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TOWARDS A JUST TRANSITION

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Understanding the Future Labour Market: A Microsimulation and Distributive Analysis

ABOUT THIS REPORT

This research paper was commissioned by the Presidential Climate Commission (PCC) and the African Climate Foundation.

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The Presidential Climate Commission (PCC) is a multi-stakeholder body established by the President of South Africa to advise on the country's climate change response and support a just transition to a low-carbon climate-resilient economy and society. The PCC facilitates dialogue between social partners on these issues—defining the type of economy and society we want to achieve, and detailed pathways for how to get there.

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Executive Summary

This report examines how South Africa's energy transition toward a low-carbon economy could reshape the labour market and inequality dynamics. Using an integrated macro–micro simulation approach, it links employment projections from the SATIM computable general equilibrium (CGE) model to household-level data through a microsimulation model. This allows the analysis to move beyond aggregate employment trends to explore who gains and who loses from the transition — by skill, gender, race, and sector.

The SATIMGE model simulates multiple emissions pathways (8, 9, and 10 gigatonnes (GT) CO_2 by 2050) under medium (1.5%) and high (3%) GDP growth assumptions. Across all scenarios, employment is projected to grow steadily from roughly 17 million in 2025 to between 24 and 36 million by 2050, with no evidence of net job losses. The results show that decarbonisation and net-zero pathways can coincide with positive labour market outcomes, although the magnitude of employment growth depends strongly on the assumed rate of economic growth.

Microsimulation results suggest that inequality, measured by the Gini coefficient and 90/10 earnings ratios, declines across all scenarios. These reductions are driven primarily by employment expansion among unskilled workers and by improved labour absorption at the lower end of the earnings distribution. Employment growth is especially strong in the services sector, which accounts for most new jobs and is likely to benefit women disproportionately — suggesting that the transition could be gender-equalising. However, a significant skills bottleneck emerges: by 2041, the model "runs out" of skilled unemployed workers to meet projected demand, highlighting the need for targeted skills development policies.

Transitions into unemployment are relatively small and concentrated in the first decade (2025–2035), particularly among African, female, youth, and agricultural workers — groups already vulnerable in the South African labour market. By contrast, transitions into employment outpace these losses throughout the period, with most new entrants coming from previously unemployed or economically inactive populations.

Overall, the findings indicate that South Africa's energy transition could be both employment-positive and inequality-reducing if accompanied by strong economic growth, proactive skills investment and social protection measures. The report concludes that achieving a *just transition* requires not only green growth but also attention to who participates in, and benefits from, the emerging green economy.

CONTENTS

List of acronyms

CGE - Computable General Equilibrium
EE - Energy Efficiency
ESRG - Energy Systems Research Group
ESAGE - Energy-South African General Equilibrium
EU - European Union
EV - Electric vehicle
GDP - Gross Domestic Product
GT - Gigaton
GVA - Gross Value Added
IRENA - International Renewable Energy Agency
JET IP - Just Energy Transition Investment Plan
MW - Megawatt
NDP - National Development Plan
PCC - Presidential Climate Commission
PEP - Partnership for Economic Policy
PV - Photovoltaic
QLFS - Quarterly Labour Force Surveys
REAL - Centre for Researching Education and Labour
SAM - Social Accounting Matrix
SATIMGE - South African Times Model – General Equilibrium
USA - United States of America

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Introduction

Globally, estimates for the impact of a "green transition" on employment are based largely on scenarios for the reduction of carbon emissions through a reduction in energy production from fossil fuels, and the increase in renewable energy production.

While the evidence is somewhat mixed, most projected scenarios suggest a net positive impact on employment for decarbonisation and renewable energy generation. For example, Gielen et al. (2019) estimate that the global energy transition could create 19 million jobs by 2050, while leading to roughly 7.4 million job losses in the fossil fuel intensive sectors, hence resulting in a net positive impact on employment. Results vary, however, and comparisons remain difficult across both contexts and studies because projections tend to be influenced by model choice and underlying assumptions.

In particular, the assumption that there are no "frictions" or transaction costs associated with the switch from jobs in the fossil fuel sector to jobs in the renewables sector may impact the results of a number of popular models. In addition, there are important considerations related to trade. Countries that are net exporters of renewable energy products will reap the positive economic benefits and employment opportunities associated with the transition while countries that are net importers will need to rely on carefully designed mitigation strategies to protect against job losses (Frondel et al., 2010).

Macro estimates of employment impacts therefore tend to obscure a number of important labour market, trade and structural features of the green transition's effects on employment levels. Projections for net aggregate changes in employment levels, moreover, do not reveal the underlying distributional outcomes of an energy transition. In other words, a net positive impact on employment or economic growth could still be "unjust" and, at the same time, employment losses would not necessarily result in an unjust transition.

Understanding the future of the labour market within the context of the energy transition therefore requires an understanding of the potential "winners and losers".

Within the context of the world's most unequal country, South Africa, there is a particular urgency to an analysis of whether potential employment changes will lead to a progressive or regressive change in the structure of employment opportunities and earnings.

There are, in addition, several important questions about the likely shifts in skills required in the labour market, which households will benefit from these changes in demand and which households will require support to adapt to a restructuring of the skills and sectoral profile of the labour market. Similarly, spatial changes in employment demand are likely to be accompanied by a number of labour market frictions that will require policy responses.

With reference to the South African context, there have been a number of studies examining the effects of the energy transition and decarbonisation on the labour market (see Merven et al., 2018). However, there are still gaps in the literature, especially pertaining to micro-distributional impacts.

The South African context has been studied on a macro scale, with a number of studies finding that specific regions, such as Mpumalanga, might be adversely affected (see Bhorat et al., 2024). However, there is still a limited understanding of which households and individuals will be adversely or positively affected by the energy transition and how this will impact on earnings inequality.

The aim of this report is to illustrate a relatively new and innovative macro–micro modelling approach to examine the potential distributional impacts of the South African energy transition on the labour market through its distributional effects on individual labour market participants and their households.

The remainder of this report is structured as follows

1. The next section outlines a number of key lessons from the international literature in terms of how labour markets respond to changes in demand due to an energy transition.
2. Section three provides an overview of an emerging literature on the distributional impacts of both climate change and the energy transition at the micro (household) level.
3. Section four describes the South African context with respect to the potential impacts of the energy transition on the labour market.
4. Section five offers a detailed description of the macro–micro modelling approach that is used to estimate distributional outcomes from several macro-projections of energy transition scenarios.
5. In section six the results of the simulation are provided for both the employment outcomes for key sub-groups and aggregate measures of earnings inequality simulated for a 25-year period.
6. Finally, the concluding section considers the implications for the skills mix as well as possible policy priorities for accompanying social protection measures.

International evidence

The broader international literature is largely optimistic about the impacts of decarbonisation and the energy transition on employment and much of this optimism appears to come from the employment potential in the renewable energy sector.

A job creation model which synthesised data from 15 studies in the United States of America (USA) found that decarbonisation, green energy and the renewable energy industry create more jobs per unit of energy than coal or natural gas alternatives (Wei et al., 2010). Moreover, these findings suggest that coal and natural gas jobs will be lost at a lower rate than the jobs created in the renewable energy sector (Wei et al., 2010).

In terms of investment, Pollin et al. (2009) found that investing in clean energy programmes in the USA will have larger positive impacts on employment than spending in other areas, such as the oil industry. The results suggest that job creation in the renewable energy sector is 2.5 to 3 times more for every $1 million invested, than that for oil and gas (Pollin et al., 2009; see also Mayfield et al., 2023).

In contexts such as the European Union (EU), which is a net importer of gas and coal, a large share of employment created by coal and gas supply is created outside the EU (Fragkos and Paroussos, 2018). Within the EU, there is a projected decline of 250 000 jobs in the coal mining industry from 2015–2050 due to a drop in the demand for coal (not only related to the transition), while employment attached to the extraction and transformation of fossil fuels is estimated to decline from 1.8 million to 1.3 million jobs over the same period. In contrast, solar photovoltaic (PV), wind power and biofuels are estimated to become the largest job creators by 2050, employing an estimated 1.5 million people (Fragkos and Paroussos, 2018; see also Corona et al., 2016).

These optimistic projections are supported by past evidence from employment shifts due to the green transition in the EU from 1995–2009. During this period the share of renewable energy generation increased from 5% to 10% of total generation while coal decreased from 22% in 1995 to 16% in 2009 (Markyanda et al., 2016). These changes in the input structure of the electricity supply sector in the EU resulted in a net positive employment impact, creating an estimated 530 000 jobs (Markyanda et al., 2016; see also Blazejczak et al., 2014).

Evidence from other contexts also suggests a slight but positive net effect of decarbonisation on employment. In Japan, estimates suggest that reducing Japan's fossil and nuclear power reliance, and shifting towards renewable energy, will result in a slight (0.08%) increase in net employment by 2030 (Pollitt et al., 2014: 254). In the world's most populous country, India, Chaudhuri et al. (2024) project the impact of the green transition on employment based on a social accounting matrix (SAM) model. They find that scenarios modelling an increase in renewable energy result in higher employment compared with a scenario based on continuing with fossil fuels (see also Malik and Bertram, 2022).

There is also some particularly encouraging evidence that fossil fuel producing countries are likely to experience employment gains during the energy transition. Montt et al. (2018) found that China, Taiwan and Indonesia are projected to see employment gains of around 1% by 2030 under renewable energy scenarios relative to a baseline scenario. This could be explained by the “significant efforts” that these countries still need to make in order to switch to renewable energy sources and to decarbonise their economies.

This finding is positive for a coal-exporting country, such as South Africa, and points to the possibility that countries with economies skewed towards fossil fuels can still benefit from the transition. In fact, Montt et al. (2018) found that out of 44 countries, South Africa ranks 10th in terms of its potential to benefit most from the transition.

However, there is also a literature which is more cautious about the employment outcomes of the energy transition (see Frondel et al., 2010; Rutovitz et al., 2020). Some studies even suggest a negative impact of decarbonisation on employment (Alton et al., 2014; Frondel et al., 2010; Hauenstien and Hals, 2022; Malik et al., 2021; Rutovitz et al., 2020, Wang and Lo., 2022).

The explanation for these negative employment impacts appears to be the lower long-term labour absorption capacity of renewable energies. Due to technological advancements in the renewable energy industry, the time taken to assemble, install and manufacture renewable energy technologies may decrease over time as the generational capabilities of the technologies increase (Rutovitz et al., 2020: 30).

For example, although renewable energy technologies require more jobs than non-renewables per megawatt (MW), the exponential uptake of renewables “is accompanied by steeply decreasing employment factors” due to increased labour productivity and decreasing capital costs (Malik et al., 2021: 4). Moreover, the energy transition is expected to create far more employment opportunities in the initial stages, especially in construction and maintenance, before labour absorption declines as the transition stabilises.

Overall, the results are mixed with regards to the impact of the energy transition (decarbonisation) on employment. While not conclusive, most studies do point to a neutral to slightly positive impact of decarbonisation on employment (Bernardo and D’Allesandro, 2016; Blazejczak, 2014; Fragkos and Paroussos, 2018; Gielen et al., 2019; Godinho, 2022; Lehr, 2012; Pollitt et al., 2014; Pollin et al., 2009; Wei et al., 2010).

Crucially, the impact on employment depends on a number of factors, including but not limited to spatial or regional dynamics (Bhorat et al 2023; Burton et al 2018; Jacobs et al 2022; Nel et al 2023; Wang and Lo 2018; Wehnert et al 2019), the trade characteristics of the country/region (Burton et al., 2018; Holz et al., 2018; Nicholas and Buckley, 2019; Oei and Mendelevitch, 2018; Richter et al., 2018; Wehnert et al., 2019) and other factors, such as the timing of the transition.

In terms of low- and middle-income country contexts, the literature is also generally positive about the employment effects of the transition (Burton et al., 2018; Holz et al., 2018; Jacobs et al., 2022; Mervin et al., 2021; Nel et al., 2023; Nicholas and Buckley, 2019; Strambo et al., 2019). Findings from these studies, largely based on computable general equilibrium (CGE) models, suggest that the energy transition will bring about net positive employment gains and that even economies that are fossil fuel producers could gain from the transition.

Distributional effects of the transition

Overall employment gains or losses are an important feature of the energy transition but somewhat less is known about the potential distributional effects of aggregate employment changes. Understanding whether the overall impact on the labour market will be regressive or progressive requires an analysis of who benefits (and who does not) from a transition away from fossil fuels.

Not surprisingly, there is often a spatial element to such distributional effects. In the Indian context, for example, coal regions are often poorer and feature a path dependency due to heavy reliance on a single commodity. As a result, in the absence of mitigating strategies, the transition will redistribute investment and employment from poorer, coal-rich regions to other regions that have already started to embrace the transition (see Malik and Bertram, 2022).

Beyond spatial distributions, understanding the individual or household level effects is important for estimating the distributional effects of the transition.

Cockburn et al. (2018) adapted a combined CGE microsimulation approach to determine individual- and household-specific poverty and inequality outcomes from changes in wage rates, employment and consumer prices as a result of energy subsidy cuts in Jordan and Egypt.

They found that, in both countries, energy subsidy reforms reduced fiscal deficits, increased economic growth and boosted investment. However, these positive outcomes were not distributionally neutral and would adversely impact vulnerable households and increase income poverty.

The key finding was, therefore, that the simulated increase in gross domestic product (GDP) growth was not sufficient to offset the adverse effects of the subsidy cuts on vulnerable households, particularly in the short and medium term. Such an example illustrates the importance of understanding the distributional implications of outcome that are positive at the macro level (Cockburn et al., 2018).

There are also indirect ways in which the energy transition could be regressive in terms of its distributional effects. In an example from India, Rajagopal (2023) estimated the impact of a switch to electric vehicles (EVs).

The study found that an increase in the EV industry would result in a relative reduction in tax revenue by roughly 85% (largely through a reduction on excise taxes on fuel). This reduction in revenue would then put pressure on fiscal policy to ensure that expenditures on key services, such as social protection, healthcare and education on which lower income households depend, are not compromised.

The South African context

There is already a relatively large and growing literature on the likely impacts of decarbonisation on the South African labour market. One of the most comprehensive studies on the employment outcomes from emissions reductions has suggested that there would likely be different outcomes for different levels of emissions reductions targets (Mervin et al., 2018: 14). In particular, the findings suggest that under a larger (10 gigaton (GT), 9GT and 8GT)[1] emissions cap scenario, the gross value add (GVA) loss will be 1.4% or less but GDP under these scenarios would be no different from the baseline scenario of "no planned mitigation policies and measures".

However, there would be a net negative impact on GDP when the emissions cap ranges from 6–7 GT and GDP losses outweigh the mitigation gains when "shifting beyond the 8GT emissions cap" (Mervin et al., 2021: 14). This is due to the larger cost of meeting clean energy standards under the 6GT and 7GT baseline scenarios.

In the presence of planned mitigation policies and measures, there would be a positive impact on GVA under the 10GT and 9GT emissions cap scenarios (Mervin et al., 2021: 15). Under

[1] The GT scenarios refer to the emissions cap which is an upper limit of cumulative CO_2 emissions from the energy sector and industrial processes between 2020 and 2050.

the emissions cap scenarios, if there are no planned mitigation policies and measures in South Africa, the transition to a low-carbon economy would have a negative impact on employment in each baseline scenario ranging from a 10GT–6GT emissions cap, with employment losses ranging from 23 000–1.4 million. However, in the presence of mitigation policies and measures there would be a net positive impact on employment for the 10GT–8GT emissions cap scenarios (Merven et al., 2018: 20).

In addition to these emission-reduction scenarios, there is also evidence on the impact of renewable energy production and investment on employment outcomes in South Africa. According to the International Renewable Energy Agency (IRENA) (2020), decarbonising the power production sector in South Africa could lead to a net increase in employment from 2018–2030 if the switch is made to a renewable energy mix.

Despite significant job losses in the coal sector, there would be an estimated 580 000 jobs created, resulting in a net positive impact on employment if the energy sector is decarbonised (IRENA, 2020: 128). Other projections are somewhat less optimistic but, nonetheless, point to a net employment gain. For example, Hartley et al. (2017) project that an increase in renewable energy generation to 72% by 2050 would result in a net employment increase of 0.8% by 2030 and 5.5% by 2050. Furthermore, they show that the reduction in employment in the coal sector would be mitigated by other opportunities for South Africa's mining sector as a result of the energy transition. These include the mining of metals, such as copper and cobalt for electric vehicle batteries, which could create new employment opportunities (Hartley et al., 2017).

Similarly, Mervin et al. (2021b) found that considerably more jobs are created per unit of electricity produced by solar and wind than coal. The jobs that are lost in the coal mining sector as a result of the transition are offset, in aggregate levels, by new jobs created in the renewable energy sector and elsewhere in the economy as a result of the transition (Mervin et al., 2021b: 13). Moreover, they show that renewable energy has increased benefits on employment because cheaper electricity "has broader positive economic impacts, allowing households to spend and firms to grow" (Mervin et al., 2021b: 13).

However, the ability of the South African labour market to benefit from the transition depends on a range of complex factors. These include a strong dependence on coal for electricity generation, synthetic fuels and especially for the "heavy energy needs of the historic core of South Africa's economy" (Nel et al., 2023: 3).

Coal has been an important source of economic growth in South Africa: attracting foreign investment, creating jobs and enabling cheap access to electricity supply (Strambo et al., 2019: 5). The number of job losses in the coal sector will depend on the number of coal power plants that are decommissioned. Therefore, the pace of the decommissioning of plants and the transition need to be matched by faster upscaling of renewable and clean energy industries (Jacobs et al., 2022: 4).

As of 2018, more than 80% of coal mining by volume occurred in Mpumalanga, where coal mining is the single largest contributor to the province's GDP (Burton et al., 2018: 11). Mpumalanga is the centre of South Africa's coal industry and the regional economy of the province is highly reliant on coal exploration (Jacobs et al., 2022: 3).

The Mpumalanga case is consistent with other coal mining regions globally, which stresses the importance of economic diversification in these regions with intensive coal dependency in order to improve socio-economic development (Burton et al., 2018: 11). Coal mining directly employed more than 77 000 people in 2015 (Burton et al., 2018: 11), with this number growing to approximately 91 000 in 2022 (StatsSA, 2023).

In addition to the concentration of job losses in the Mpumalanga province, there is evidence to suggest that the restructuring of the labour market in response to the energy transition may be uneven.

Davidson et al. (2024) estimate that 4.6% of the South African workforce in 2018 was employed in “green increased demand” occupations, that is, existing occupations likely to see an increase in demand as a result of the transition.

At the same time, only 1% of the workforce could be categorised as working in “green new and emerging” occupations while 3.5% of the workforce could be categorised as having “green enhanced skills”. Currently, white workers are overrepresented among “green new and emerging” occupations and “green enhanced” skills groups and these occupations are relatively high paying.

The implication is that, without careful management, the transition is expected to increase the percentage of white workers from 12% of the total workforce to 17% of the total workforce, whereas the proportion of black workers will decrease from 75% of the workforce to 69% of the workforce (Davidson et al., 2024). There are also potential gender implications based on the “green” profile of the existing workforce with the possibility of men being more likely to benefit from the transition than women (Davidson et al., 2024).

Taken as a whole, the existing literature on the South African transition suggests that the switch away from fossil fuels (primarily coal) will lead to job losses but that these losses will be offset by employment gains in other existing sectors as well as in new and emerging sectors, particularly if relevant supporting policy is in place. \

Therefore, similar to the international literature, there is evidence that suggests there will be net employment gains from the energy transition, although the magnitude of these gains is contested. Perhaps the two key features of the energy transition which require policy attention are, first, that job losses are likely to concentrated in one region (Mpumalanga) and it appears unlikely that the new jobs that will be created will be located in this region. Therefore, even with an aggregate net employment gain, a policy intervention will be required to address the regional imbalance.

Second, there is at least some evidence that race and gender differences in the occupations that are likely to adapt to the transition will also make the transition regressive without policy support.

The finding that male, white and higher earning workers are more likely to be in “green” occupations suggests that even an increase in aggregate employment could coincide with an increase in earnings inequality.

To date, however, there has been no micro-level analysis of workers and households with which to assess the distributional effects of the transition and it is towards this particular task that the report now turns.

Methodology

Scenarios

In order to simulate the distributional implications of the energy transition, macro-scenarios for the aggregate employment changes have to be selected. The scenarios outlined below (Table 1) have been derived from a national combined energy and economic model (South African Times Model – General Equilibrium). The model (SATIMGE) combines the South African TIMES (SATIM) model – an economy-wide partial equilibrium linear optimisation model from the TIMES platform, developed and curated by the Energy Systems Research Group (ESRG) at the University of Cape Town – with the Energy-South African General Equilibrium (ESAGE) model, a CGE model of the South African economy. An additional advantage of using this model is that it aligns well with South Africa's policy framework since it was used to estimate investment requirements as part of government's Just Energy Transition Investment Plan (JET IP).

Following consultations with the ESRG and the Presidential Climate Commission (PCC), three emissions reduction scenarios from the SATIMGE model have been selected for the micro-distributional analysis. The logic is to test the distributional outcomes for each scenario by comparing different results across the scenarios as emissions caps become more stringent, while all others are held constant. For each scenario, only two parameters are varied – the level of the emissions cap (8GT, 9GT and 10GT) and the assumption about the rate of growth in factor productivity. In order to simulate GDP growth under each scenario, total factor productivity was set at either 1.5% growth or 3% growth in each sector of the economy. The "medium" scenario of 1.5% reflects the growth that the South African economy has been experiencing over the past several decades while the 3% growth assumption is higher than actual growth but is still somewhat lower than expectations outlined in the National Development Plan (NDP). Each scenario assumes a strong multilateral policy environment that prioritises decarbonisation (World A) and models a 2050 net zero date. The analysis compares the different impacts of net zero scenarios across emissions caps of 8, 9 and 10GT (the "no regrets" scenario) as well as differences by the assumed GDP growth rates (1.5% vs 3% year-on-year). Table 1 outlines the scenarios from the SATIMGE model that were fed into the microsimulation model.

Table 1 Selected scenarios from the SATIMGE Model

Scenario/ Net zero year	TFP growth	Global context	CTL	CHG limit	CO_2 Tax	Energy efficiency
8GT emissions cap- 2050 Net Zero- medium	1.5% (Medium)	A	SS	8 Gt	Current levels (CPAM)	EE
9GT emissions cap- 2050 Net Zero-medium	1.5% (Medium)	A	SS	9 Gt	Current levels (CPAM)	EE
9GT emissions cap- 2050 Net Zero-high	3% (High)	A	SS	9 Gt	Current levels (CPAM)	EE
10GT emissions cap- 2050 Net Zero-medium	1.5% (Medium)	A	SS	10 Gt	Current levels (CPAM)	EE
10GT emissions cap- 2050 Net Zero-high	3% (High)	A	SS	10 Gt	Current levels (CPAM)	EE

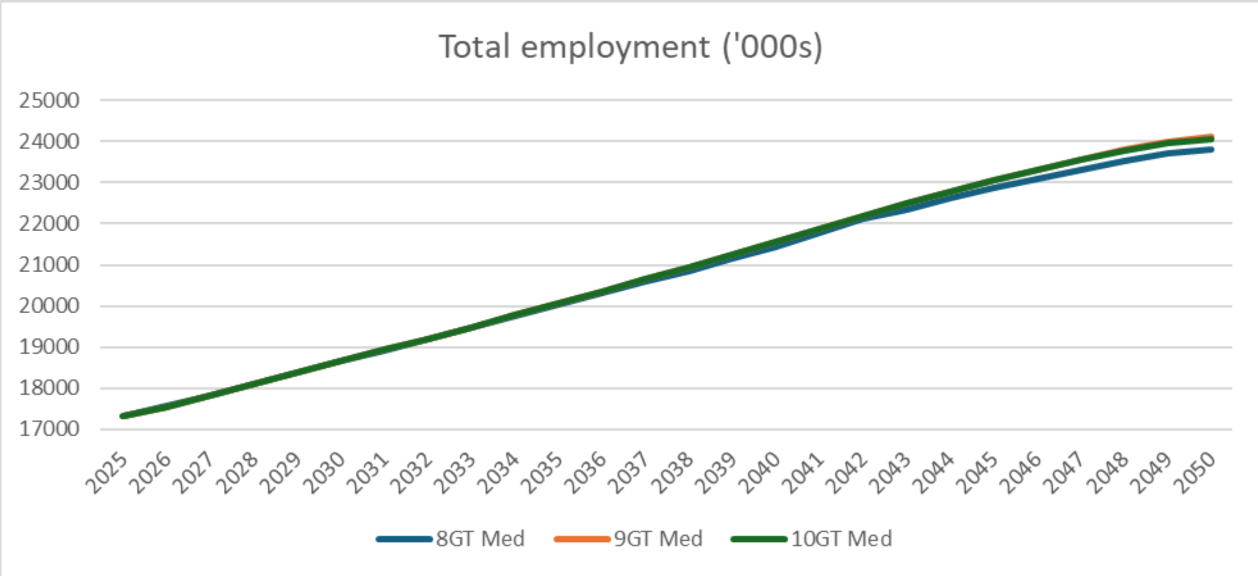
Notes: CTL = (Sasol – SS – phase down from 2030; SF – phase down from 2045; SE – Sasol endogenous retirement from 2035). Energy efficiency = (EE = with energy eff, NE = without).

Figure 1 below shows projected employment numbers for all three emissions scenarios at a GDP growth rate (1.5%), which is largely reflective of current growth rates in South Africa. There are two important findings from the graph. The first is that employment projections are almost identical across the three scenarios.

There is some divergence towards the end of the modelled period but the differences are likely to fall within the survey margin of error. Second, the estimates from SATIMGE all project positive employment growth over the period.

There is no evidence of a period of net employment loss and total employment increases from just over 17 million in 2025 to roughly 24 million by 2050. Thus, all microsimulations presented in this report are based on these projections of steady employment growth.

Figure 1 Total employment estimates from the SATIMGE model, 2025-2050

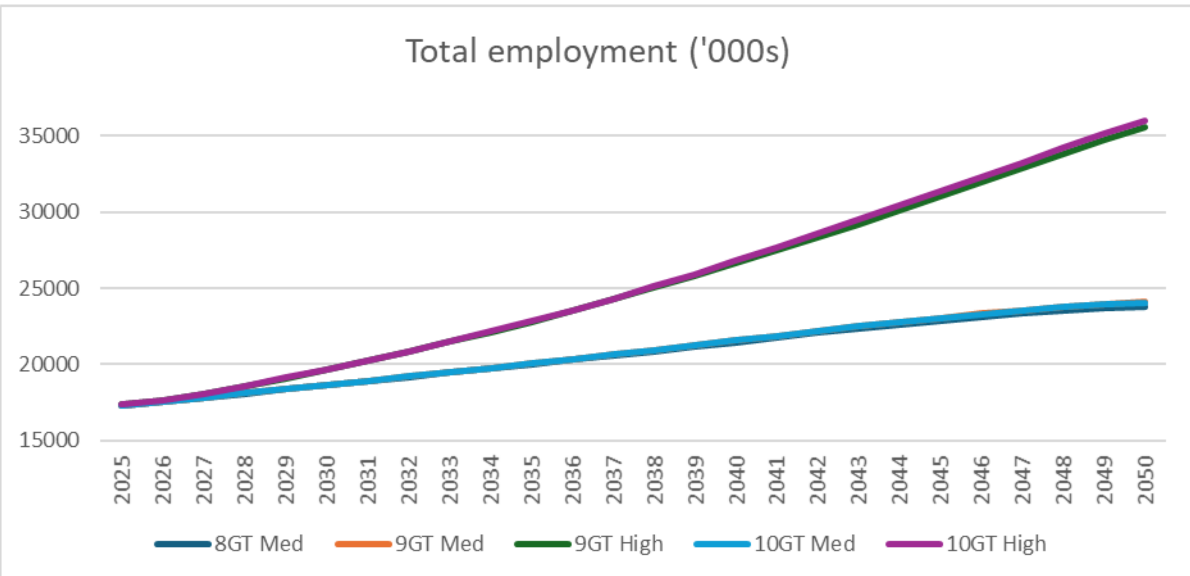


Source: Estimates from the SATIMGE model (ESRG-UCT)

However, one important source of variation in employment in the SATIMGE model comes from the assumption about GDP growth rates. In Figure 2, employment numbers for the 8, 9 and 10GT emissions scenarios under the assumption of medium (1.5%) growth are compared with 9 and 10GT scenarios modelled at the higher growth rate (3%).

The results clearly show that employment estimates are very sensitive to the growth assumption. When growth is exogenously determined to be at 3%, then both the 9GT and 10GT scenarios result in a projected workforce of about 36 million by 2050. This is much higher than the scenarios modelled at the lower growth rate and is roughly double total employment in 2025. Moreover, these large differences will have obvious implications for the analysis of welfare measures as shown later in the report.

Figure 2 Total employment estimates from the SATIMGE model, 2025-2050 (medium and high growth)



Source: Estimates from the SATIMGE model (ESRG-UCT). The top two lines (purple and green) denote high growth scenarios while the bottom three lines (dark blue, orange and light blue) denote medium growth scenarios.

A macro–micro simulation

This section outlines the approach to linking the SATIMGE CGE to a microsimulation model based on the work of Tiberti et al. (2017).[2] Tiberti et al. (2017) created a Stata module that performs microsimulations that implement CGE shocks in a top-down fashion to examine the impact of macro policy on poverty and inequality. The module parametrically estimates individual and household income where CGE shocks come in the form of movement across sectors, as well as changes in wages and earnings (by the skill levels of workers).

The module captures changes in purchasing power by using household-specific price deflators based on individual utility functions. Specifically, changes estimated by the CGE model in employment, wages, earnings from self-employment and commodity prices are consistently fed into the microsimulation model. The tool then estimates a new vector of earnings and performs distributive analysis, such as standard poverty and inequality indices that can be further decomposed by sub-group. This can then be compared to a baseline to see the effect of the policy or shock on household/individual welfare.

The module is based on repeated imputations of the CGE shock (simulations) into survey data from the annualised Quarterly Labour Force Surveys (QLFSs) from 2019. This is done multiple times (e.g. 100) and the median values of the results are selected. Further, the simulation is conducted into the future i.e. for each of the years used by the CGE model. Lastly, to conduct a distributive analysis the microsimulation compares two counterfactual scenarios. For example, a typical comparison would focus on how CGE shocks from a CGE model that simulate a “business as usual” or “no regrets” scenario (i.e. the economy continues on its current trajectory without any changes in terms of policies on energy transition (call this scenario 1)) into the future compares with the result of a CGE model that put an X GT carbon budget by 2050 (i.e. a scenario where emission is restricted to X gigatonne (call this sccenario2)). For each year there are a vector of shocks to employment, income and commodity prices from both scenarios and by comparing the distribution of wellbeing measures under the scenarios, it is possible to recover an estimate of the impact of the X GT carbon budget on welfare for that year.

In summary, there are two dimensions to the simulation:

- Loop 1: Code to impose shocks to the survey data via the microsimulation model and this is done multiple times (100).
- Loop 2: Loop 1 is conducted for each year into the future to trace the trajectory of welfare measures over time.

In what follows, we describe each section of a stripped-down version of the microsimulation code.[3] This is done by focusing on the core microsimulation models for only one instance of one scenario.

Population

[2] This is part of the Partnership for Economic Policy (PEP) toolbox and is freely available at https://www.pep-net.org/sites/pep-net.org/files/files_microsim/TDBmicrosim_Manual.pdf

[3] One caveat is that, while the QLFS is the most comprehensive labour force survey in South Africa, it does not contain household commodity prices. It will therefore be difficult to compute the household-level poverty line based on commodity prices. One solution to this is to base our distributive analysis on income and not necessarily the basket of goods households buy.

Since we are simulating into the future, the microsimulation model needs to take account of population growth. This is implemented in the PEP toolbox by the "static ageing" or sampling reweighting approach. The example provided by the PEP toolbox assumes a population growth of 3%. This part is dealt with in section 1 "POPULATION GROWTH" in the do file. This is done in the following steps:

- Obtain an estimate of the population by region (e.g. by rural-urban divide in South Africa);
- Impose the projection from the population growth model on population by region i.e. multiply population totals by population growth estimate (our understanding is that SATIMGE uses the median estimate of the United Nations' world population prospect probabilistic projections (UCT));
- Take the computed weight as new sampling weights (for year 1) and calibrate (get new individual weights) such that the regional ratios and new population totals are satisfied.

Note that this approach assumes that there is no change in population structure over time, for example, population ratios by region or sex do not change over time. It is, therefore, more appropriate for short-to-medium-run simulations.

A matrix of shocks

Next, we create the matrix of shocks that are used by the code to pass on the CGE shocks to the microsimulation. Two shocks are considered: (i) shock to employment (by skill) and (ii) shock to earnings (by skill). To pass these shocks, cells are created. In the PEP example, which we initially follow in our application, the cells in the employment shock category are based on

- Employment categories
    - 1 "Agriculture"
    - 2 "Mining"
    - 3 "Manufacturing"
    - 4 "Services"
    - 5 "Not employed"
- Skills categories
    - 0 "unskilled" (secondary school education and below)
    - 1 "Skilled" (higher than secondary school education)

By combining the categories, we have 8 cells – a total of 10 minus the 2 cells defined by the "not employed" category – defined by the intersection of skill/employment categories. Note all these changes are percentage changes.

Microsimulation model

The code iterates over skill levels (skilled and unskilled) and estimates a multinomial logit model of the form

$$log\frac{P(employment_i = m)}{P(employment_i = 5)} = \alpha_m + \sum_{j=1}^{m} \beta_{mj}X_{ij} + u_{ij} = Z_{mi} \dots\dots.. (1)$$

for each skill level, where X is a vector of characteristics that include geographic location (rural/urban), gender, household head dummy, age, education, number of children and marital status. The employment category of individual i is denoted by $employment_i$ and $m = 1 \dots 5$ represent the 5 employment categories in section 1.2 (note $m = 5$ is the unemployment category), u_{ij} are individual residual terms. The multinomial logit model is weighted using the base survey weight in the data.

Two predictions are made from this model:

- The probability of an individual being in each of the 5 employment states/categories is estimated "pr_i" (note that these probabilities sum to 1 for each individual and are estimated by the "predict" post estimation command in Stata).
- Values of linear predictions Z_{mi}that is associated with being in each of the 5 employment states from the model (i.e. using the "predict, xb" in Stata), note that these are not probabilities; they are values based on observed characteristics included in the model.

The idea behind the linear predictions is that they represent the utility of being in each of the 5 states given observed attributes. For simulation purposes, the programme "draw" in the do file generates random numbers u_{ij} from an extreme distribution (Gumbel distribution). By adding the linear predictions to the random numbers, the code simulates utilities of being in the 5 different states (for each individual) i.e. individual i is observed in state m if

$$Z_{mi} > Z_{si}, m = 1 \ldots.5; m \neq s \ldots \ldots \ldots (2)$$

The code finds the value of u_{ij} such that the observed employment status is consistent with equation (2).

Lastly, based on the computed utility values, new probabilities of being in any of the 5 states are computed. For example, the probability of individual i being in state $m, m = 1 \ldots 3$ is computed as

$$P(employment_i = m) = \frac{\exp\,(Z_{mi})}{1 + \sum_{m=1}^{3} exp\,(Z_{mi})} \ldots \ldots. (3)$$

and for $m = 4$ we have

$$P(employment_i = 4) = \frac{1}{1 + \sum_{m=1}^{3} exp\,(Z_{mi})} \ldots \ldots. (4)$$

Probabilities computed by equations (3) and (4) determine how individuals are allocated into employment categories based on the shock from the CGE model. For example, if the CGE predicts an increase in the number of people employed in the skilled mining cell, then all working-age skilled individuals are ranked according to their probability of being in that sector. The code then selects individuals from other sectors in descending order of probability of being in the skilled mining sector until the number of people employed in the skilled mining sector is consistent with the CGE result. Note that this assumes perfect mobility across sectors and perfect rigidity across skill categories.

After implementing the changes according to the CGE shocks, we have a new employment status variable that is consistent with the CGE shocks.

Simulation of income using the Heckman selection model

After the new employment variable that incorporates the CGE model shocks is derived, the next microsimulation model estimates income based on the new employment status variable. The microsimulation estimates a Mincer-type wage equation using the Heckman two-stage model. Just like the employment model, it is done by skill. For each skill level, the selection equation is based on

$$s_i^* = \gamma z_i + \varepsilon_i \ldots \ldots.. (5)$$

where z_i is a set of controls, s_i is a binary variable that indicates if the employed individual is in the wage sector or not, s_i^* is an unobserved index that determines s_i based on

$$s_i = \begin{cases} 1\, if\;\; s_i^* > 0 \\ 0\, if\;\; s_i^* \leq 0 \end{cases} \ldots \ldots.. (6)$$

Lastly, the wage equation is estimated as

$$w_i = \begin{cases} \beta x_i + v_i \; if \;\; s_i^* > 0 \\ . \qquad\quad\;\; if \;\; s_i^* \leq 0 \end{cases} \dots\dots\dots (7)$$

This approach is adopted because of the possible endogeneity of being a wage worker, which means ε_i and v_i are correlated (which may bias the result). The conditional expectation of wages is estimated as

$$E(w_i|x_i, s_i^*) = \beta x_i + \sigma_{sw}\lambda(\gamma z_i) \dots\dots..(8)$$

where σ_{sw} is the covariance between ε_i and v_i and λ is the inverse of Mill's ratio.

For simulation purposes v_i, which represents individual fixed effects or individual heterogeneity, is easily estimated from equation (7) i.e. for individuals employed in the base year. For those who are not in the wage sector but may change status due to CGE shock, the residual is estimated from the normal distribution with the relevant (skilled or unskilled) observed variance. Finally, CGE shocks are integrated such that changes in average wages are consistent with the changes in wages obtained from the CGE model.

Skills restrictions

As outlined earlier, the SATIMGE's assumption of GDP growth rates of 3% (year-on-year) results in a more than doubling of the total number employed between 2025 and 2050. Such a large increase in employment nearly eliminates unemployment by 2050 and, as a result, has a large effect on the microsimulation results. Given the structural nature of unemployment in South Africa where a large pool of unskilled unemployed do not have the skills required by the labour market, the microsimulation model is unable to match the unemployed with the jobs projected by the CGE model. In other words, when we retain the microsimulation restriction that a "skilled" job can only be filled by a skilled worker, then the microsimulation is only able to run for 21 periods (until 2041).

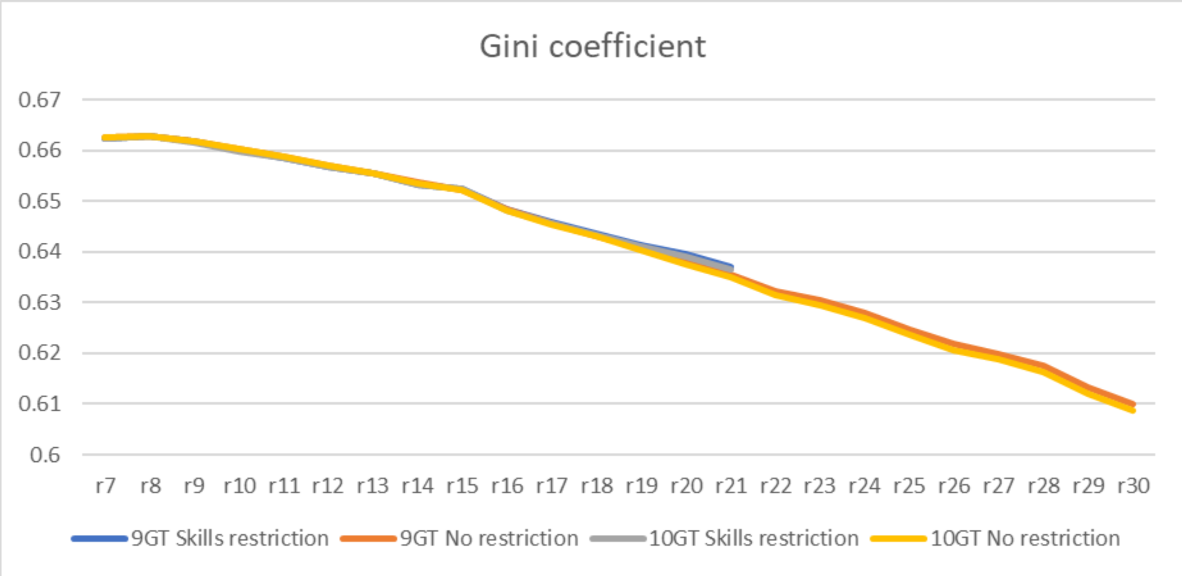
The reason is simply that there are not enough unemployed workers in South Africa to fill the requirements for skilled employment modelled by the CGE. However, if we relax this restriction by allowing an unskilled unemployed person to "move into" a skilled job, then the microsimulation runs for the entire period (until 2050). This is both an important methodological point and a substantive finding. The key takeaway is that many of the jobs that will be required by the energy transition are likely to be "skilled" and this would exacerbate the mismatch between skills demand and supply in South Africa. Put differently, without a skills intervention, the South African economy risks not being able to maximise the benefits of employment creation from the energy transition.

In order to illustrate how this skills shortage impacts on our microsimulation results, Figure 3 below plots a popular inequality measure – the Gini coefficient of income) – both with and without the skills restriction in the microsimulation model.

The decrease in inequality is evident both with and without the restriction but the model stops at the 21st period (2041) when there are no longer any skilled unemployed workers to fill the requirements of the CGE projections. The yellow and orange lines, in contrast, continue the downward trajectory of inequality and illustrate that aggregate inequality would continue to decrease if unskilled workers were "allowed" to move into skilled employment.

Note, however, that the inequality trends continue at a fairly consistent downward trajectory. This is because employment growth is relatively constant and because wages are predicted by individual characteristics in the microsimulation model, so unskilled workers will continue to earn relatively low wages even though they are simulated to be working in "skilled" employment.

Figure 3 Gini coefficients of income with and without the "skills restriction" in the microsimulation model (high growth scenarios)



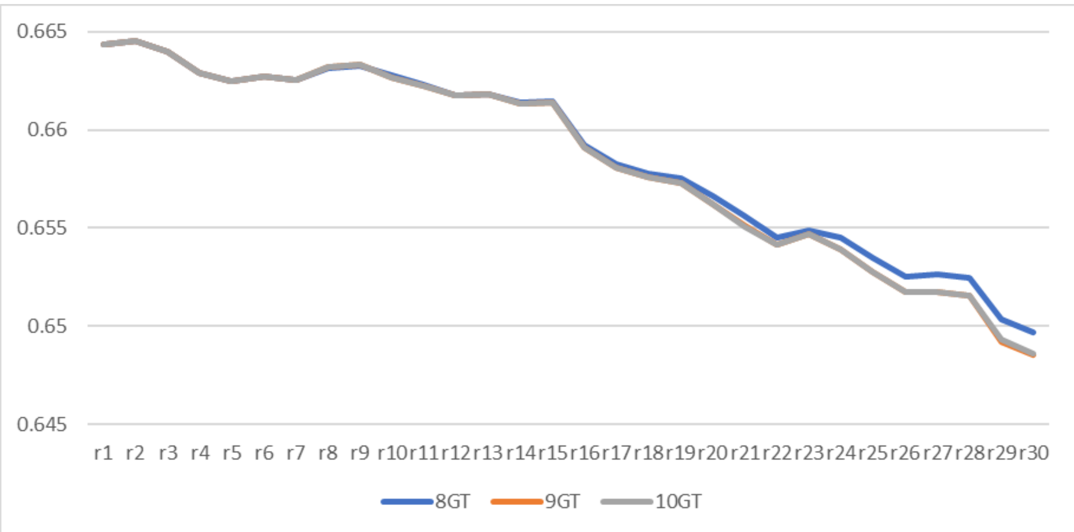
Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Results

Aggregate inequality measures

Turning now to the first set of results from the microsimulation model, Figure 4 presents simulated Gini coefficients of income from 2019 (r1) to 2050 (r30). All three scenarios are simulated at the medium growth rate (1.5%) and the key result is that earnings inequality decreases under all scenarios. Based on the employment projections from the SATIMGE model, inequality could be expected to decrease from about .67 to about .65 over the 30-year period. This is not a large decrease in absolute terms but demonstrates that inequality can be reduced at the same time that CO_2 emissions are decreased. Moreover, there appears to be very little difference in inequality reduction between the more generous emissions cap (10GT) and the more ambitious target of an 8GT emissions cap. Towards the end of the simulated period, inequality is slightly (but not significantly) lower under the 10GT "no regrets" scenario but, otherwise, inequality outcomes are very similar across the three scenarios.

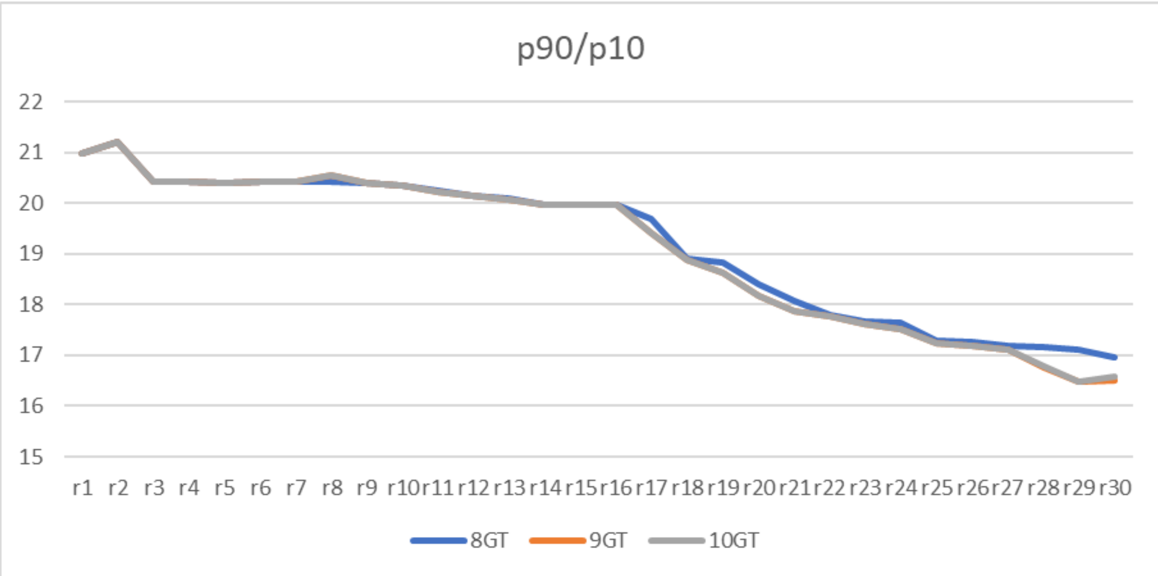
Figure 4 Gini coefficients under the 8, 9 and 10GT scenarios (medium growth assumption)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Another way of measuring inequality is to estimate the ratio of the earnings distribution at the 90th percentile (the highest earning 10%) and the 10th percentile (the lowest earning 10%). This ratio offers a more tangible way of understanding earnings disparities. Figure 5 below estimates these ratios for the period under review for each of the emissions cap scenarios. Once again, the key finding is both that earnings inequality decreases under all scenarios and that there are only very small differences between the scenarios. For example, in 2025, the top 10th percentile of earners earned about 20 times more than the bottom 10th percentile. By 2050, this is projected to decrease to about 16.5 times under the 9GT and 10GT scenarios and to about 17 under the 8GT scenario.

Figure 5 90/10 percentile earnings ratios under the 8, 9 and 10GT scenarios (medium growth assumption)

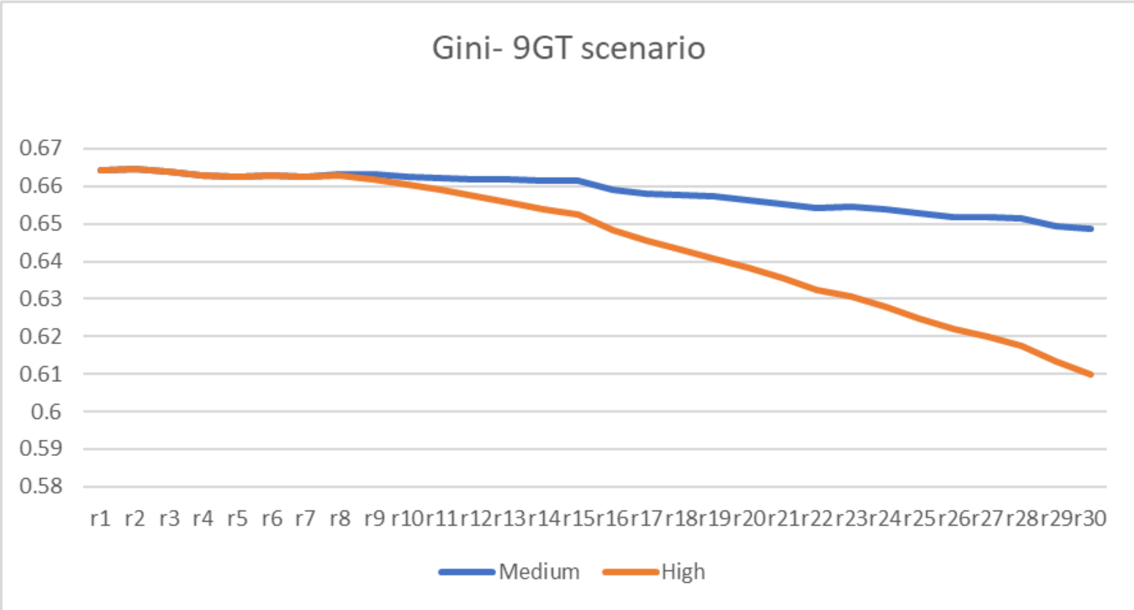


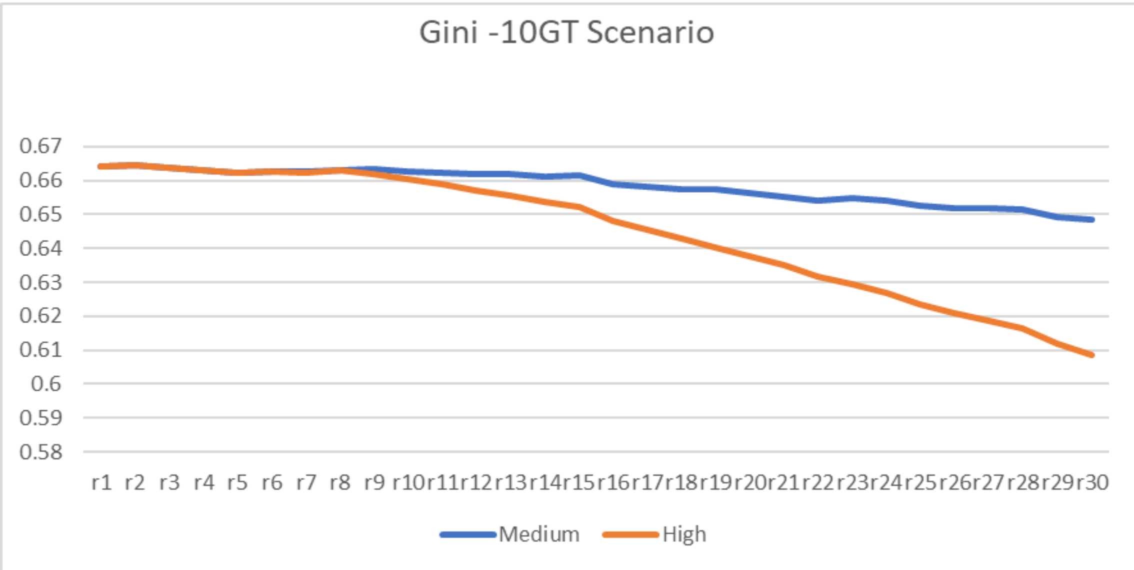
Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

While there are only very small differences in aggregate inequality outcomes between the three emissions cap scenarios, there are, as expected, relatively large differences between the medium and high growth assumptions. Figure 6 plots Gini coefficients for the 9GT and 10GT scenarios and compares the results for the two different growth levels. In both panels, the blue line denotes the relatively modest decreases in inequality (from Figure 4) under the medium growth assumption or, in other words, if economic growth continues much as it has over the past ten years. The orange lines, in contrast, depict inequality trends under the higher growth assumption and show that the Gini coefficient could be expected to decrease from about .66 to .61 over the simulated period.

Thus, the strong employment growth modelled in the SATIMGE could be expected to translate in reductions in overall inequality. Perhaps the key take away is that, irrespective of growth levels, inequality can be reduced at the same time that emissions are capped as the economy moves towards a net zero target. The remaining caveat, however, is that (as outlined above) the microsimulation is only able to run the high growth scenarios by removing the skills restriction and “allowing” unskilled unemployed workers to move into skilled jobs.

Figure 6 Gini coefficients of income under the medium and high growth assumptions (9 and 10GT scenarios)





Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

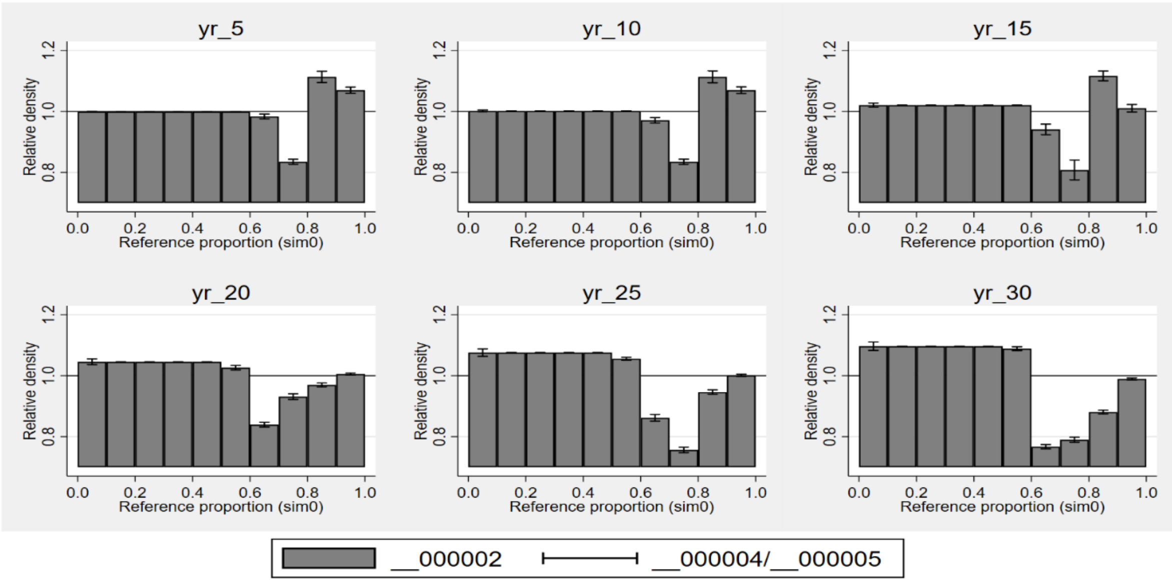
In order to better understand how earnings inequality is expected to decrease under the SATIMGE scenarios, Figures 7–9 estimate the relative density of employment relative to the 2019 baseline year. Each earnings decile is measured as a proportion of employment relative to 2019 with the horizontal line denoting the reference year. In Figure 7, earnings are simulated under the 8GT SATIMGE scenario (medium growth) and the results suggest that the earnings distribution becomes more progressive in the second half of the simulated period. For example, in year 10 (2030), employment density in the bottom half of the earnings distribution is almost identical to the reference year. Growth in employment in year 10 is concentrated in the top two earnings deciles. By year 20 (2040), growth in the bottom half of the distribution starts to exceed the reference year while growth at the top falls below the reference period. By the end of the simulation period (2050), employment growth is dominated by the bottom deciles in the earnings distribution.

There are two possible explanations for the shift in relative densities over the 30-year period. The first is that the types of employment (by skill and sector) that are projected under the

SATIMGE scenarios are well matched with the characteristics of the labour force. This might be the case, for example, if employment in sectors with low skill requirements begin to absorb more workers towards the end of the period, for example, related to the mining of new materials or the maintenance of renewable energy infrastructure. Support for this explanation comes from the relatively largely increase in unskilled employment in the largest sector (services), particularly at the end of the period (see appendix). The second explanation comes from the design of the microsimulation model itself.

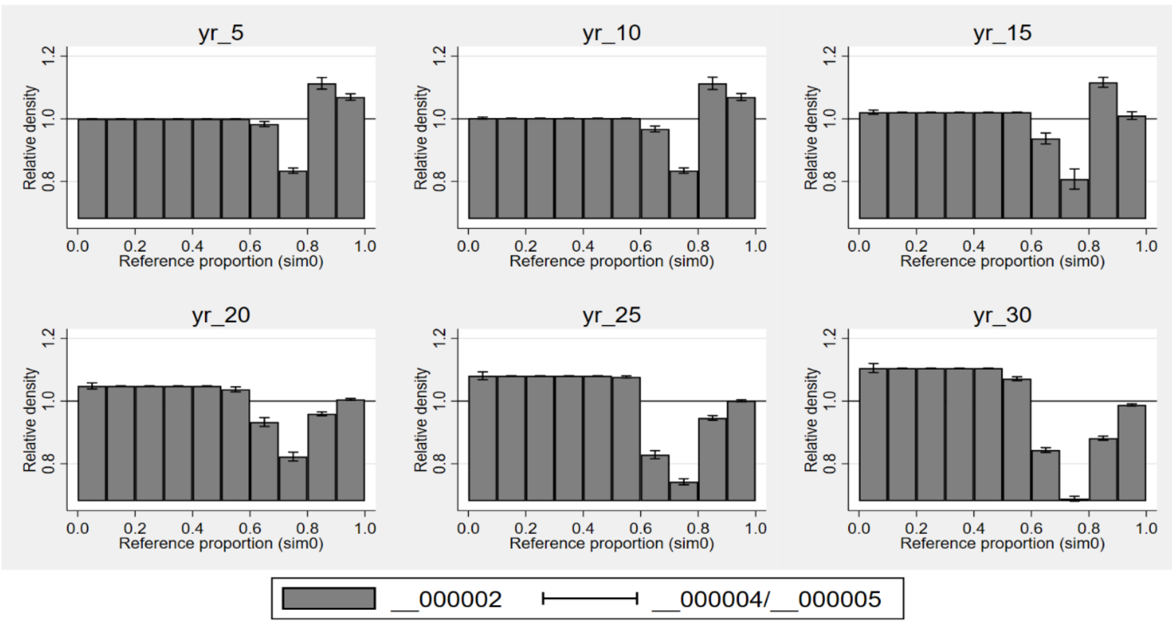
As employment growth increases relative to population growth, the probability calculations underpinning the microsimulations draw increasingly from the pool of unemployed to meet the requirements of the CGE outputs. The unemployed have lower levels of skill and therefore have lower predicted earnings, meaning that growth at the bottom of the earnings distribution is greater than the top towards the end of the period.

Figure 7 Relative employment density estimates 2025–2050 (8GT scenario – medium growth)



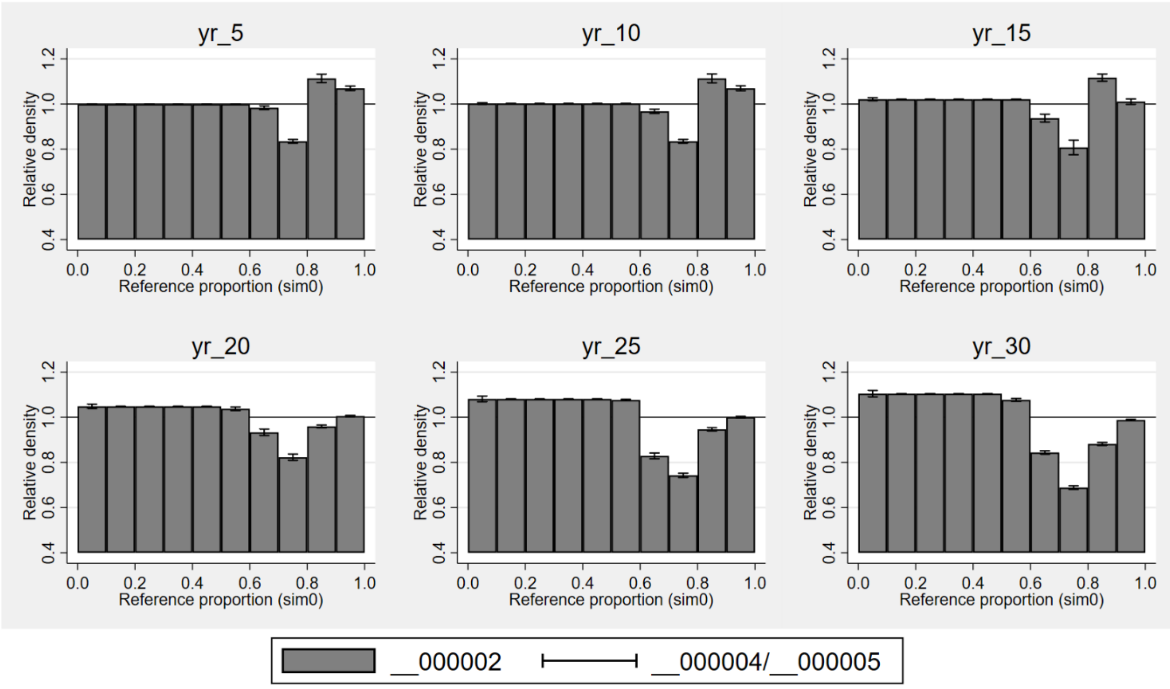
Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Figure 8 Relative employment density estimates 2025–2050 (9GT scenario – medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Figure 9 Relative employment density estimates 2025–2050 (10GT scenario – medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Overall, the inequality results from the microsimulation are driven largely by a high level of employment growth from the CGE model, which, in turn, is driven by the exogenous determination of total factor productivity. Nonetheless, the results do point towards several interesting findings. There is evidence, for example, that holding GDP growth constant, similar levels of inequality reduction can occur alongside varying levels of emission reductions. While the mechanisms that might explain this are difficult to untangle without a more detailed analysis of the CGE outputs, the results are encouraging. In addition, employment growth at the bottom of the distribution appears to be driving the steeper declines in inequality towards the end of the simulated period. For a country with high levels of structural unemployment alongside extreme levels of earnings inequality, this is precisely the type of employment growth that is required.

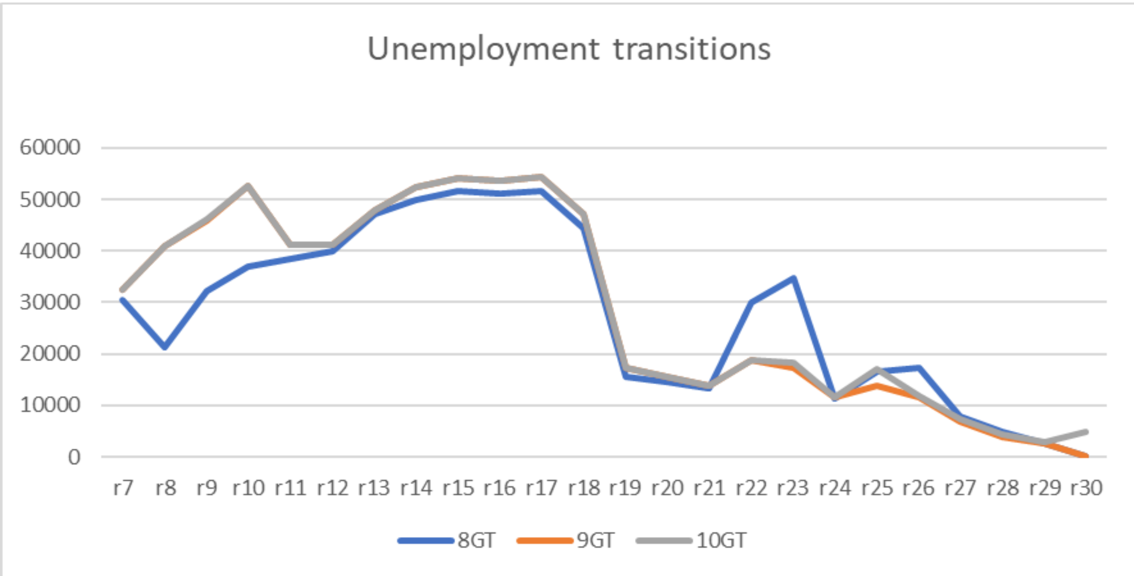
A profile of transitions into unemployment

While net employment growth is positive under all SATIMGE scenarios, and particularly strong under the high growth assumption, some workers are still likely to become unemployed. Intuitively, this would occur in regions that are fossil fuel intensive as outlined earlier in the report (e.g. in Mpumalanga).

The microsimulations use some of this information but without a strictly spatial lens. Whereas the CGE provides information on total employment changes by sector and skill level, the microsimulation uses individual characteristics, such as education, race and province of residence, to predict which workers are more likely to stay in the same sector, move to another sector or to become unemployed.

The results of the microsimulation are, therefore, driven largely by the match between overall changes in sectors and skills and the individual characteristics of workers. Figure 10 below depicts the total number of predicted transitions into unemployment for all three emissions cap scenarios. The pattern is largely the same with unemployment transitions largely confined to the first half of the period. By the end of the period, the number of transitions into unemployment are not statistically different from zero. Again, it is important to emphasise that these unemployment transitions are predicted to occur within the context of overall employment growth.

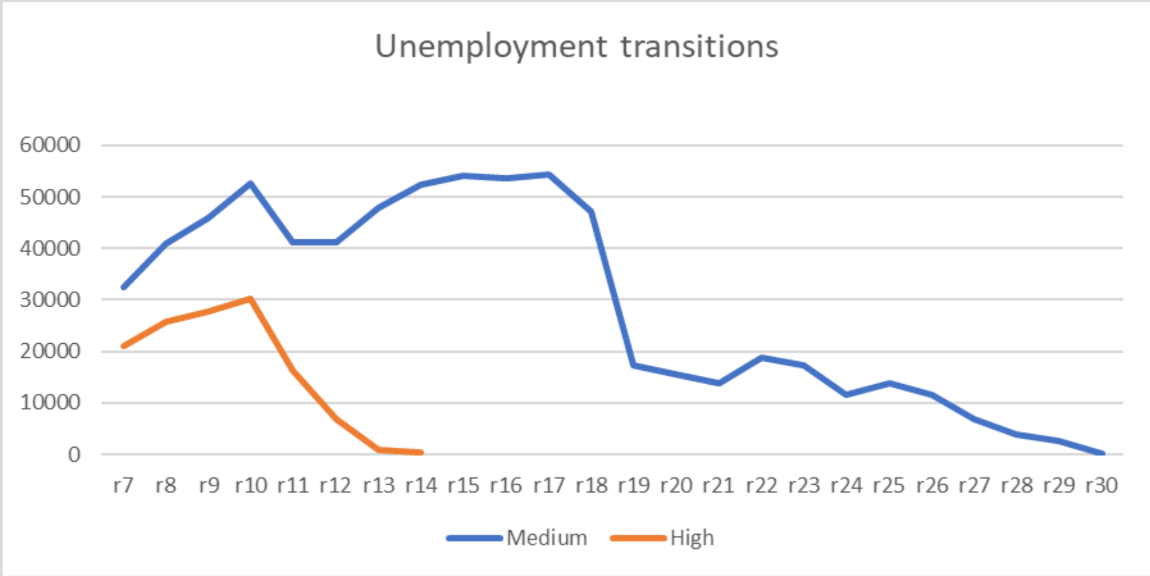
Figure 10 Total number of transitions from employment to unemployment 2025–2050 (medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Relatedly, the actual number of unemployment transitions is particularly sensitive to the assumption about GDP growth. Figure 11 below compares unemployment scenarios between the medium and high growth assumptions under the 9GT emissions cap scenario. The blue line denotes unemployment transitions under the medium growth assumption and the orange line represents high growth. Quite clearly, and intuitively, there are more transitions into unemployment under the medium growth assumption. Moreover, employment growth is so strong under the high growth assumption that the microsimulation stops allocating workers to unemployment after about five years (roughly in 2030). Clearly this outcome is driven largely by employment growth and not the changes to sectors and skills demand under the emissions cap scenario itself.

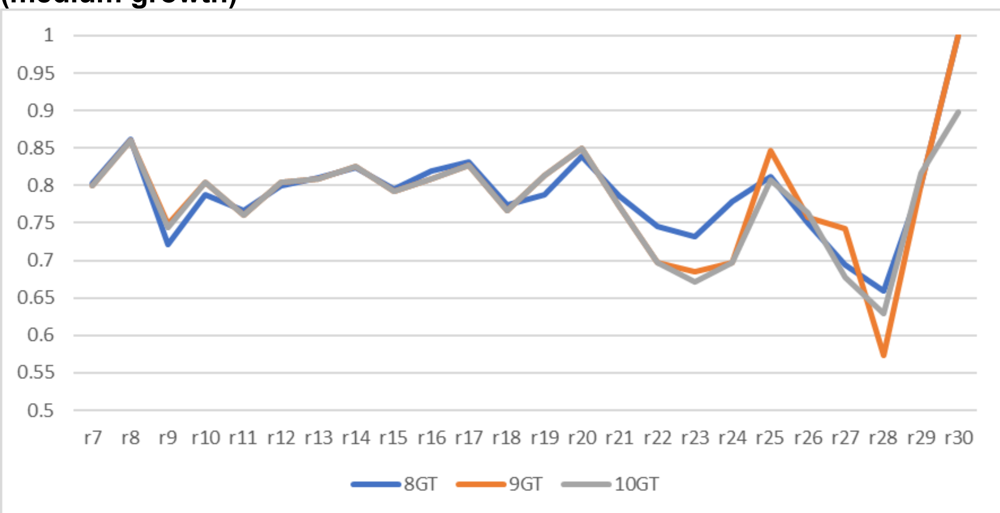
Figure 11 Total number of transitions from employment to unemployment 2025–2050 (9GT scenario)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

While the outputs from the CGE model do not allow for a nuanced comparison of unemployment transitions (or risks) that flow from sectoral changes in employment demand, it is possible to give a broad indication of the profile of workers who are likely to transition into unemployment from a previous state of employment. Figure 12 below depicts the proportion of workers transitioning into unemployment. Based on the numbers presented in Figure 10, which showed that most of these transitions occurred during the first half of the period under review, periods 7–20 (roughly 2025 to 2038) are the main focus. After this period, there is certainly more variation between the three scenarios (in Figure 12) but the sample sizes are very small and transitions to unemployment ultimately are not statistically significant from zero. The overall conclusion is that about 80% of unemployment transitions are among African workers during the period in which the greatest number of workers are predicted to lose their jobs. For context, black South Africans accounted for 75% of total employment in the baseline year (2019) so are slightly overrepresented among "job losers" relevant to their share of the workforce (own calculations from the 2019 LMD).

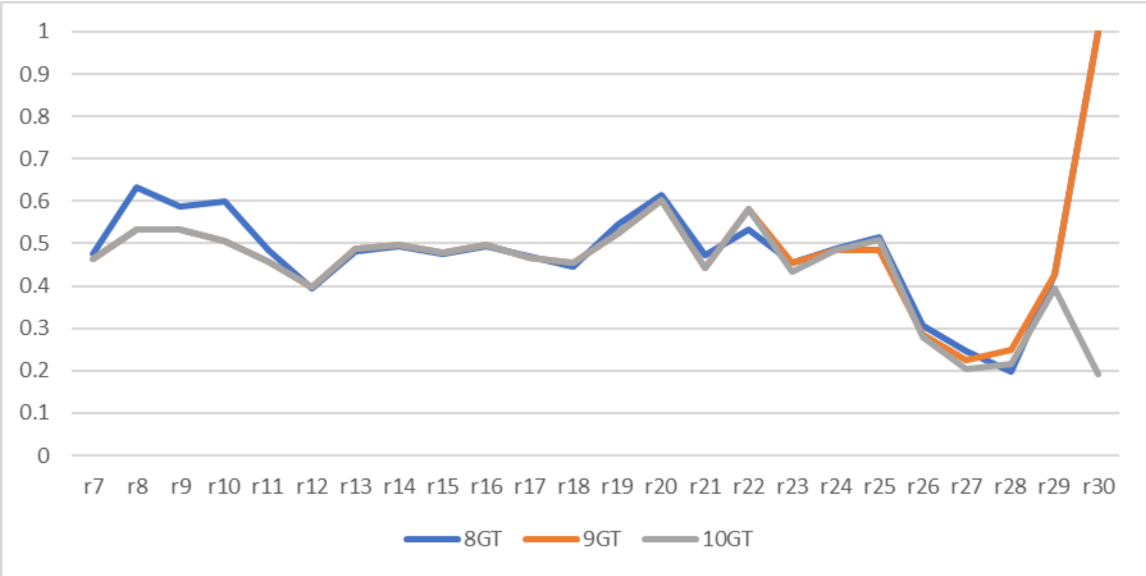
Figure 12 African share of transitions from employment to unemployment 2025–2050 (medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Similarly, in the first half of the period under review, women's share of workers who are predicted to transition to unemployment (Figure 13) is just slightly above their share in total employment at baseline (44% own calculations, not shown). During the period that corresponds with the largest number of unemployment transitions (from Figure 10), about half of the workers who are predicted to transition to unemployment are women. Again, these predictions are not based on job losses in specific industries, such as coal mining in Mpumalanga, but are rather based on the characteristics of women in the workforce and the relative changes in demand for workers by sector and skill level.

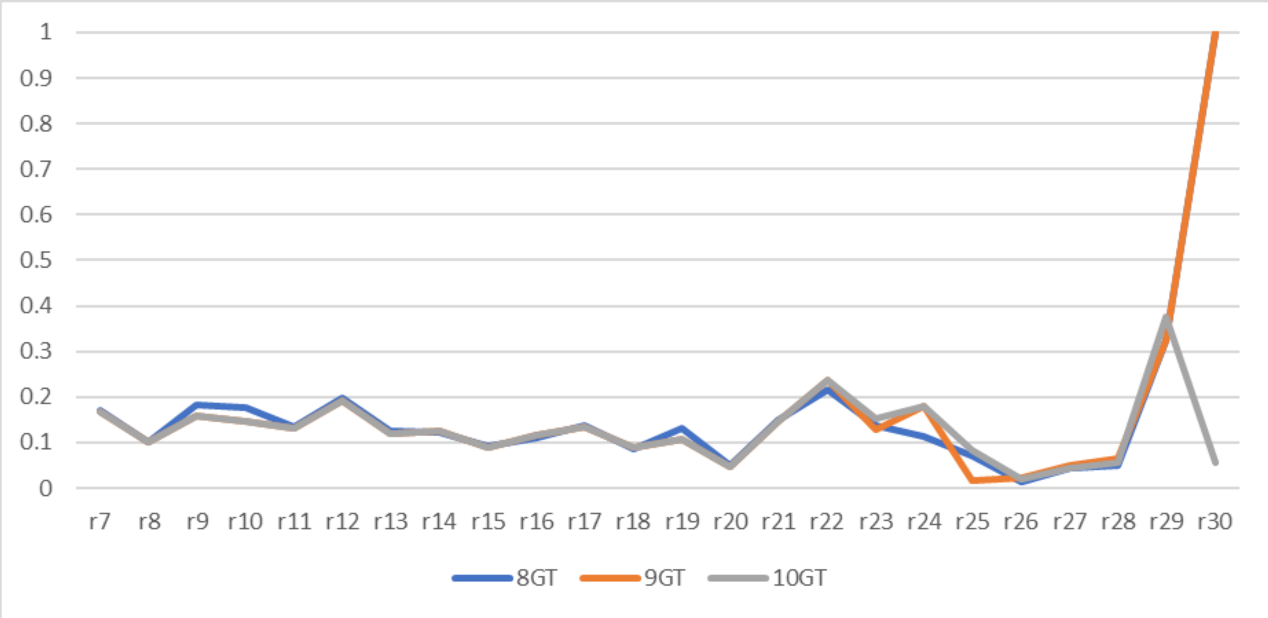
Figure 13 Women's share of transitions from employment to unemployment 2025–2050 (medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

The other group that is overrepresented among "job losers" is the youth (age 15–24). This group makes up only about 6% of total employment, at baseline-own calculations, not shown, but up to 20% of workers who transition from employment to unemployment in the first half of the simulated period. Once again, sample sizes and predicted transitions are too small to interpret in the second half of the period but, consistent with the previous graphs, there is evidence that workers who traditionally are more vulnerable in the labour market are slightly more likely to transition into unemployment in the initial half of the modelled/simulated period. Thus, while job opportunities will actually increase over this period, not all workers are equally likely to benefit from the employment gains.

Figure 14 Youth (15-24) share of transitions from employment to unemployment 2025–2050 (medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

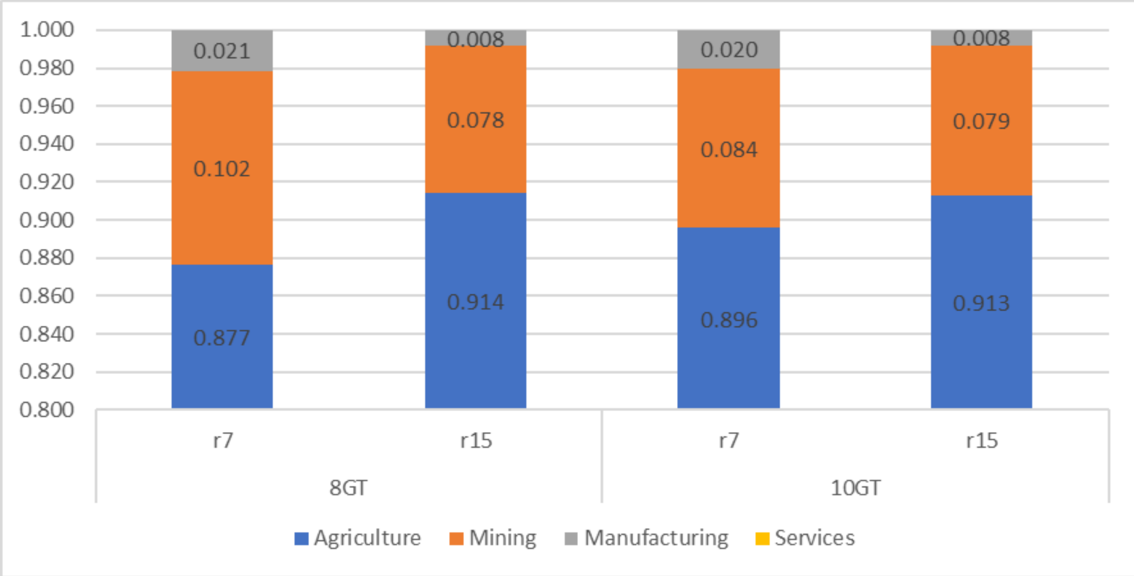
Finally, Figure 15 identifies the sectors from which workers are predicted to enter into unemployment. Unlike the CGE, which identifies employment changes at the sector level, the microsimulation is based on the labour market as a whole and identifies which workers will be "crowded out" when individual characteristics are matched with the profiles of employment sectors.

In other words, the results in Figure 15 should not be interpreted as simulating a reduction in agricultural employment but rather that the characteristics of workers in the agricultural sector make them far more vulnerable to transitioning to unemployment than workers in other sectors. This is perhaps not surprising since agricultural workers tend to have lower levels of education and are based in the more rural provinces.

In addition, the CGE results predict that relative employment growth in the services sector and in manufacturing are higher than in mining and agriculture (see appendices) such that some agricultural workers will be at risk of being "crowded out" of employment despite positive employment growth in all sectors.

While this interpretation might be somewhat unintuitive in the context of the specific SATIMGE results, it would likely align more closely with results that differed substantially by employment sector. In addition, there are spatial considerations that would also come into play in the sense that neither the SATIMGE nor the microsimulation make any assumptions about where employment growth will occur or which workers would be able to move for employment opportunities and which would not.

Figure 15 Sectoral shares of transitions from employment to unemployment 2025–2050 (medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Notwithstanding several important caveats about the employment projections from the SATIMGE model and the microsimulation, the analysis of unemployment transitions offers two potentially important insights. The first is that a large projected increase in employment towards the end of the period, which also includes a (relatively) greater increase in unskilled employment, means that there are very few simulated transitions into unemployment in the second half of the period. Rather, any unemployment transitions, under the SATIMGE scenarios, would be expected to occur over the next 10 to 15 years before employment growth precludes any relative job losses.

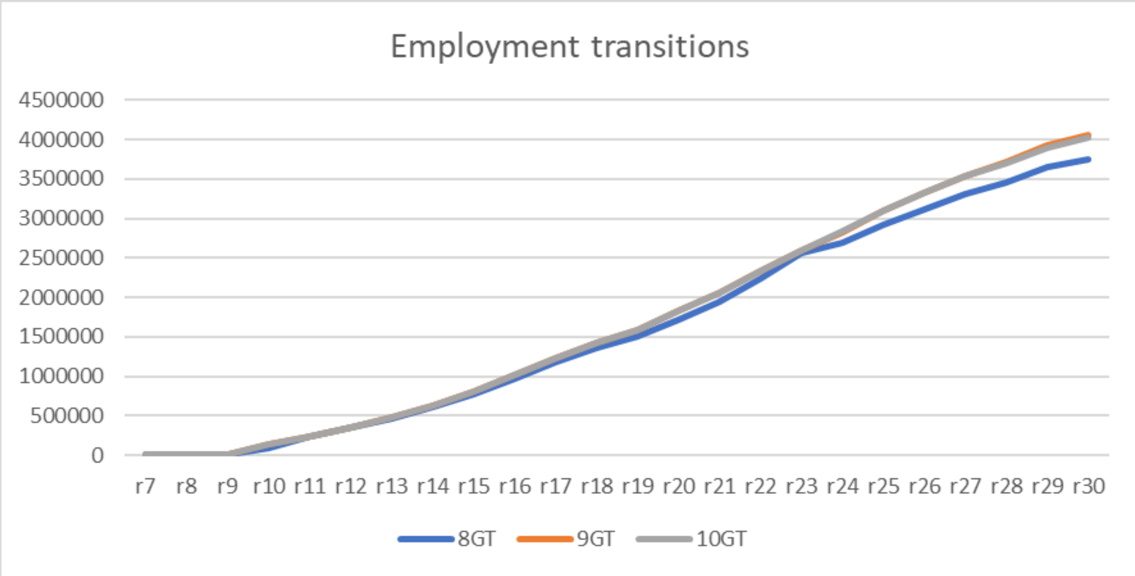
The second is that several groups of workers are at greater risk in the first part of the period. More specifically, during the period where there is some predicted "churn" into unemployment, black Africans, women, the youth and agricultural workers all have predicted unemployment transition shares that are greater than their shares in total employment. In other words, these particular groups are predicted to be at greater risk of moving into unemployment relative to other workers, even while there is a net gain in employment at the same time.

A profile of transitions into employment

Since the main finding from the SATIMGE model is employment growth which exceeds population growth over the period, transitions into employment from unemployment and non-participation far exceed the number of transitions into unemployment. Moreover, by the end of the period, transitions into employment from a state of "not working" are predicted to increase to about four million workers (Figure 16).

As demonstrated earlier in the report, this strong employment growth accompanied by relatively stronger growth in unskilled employment means that the employment dynamics predicted by the SATIMGE model would be expected to be inequality reducing. This section now examines this finding further by identifying which workers are more likely to transition into employment from a state of "not working".

Figure 16 Total number of transitions from "not working" to employment 2025–2050 (medium growth)

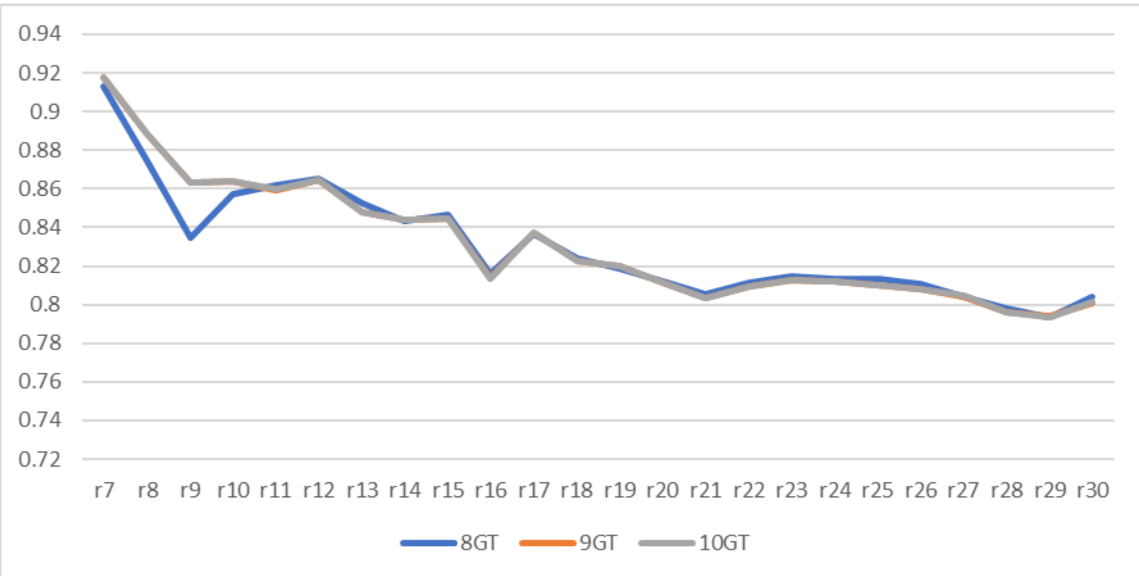


Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Figure 17 shows that roughly 92% of employment transitions are predicted to be black Africans at the beginning of the period. This corresponds closely with the African share of total unemployment at baseline (2019 own calculations, not shown). This decreases towards the middle of the period and stabilises at 80%–82% of positive transitions in the latter half of the period. After the unemployed are "selected" into unemployment, the simulation draws more from the larger pool of those not in employment, which includes the strictly unemployed, discouraged workers and those not participating in the labour market – the economically inactive. Among this broader category of those not in employment, the African share was roughly 83% at baseline (own calculations, not shown).

Therefore, the results in Figure 17 suggest that the African share of transitions into employment roughly correspond with their share in strict unemployment at the beginning of the period and their share among those not in employment (unemployed, discouraged and economically inactive) by the end of the period.

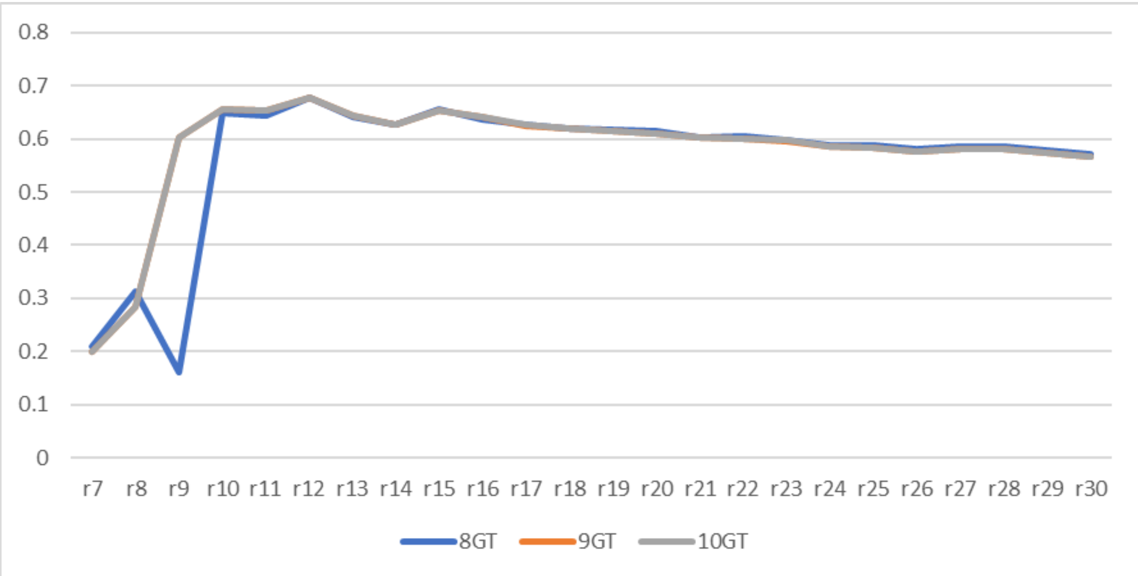
Figure 17 African share of transitions "not working" from to employment 2025–2050 (medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Figure 18 suggests that there is likely to be a strong gender component to employment transitions. At baseline, women accounted for about 54% of working-age adults who were not in employment and about half of those who were unemployed or discouraged workers (own calculations, not shown). However, for most of the period, women are predicted to account for about 60% of transitions into unemployment. At the very beginning of the period under review, men are predicted to make up the vast majority of those moving into unemployment but this changes after about four years. It is difficult to discern what might be driving this relatively rapid change in the gender composition of employment transitions but, in the longer term, the expansion of the services sector is likely to be a key factor in the gendered employment transitions, as depicted in Figure 18.

Figure 18 Women's share of transitions from "not working" to employment 2025–2050 (medium growth)

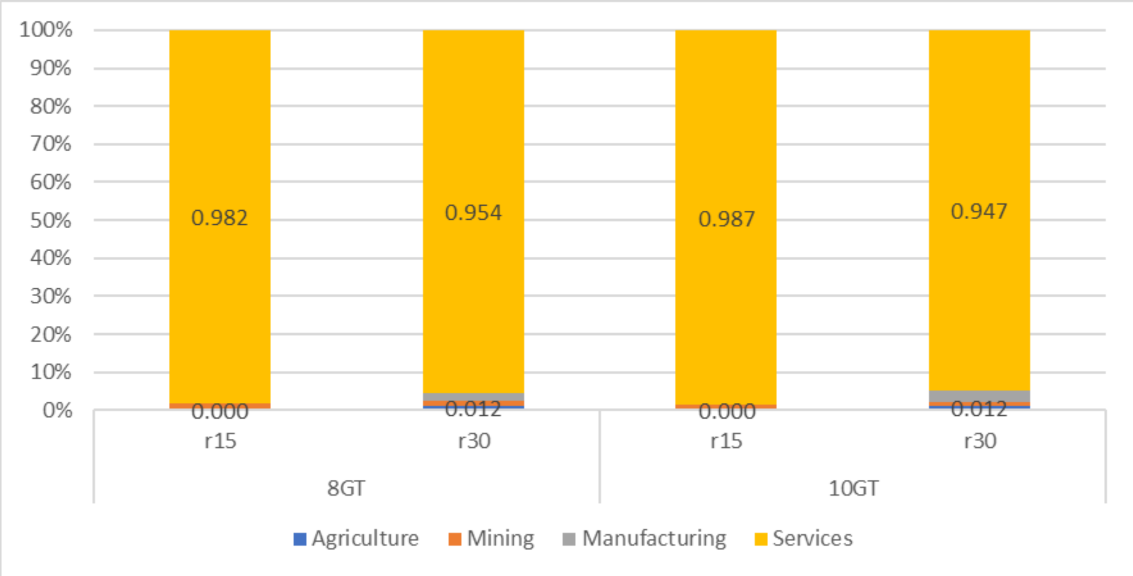


Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Providing some support for this interpretation, Figure 19 shows the sectors into which the unemployed are predicted to transition in year 15 and year 30. Under both the 8GT scenario and the 10GT scenario about 98% of the predicted transitions in year 15 and 95% in year 30 are likely to be into the services sector, the single largest sector in the simulation model. Women are particularly overrepresented in specific sub-sectors of the broader services sector, for example, women make up about 63% of community and social services and about 46% of wholesale and retail trade, and this sector accounts for the vast majority of transitions into employment under the microsimulation scenarios.

While more nuanced analyses by sub-sector are likely to provide a more comprehensive picture of which sectors are driving these predicted gender dynamics in employment transitions, and whether the gender differences still hold when services are disaggregated further, this initial analysis suggests that the SATIMGE scenarios may be gender equalising. More broadly, however, a key insight from Figure 19 is that employment shifts in the services sector should form the focus of additional analysis.

Figure 19 Sectoral shares of transitions from "not working" to employment 2025–2050 (medium growth)



Source: Own calculations from the 2019 pooled Quarterly Labour Force Survey (QLFS) and using the PEP microsimulation package (Tiberti et al. 2017). Data are weighted with population growth adjusted survey weights.

Conclusion

It is now widely acknowledged that a transition that is characterised by net positive employment growth is not necessarily a "just transition" and, conversely, net job losses in the course of the transition are not necessarily "unjust". Rather, the way in which individual workers (and their households) are impacted by changing demands in the labour market influences whether the transition is likely to be "just" or equalising.

Macro models are able to generate broad estimates of likely employment shifts by industry, sector, skill level and region. However, they are not able to predict the probability of being affected by these changes at the individual level. In this report, we have illustrated how a microsimulation model can be used to "interpret" the likely outcomes of a series of "shocks" generated by a macro model of the energy transition in South Africa.

In line with much of the international and existing South African literature, the SATIMGE model suggests that there will be relatively strong net employment growth across a range of different net zero pathway scenarios. One unique feature of the SATIMGE model, however, is that its employment projections are influenced quite strongly by exogenous growth assumptions, as opposed to GDP outcomes predicted by the model itself.

In this report, we do not make any claims as to the veracity of the modelled outcomes. Rather, our point of departure is an examination of the likely labour market implications of the modelled outcomes on several measures of inequality, and we also present an analysis of transitions into and out of employment based on the "contours" of the macro model's employment shocks. We do this by analysing the modelled changes in employment by sector and skill level and estimate a probability model that was specified with a number of variables that are commonly used in the labour market literature.

Our microsimulation offers several key insights that, we believe, should be explored further in the context of South Africa's ongoing energy transition. Perhaps first and foremost, the microsimulation points towards a potential bottleneck in skills.

When the SATIMGE scenarios are modelled under an assumption of relatively high GDP growth (3%), employment more than doubles over the period between 2025 and 2050. While this would be an unprecedented level of growth for the post-apartheid period, it also highlights an important feature of the South African labour market, namely, a skills gap.

More specifically, the microsimulation model "runs out" of unemployed people to meet the skills requirements of the macro model by about 2041. In other words, the growth in demand for skilled workers exceeds the number of skilled workers before the end of the simulated period. Such a finding suggests two potential ways forward.

First, more work on the specific skills demands or requirements under different energy transition scenarios is a matter of some urgency. Second, but related, the needs of the energy transition should be used to highlight the importance of skills interventions. This is work that is currently being explored by colleagues as part of this consortium, led by Presha Ramsarup from the Centre for Researching Education and Labour (REAL) at the University of the Witwatersrand. The results of the microsimulation suggest that, without targeted skills interventions, South Africa is not yet in a position to maximise the opportunities that are likely to arise from an energy transition that is accompanied by a level of economic growth that is moderate from a policy perspective. For example, the NDP calls for 6% growth.

Second, the relatively optimistic employment projections from the SATIMGE model "translate" into similarly positive findings from the perspective of a just transition. Inequality decreases under all scenarios and the decrease is particularly large under the high economic growth scenarios from the macro model.

Somewhat encouragingly, the decreases in inequality appear to be driven by the increase in employment among the unskilled in the labour force. In other words, the projected increase in employment is driven, to some extent, by a slightly greater relative increase in unskilled jobs that can be filled by the large pool of unemployed. In other words, and notwithstanding the skills bottleneck described above, there is still a low-skilled labour absorbing component to the SATIMGE projections that is predicted to benefit workers at the bottom of the earnings distribution.

Third, the profile of workers who are likely to "win or lose" from the employment changes modelled from the SATIMGE scenarios suggests a need for policy nuance. While transitions into unemployment – job losses – are not a large feature of the modelled scenarios, there will, nonetheless, be several short-term losses. Other work has emphasised job losses in the coal sector in South Africa and the microsimulation results complement these findings by showing that black Africans, women, the youth and agricultural workers all have a relatively higher risk of transitioning to unemployment, relative to other groups of worker. Again, these are predicted to be relatively small numbers and the second half of the simulated period suggests that employment growth will all but offset any short-term transitions into unemployment.

Nonetheless, the microsimulations suggest that workers with characteristics that are currently correlated with vulnerability in the labour market may be at higher risk of transitioning to unemployment. These simulations are based purely on individual characteristics, however, and do not account for any labour market frictions. As such, it is expected that the microsimulations are presenting a lower bound estimate of potential (relative) employment losses.

In terms of transitions into employment, the key finding is that women are predicted to gain more from employment opportunities than men. This is because of the large role of the services sector in generating employment under the SATIMGE scenarios. While this is a positive finding given women's general disadvantage in the labour market, it is also important to reiterate that more work is required to understand which sub-sectors of the services sector are likely to contribute to employment growth.
In other words, it is possible that the high level of disaggregation of the services sector is driving the results of the microsimulation.

The services sector includes a wide range of sub-sectors and it is important to unpack this finding further to identify the gender composition of the sectors that are predicted to expand the most. As such, the gendered findings presented here, while encouraging, should be treated with some caution and should serve as a motivation to investigate services in more detail.

As a final comment on the microsimulation model presented in this report, we would argue that the methodology is likely to yield more insights when used to simulate scenarios that contain a greater diversity of employment outcomes. The SATIMGE scenarios have a number of appealing features but the employment estimates across different scenarios are very similar. As such, the potential value of the microsimulation as a comparative policy tool was not fully illustrated in this report.

We would argue that the real value of the microsimulation methodology could be realised when evaluating the potential trade-offs between energy transition scenarios that project large differences in employment outcomes across sub-sectors of the economy. Understanding the characteristics and the profile of “winners and losers” from a restructuring of the labour market could add a policy relevant analysis to supporting the energy transition and identifying the key policy levers to ensure a just transition.

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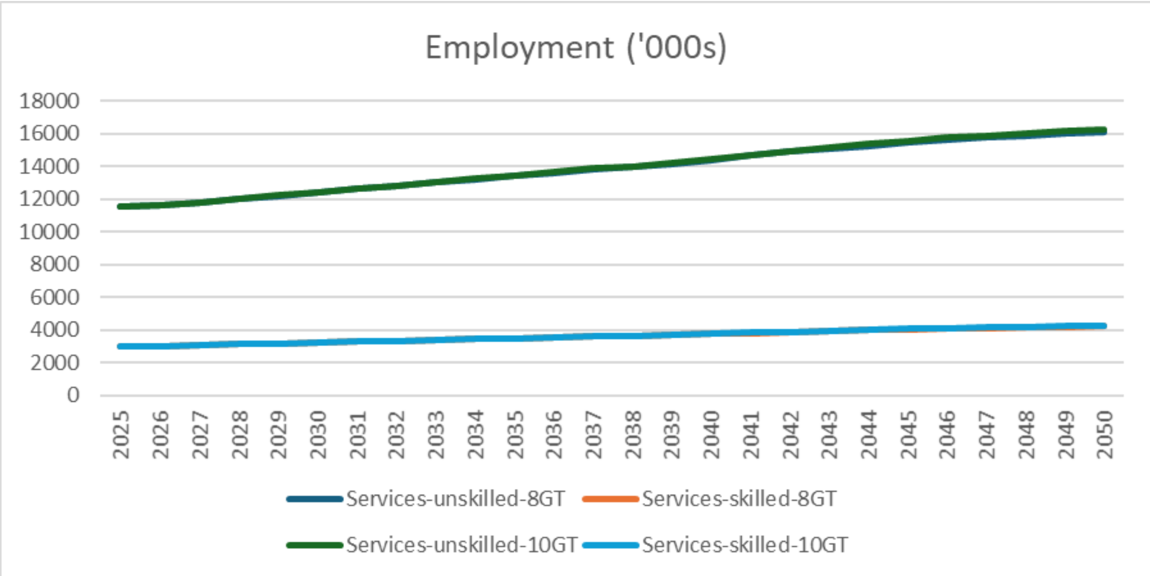
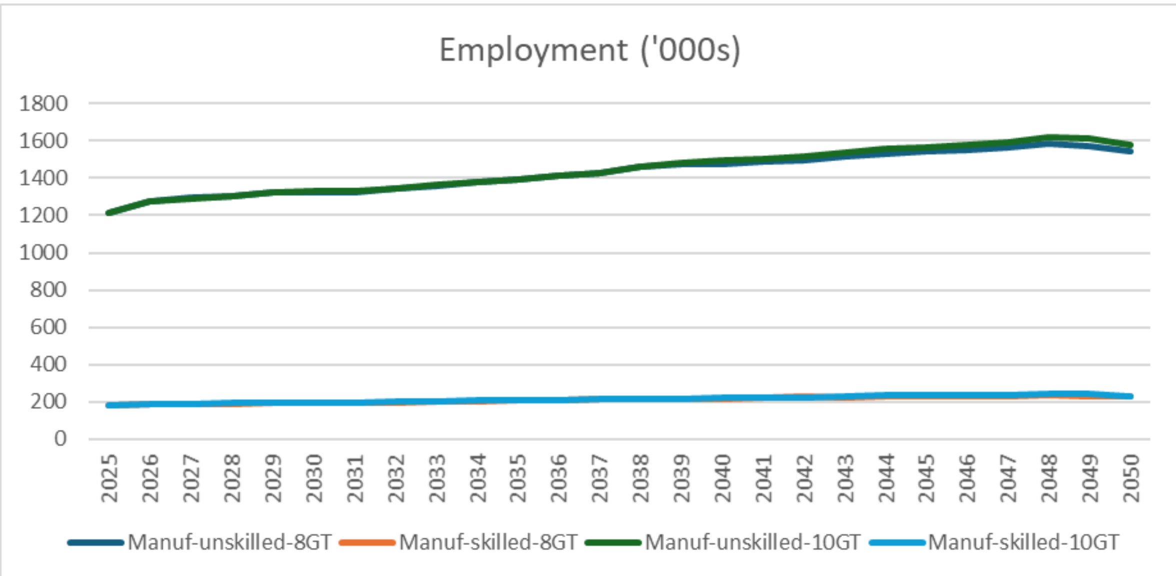
Appendices:

Figure 1A Projected skilled and unskilled employment growth in the services sector 2025–2050 (8GT and 10GT medium growth scenarios)



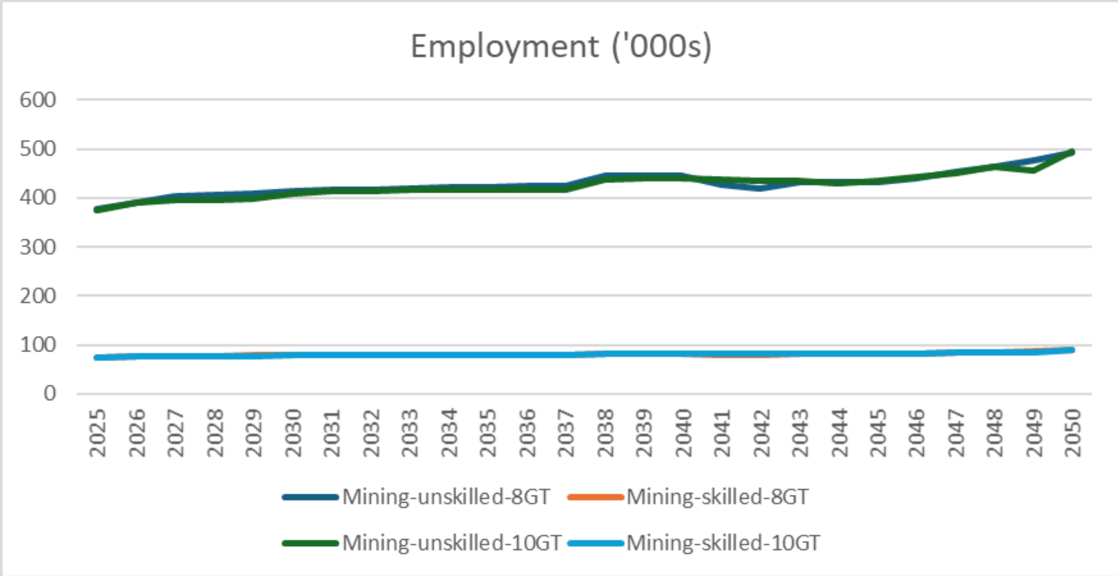
Source: Estimates from the SATIMGE model (ESRG-UCT)

Figure 1B Projected skilled and unskilled employment growth in the manufacturing sector 2025–2050 (8GT and 10GT medium growth scenarios)



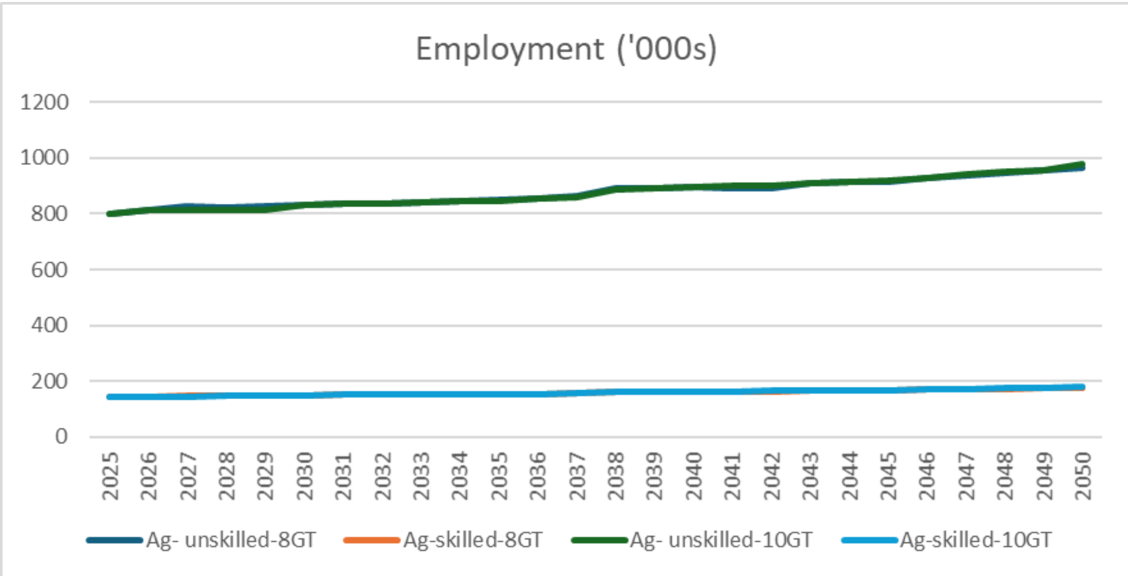
Source: Estimates from the SATIMGE model (ESRG-UCT)

Figure 1C Projected skilled and unskilled employment growth in the mining sector 2025–2050 (8GT and 10GT medium growth scenarios)



Source: Estimates from the SATIMGE model (ESRG-UCT)

Figure 1D Projected skilled and unskilled employment growth in the services sector 2025–2050 (8GT and 10GT medium growth scenarios)



Source: Estimates from the SATIMGE model (ESRG-UCT)