	0.00	0.00	Intermediate
73	Safety, health and quality inspectors	3.45	0.47	0.63	1.64	0.21	0.49	Intermediate
74	Sheet-metal workers	3.22	0.44	0.00	2.70	0.04	0.03	Intermediate
75	Electrical mechanics and fitters	1.25	0.16	0.03	0.99	0.07	0.00	Intermediate
76	Painters and related workers	0.03	0.00	0.00	0.03	0.00	0.00	Intermediate
77	Medical equipment operators	0.08	0.08	0.00	0.00	0.00	0.00	Intermediate
78	Compositors, typesetters and related workers	0.07	0.00	0.00	0.00	0.00	0.07	Intermediate
79	Construction and maintenance labourers: roads, dams and similar constructions	0.46	0.02	0.00	0.36	0.00	0.08	Intermediate
80	Power-production plant operators	0.04	0.00	0.00	0.04	0.00	0.00	Intermediate
81	Receptionists and information clerks	0.36	0.09	0.00	0.16	0.03	0.09	Intermediate
82	Carpenters and joiners	0.67	0.00	0.00	0.55	0.00	0.12	Intermediate
83	Chemical and physical science technicians	0.18	0.00	0.00	0.07	0.00	0.11	Intermediate
84	Telegraph and telephone installers and servicers	0.06	0.00	0.00	0.06	0.00	0.00	Intermediate
85	Library and filing clerks	0.04	0.00	0.00	0.04	0.00	0.00	Intermediate
86	Other office clerks	3.21	0.33	0.17	2.06	0.06	0.60	Intermediate
87	Building and related electricians	1.31	0.28	0.28	0.68	0.00	0.08	Intermediate
88	Draughtspersons	0.08	0.00	0.00	0.08	0.00	0.00	Intermediate
89	Blacksmiths, hammer-smiths and forging-press workers	0.11	0.00	0.00	0.11	0.00	0.00	Intermediate
90	Secretaries	0.35	0.08	0.00	0.23	0.00	0.04	Intermediate

Rank	Occupation description	Share of merSETA employment (%)	Distribution of employment by chamber					Risk of automation
			Auto	Auto components	Metals	New Tyre	Plastics	
91	Precision-instrument makers and repairers	0.07	0.00	0.00	0.07	0.00	0.00	Intermediate
92	Shop salespersons and demonstrators	0.89	0.00	0.18	0.68	0.00	0.03	Intermediate
93	Varnishers and related painters	0.38	0.10	0.05	0.22	0.00	0.00	Intermediate
94	Transport clerks	0.23	0.00	0.12	0.06	0.00	0.05	Intermediate
95	Incinerator, water-treatment and related plant operators	0.36	0.00	0.00	0.27	0.00	0.09	Intermediate
96	Statistical and finance clerks	0.47	0.00	0.00	0.38	0.00	0.09	Intermediate
97	Electronics and telecommunications engineering technicians	0.47	0.11	0.00	0.33	0.00	0.03	Intermediate
98	Electrical engineering technicians	0.29	0.14	0.00	0.16	0.00	0.00	Intermediate
99	Physical and engineering science technicians not elsewhere classified	0.03	0.03	0.00	0.00	0.00	0.00	Intermediate
100	Business services agents and trade brokers not elsewhere classified	0.34	0.00	0.00	0.34	0.00	0.00	Intermediate
101	Mechanical engineering technicians	0.61	0.10	0.01	0.40	0.00	0.09	Intermediate
102	Electronics mechanics and servicers	0.33	0.00	0.05	0.20	0.00	0.08	Intermediate
103	Production clerks	0.14	0.00	0.05	0.08	0.00	0.00	Intermediate
104	Aircraft engine mechanics and fitters	0.06	0.00	0.00	0.06	0.00	0.00	Intermediate
105	Agronomy and forestry technicians	0.07	0.00	0.00	0.07	0.00	0.00	Intermediate
106	Electronics fitters	0.19	0.03	0.00	0.15	0.00	0.00	Intermediate
107	Protective services workers not elsewhere classified	0.12	0.00	0.00	0.12	0.00	0.00	Low
108	Building frame and related trades workers not elsewhere classified	0.91	0.00	0.00	0.91	0.00	0.00	Low
109	Computer assistants	0.23	0.13	0.00	0.10	0.00	0.00	Low
110	Medical assistants	0.11	0.00	0.00	0.11	0.00	0.00	Low
111	Cartographers and surveyors	0.03	0.00	0.00	0.03	0.00	0.00	Low

Rank	Occupation description	Share of merSETA employment (%)	Distribution of employment by chamber					Risk of automation
			Auto	Auto components	Metals	New Tyre	Plastics	
112	Electrical line installers, repairers and cable jointers	0.03	0.00	0.00	0.03	0.00	0.00	Low
113	Civil engineering technicians	0.18	0.00	0.00	0.18	0.00	0.00	Low
114	Production and operations department managers in agriculture, hunting, forestry and fishing	0.08	0.00	0.00	0.08	0.00	0.00	Low
115	Production and operations department managers in transport, storage and communications	0.40	0.14	0.00	0.26	0.00	0.00	Low
116	Fire-fighters	0.05	0.00	0.00	0.05	0.00	0.00	Low
117	Appraisers, valuers and auctioneers	0.23	0.17	0.00	0.06	0.00	0.00	Low
118	Production and operations department managers in manufacturing	3.86	0.17	0.22	2.81	0.14	0.49	Low
119	Buyers	0.32	0.00	0.00	0.32	0.00	0.00	Low
120	Decorators and commercial designers	0.38	0.00	0.00	0.29	0.00	0.09	Low
121	Computer systems designers and analysts	0.06	0.00	0.00	0.06	0.00	0.00	Low
122	Computer programmers	0.10	0.00	0.00	0.10	0.00	0.00	Low
123	General managers in wholesale and retail trade	0.04	0.00	0.00	0.04	0.00	0.00	Low
124	Lawyers	0.07	0.07	0.00	0.00	0.00	0.00	Low
125	Production and operations department managers in wholesale and retail trade	0.05	0.00	0.00	0.05	0.00	0.00	Low
126	Other department managers not elsewhere classified	0.99	0.12	0.17	0.66	0.00	0.05	Low
127	General managers of business services	0.07	0.00	0.00	0.07	0.00	0.00	Low
128	Electrical engineers	0.60	0.00	0.03	0.51	0.00	0.06	Low
129	Production and operations department managers in business services	0.61	0.00	0.04	0.51	0.02	0.04	Low
130	Accountants	0.69	0.00	0.20	0.29	0.00	0.19	Low
131	Finance and administration department managers	1.13	0.11	0.00	0.86	0.04	0.05	Low

Rank	Occupation description	Share of merSETA employment (%)	Distribution of employment by chamber					Risk of automation
			Auto	Auto components	Metals	New Tyre	Plastics	
132	Supply and distribution department managers	0.12	0.00	0.00	0.12	0.00	0.00	Low
133	Computing services department managers	0.09	0.00	0.00	0.09	0.00	0.00	Low
134	Technical and commercial sales representatives	1.42	0.00	0.09	1.18	0.00	0.14	Low
135	Mechanical engineers	0.54	0.08	0.02	0.37	0.00	0.07	Low
136	Trade brokers	0.15	0.00	0.00	0.07	0.00	0.07	Low
137	Business professionals not elsewhere classified	0.59	0.12	0.05	0.42	0.00	0.00	Low
138	Personnel and careers professionals	0.26	0.00	0.04	0.22	0.00	0.00	Low
139	Chemical engineers	0.03	0.00	0.00	0.00	0.00	0.03	Low
140	Personnel and industrial relations department managers	0.43	0.06	0.00	0.25	0.00	0.11	Low
141	Sales and marketing department managers	0.47	0.03	0.00	0.26	0.00	0.18	Low
142	Directors and chief executives	0.39	0.00	0.00	0.39	0.00	0.00	Low

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).

Table A 5: Total and at-risk employment by merSETA chamber, 2018

	merSETA employment							Employment at risk						
Year	**Automotives**	**Auto components**	**Metals**	**New Tyre**	**Plastics**	**Other**	**Total**	**Automotive**	**Auto components**	**Metal**	**New Tyre**	**Plastics**	**Other**	**Total**
2010	50,321	58,850	408,250	16,344	100,086	2,226	636,077	13,253	30,075	154,645	9,443	55,778	520	263,714
2011	61,674	71,016	425,821	16,001	89,828	1,773	666,113	21,379	35,121	185,853	8,668	47,283	612	298,917
2012	42,834	65,054	421,123	19,323	76,829	1,539	626,702	15,693	33,216	169,654	11,329	36,071	605	266,570
2013	41,119	60,382	395,716	24,273	98,295	1,741	621,526	12,744	34,187	156,543	7,695	47,882	1,437	260,488
2014	47,743	62,585	380,199	16,370	91,643	692	599,232	12,608	27,492	147,072	7,170	53,236	0	247,578
2015	35,262	53,446	357,125	20,389	73,818	1,270	541,311	8,768	27,537	144,247	9,746	38,751	963	230,013
2016	36,919	44,437	348,562	22,457	72,009	948	525,332	9,243	22,077	139,780	10,202	40,588	948	222,839
2017	34,018	42,983	365,618	26,741	77,087	1,550	547,997	7,096	18,179	143,364	15,825	38,004	961	223,429
2018	43,660	38,947	368,846	16,154	85,650	2,313	555,570	10,147	17,042	157,997	8,401	44,509	1,340	239,436

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Note: 1. Employment at risk is defined as employment in an occupation with an RTI value greater than the 75th percentile of the RTI distribution in a given year.

Table A 6: Demographic characteristics of employees in MER Sector occupations by chamber and risk of displacement, 2018

	Non-Routine					Intermediate					Routine				
	Auto	Auto Components	Metals	New Tyre	Plastics	Auto	Auto Components	Metals	New Tyre	Plastics	Auto	Auto Components	Metals	New Tyre	Plastics
Age	37.71	37.92	38.07	39.34	37.21	37.69	37.20	37.68	37.09	37.06	35.55	37.39	37.37	37.90	36.76
Male	0.65	0.76	0.72	0.65	0.62	0.71	0.68	0.72	0.70	0.65	0.62	0.65	0.76	0.78	0.66
African	0.44	0.41	0.42	0.39	0.42	0.66	0.64	0.67	0.72	0.71	0.75	0.71	0.76	0.75	0.74
Coloured	0.09	0.11	0.11	0.13	0.10	0.15	0.17	0.13	0.13	0.14	0.17	0.21	0.14	0.12	0.17
Indian	0.06	0.09	0.09	0.09	0.11	0.04	0.03	0.04	0.03	0.04	0.02	0.04	0.03	0.07	0.04
White	0.41	0.39	0.39	0.39	0.36	0.16	0.15	0.17	0.13	0.11	0.06	0.04	0.07	0.07	0.05
Years of education	13.39	13.22	13.14	13.38	13.43	11.28	11.31	11.10	10.98	10.79	10.30	10.30	10.54	10.57	10.52
Hours per week	42.72	42.86	42.59	43.07	41.95	42.61	42.19	42.73	44.29	42.71	42.45	42.76	43.22	43.59	43.14
Union	0.35	0.31	0.29	0.34	0.27	0.42	0.44	0.38	0.37	0.38	0.33	0.42	0.43	0.52	0.38

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Note: 1. Occupations with an RTI below the 25th percentile of the RTI distribution are classified as non-routine, those above the 75th percentile as routine, and those in between as intermediate.

Table A 7: Regression output, various specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit marginal effects Lewandowski, Park and Schotte (2020)	**Probit marginal effects Frey and Osborne (2017)**	**OLS on continuous RTI**	**Quantile reg. Q25**	**Quantile reg. Q50**	**Quantile reg. Q75**
Female	-0.042***	0.016**	-0.003*	-0.001***	-0.005***	-0.001***
	(0.009)	(0.008)	(0.002)	(0.000)	(0.000)	(0.000)
Age	-0.003***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.076***	-0.056***	-0.012***	-0.015***	-0.008***	-0.001***
	(0.009)	(0.007)	(0.001)	(0.000)	(0.000)	(0.000)
Union	0.054***	0.054***	0.014***	0.014***	0.010***	0.000***
	(0.008)	(0.007)	(0.001)	(0.000)	(0.000)	(0.000)
Race (African as base)						
Coloured	-0.069***	-0.064***	-0.013***	-0.018***	-0.009***	-0.001***
	(0.010)	(0.008)	(0.002)	(0.000)	(0.000)	(0.000)
Indian	-0.224***	-0.126***	-0.045***	-0.043***	-0.055***	-0.025***
	(0.019)	(0.012)	(0.003)	(0.000)	(0.000)	(0.000)
White	-0.340***	-0.201***	-0.073***	-0.103***	-0.071***	-0.068***
	(0.013)	(0.007)	(0.003)	(0.000)	(0.000)	(0.000)
Education level (Primary education as base)						
Incomplete secondary	-0.046***	-0.019**	-0.004**	-0.006***	-0.001***	-0.001***
	(0.015)	(0.009)	(0.002)	(0.000)	(0.000)	(0.000)
Complete secondary	-0.183***	-0.104***	-0.029***	-0.035***	-0.018***	-0.003***
	(0.015)	(0.010)	(0.002)	(0.000)	(0.000)	(0.000)
Diploma/Certificate	-0.405***	-0.268***	-0.069***	-0.075***	-0.065***	-0.024***
	(0.025)	(0.026)	(0.005)	(0.000)	(0.000)	(0.000)
Degree	-0.516***	-0.527***	-0.128***	-0.156***	-0.144***	-0.086***
	(0.027)	(0.037)	(0.007)	(0.000)	(0.000)	(0.000)
Postgraduate degree	-0.590***	-0.769***	-0.181***	-0.188***	-0.177***	-0.177***
	(0.029)	(0.040)	(0.008)	(0.000)	(0.000)	(0.000)
Chamber (Plastics as base)						
Automotives	-0.246***	-0.063***	-0.013***	-0.026***	-0.023***	0.006***
	(0.018)	(0.014)	(0.003)	(0.000)	(0.000)	(0.000)
Auto components	-0.080***	0.019	0.004*	-0.003***	0.001***	0.008***
	(0.015)	(0.012)	(0.002)	(0.000)	(0.000)	(0.000)
Metal	-0.107***	-0.048***	-0.008***	-0.024***	-0.003***	0.008***
	(0.011)	(0.009)	(0.002)	(0.000)	(0.000)	(0.000)
New Tyre	-0.062***	-0.016	0.018***	-0.010***	0.005***	0.060***
	(0.023)	(0.021)	(0.004)	(0.000)	(0.000)	(0.000)
Firm size (5 or less as base)						
6-20 workers	0.068**	0.043*	0.015***	0.026***	0.014***	0.003***
	(0.029)	(0.023)	(0.005)	(0.000)	(0.000)	(0.000)
21-50 workers	0.080***	0.045*	0.014***	0.028***	0.015***	0.002***
	(0.029)	(0.023)	(0.005)	(0.000)	(0.000)	(0.000)
51+ workers	0.110***	0.053**	0.017***	0.032***	0.020***	0.002***
	(0.028)	(0.023)	(0.005)	(0.000)	(0.000)	(0.000)
Year (2010 as base)						
2011	0.022	0.021	0.005*	-0.001***	0.005***	0.001***
	(0.020)	(0.015)	(0.003)	(0.000)	(0.000)	(0.000)
2012	-0.007	-0.000	-0.003	-0.003***	0.001***	0.001***

	(1) **Probit marginal effects Lewandowski, Park and Schotte (2020)**	(2) **Probit marginal effects Frey and Osborne (2017)**	(3) **OLS on continuous RTI**	(4) **Quantile reg. Q25**	(5) **Quantile reg. Q50**	(6) **Quantile reg. Q75**
	(0.019)	(0.014)	(0.003)	(0.000)	(0.000)	(0.000)
2013	0.006	0.013	0.001	-0.001***	0.002***	0.001***
	(0.019)	(0.015)	(0.003)	(0.000)	(0.000)	(0.000)
2014	0.017	-0.003	-0.000	-0.006***	0.002***	0.001***
	(0.020)	(0.016)	(0.003)	(0.000)	(0.000)	(0.000)
2015	0.049***	0.029**	0.004	0.006***	0.005***	0.001***
	(0.019)	(0.014)	(0.003)	(0.000)	(0.000)	(0.000)
2016	0.029	0.011	0.001	-0.003***	0.002***	0.001***
	(0.019)	(0.015)	(0.003)	(0.000)	(0.000)	(0.000)
2017	0.026	0.044***	0.003	0.001***	0.003***	0.001***
	(0.020)	(0.014)	(0.003)	(0.000)	(0.000)	(0.000)
2018	0.036*	0.028*	0.006**	0.009***	0.005***	0.001***
	(0.019)	(0.014)	(0.003)	(0.000)	(0.000)	(0.000)
Constant			0.802***	0.778***	0.795***	0.811***
			(0.007)	(0.000)	(0.000)	(0.000)
Observations	17,641	17,641	17,641	17,641	17,641	17,641

Source: Authors' calculations from PALMS v3.3 (Kerr, Lam & Wittenberg, 2019) and O*NET (2020).
Notes: 1. *** p<0.01, ** p<0.05, * p<0.1. 2. Regressions (1) and (2) are average marginal effects estimated from an underlying probit model.

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