Multidimensional Poverty:

Future Proof with Linked Macro-Micro Modelling

Asghar Adelzadeh, Ph.D.
Director and Chief Economic Modeller at ADRS
Email: Asghar@ADRS-Global.com

Ludwe Ngangelizwe
Economic Analyst at ADRS
Email: Ludwe@ADRS-Global.com

February 2024

ADRS Working Paper 2024/01

Keywords: deprivation, linked macro-micro models, macroeconomic transmission mechanisms, multidimensional poverty

Table of Contents

ABSTRACT

Two main focuses of studies on multidimensional poverty pertain to measurement issues and using statistical techniques to identify factors that explain deprivation. This study extends the literature by proposing an approach to produce forward-looking projections of multi-dimensional poverty (MDP) indicators. The proposed approach uses multinomial logistic regression (MLR) techniques to establish statistical association between dimensions of poverty and demographic, economic and social factors, and uses the outcome of the estimation to add an MDP module to a linked macro-micro model. The final model is a policy tool that can be used to design anti-poverty policies and produce ex-ante assessment of their impact on MDP. To demonstrate the approach, we used a full General Household Survey of South Africa as the database to measure deprivation using education, healthcare, living conditions and assets as four dimensions of poverty, each measured through four indicators with low and high cut-off indicators. We then specified and estimated two multinomial logistic regression models for the two cut-offs, each with five deprivation outcomes as their categorically distributed dependent variable and a set of independent variables composed of demographic, economic and social indicators. The estimated MLR equations were used to build the MDP module of a South African linked macro-micro model, built by the Applied Development Research Solutions. In each period, the model's projections of demographic, economic and social variables are used by the MDP module to generate projections of deprivation indicators at national level and by gender, race and region. The final MDP augmented model is used to establish the current trajectory for deprivation of various population groups in South Africa and to test the direct and indirect effects of five cumulative policy measures (i.e. fiscal policy, monetary policy, private investment, public employment and social grant scenarios) on dimensions of deprivation over the period from 2024 to 2030.

Multidimensional Poverty:
Future Proof with Linked Macro-Micro Modelling

Asghar Adelzadeh and Ludwe Ngangelizwe[1]

A. INTRODUCTION

Multidimensional poverty (MDP) has significantly contributed to non-money metric poverty profiling since its use in the early 2000s. However, the approach has two known shortcomings. First, its measures of deprivations correspond to the time of the survey, which is usually sometime in the past. Second, like other poverty-inequality measurements, measures of deprivation do not empirically associate the final deprivation measures with social and economic policies. The aim of this study is to propose an approach that overcomes these shortcomings by developing a dynamic version of MDP that provides a forward-looking view of the MDP indicators under alternative policies and outlooks for the economy. To achieve this, we use multinomial logistic regression (MLR) techniques to establish statistical association between two measurements of MDP in South Africa and demographic and economic indicators. We then integrate the estimated MLR equations into the dynamic operation of a linked macro-micro economic model to use model-generated projections of economic and demographic indicators to concurrently produce projections of multidimensional poverty measures with low and high cut-off indicators. Finally, to demonstrate the utility of a dynamic MDP measurement, the augmented linked macro-micro model is used to assess the impact of a few policy scenarios on MDP during the rest of the current decade.

While this study takes a forward-looking approach to multidimensional poverty and involves economic modelling techniques, other studies have focused on constructing a single MDP index and examining the progress of deprivation over time, evaluating the impact of social policies on MDP, and exploring the determinants of MDP. Notable contributions focused on single index comprised of weighted dimensions and indicators include Alkire and Foster (2007, 2009), Alkire and Santos (2010), Gradin (2011), Statistics South Africa (2014), Burger et al. (2016), Ntsalaze and Ikhize (2018), Fransman and Yu (2019) and Jackson and Yu (2023). As examples of the second group of studies, Song and Imai (2019) developed an MDP index using the Alkire and Foster (AF) approach and subsequently employed a difference-in-differences methodology to examine the effects of Kenya's hunger safety net programme on MDP. Similarly, Robson et al. (2022) used the AF method to construct an MDP index for refugees and utilised the inverse-probability-weighted regression adjustment technique to examine the impact of an emergency social safety net cash programme on MDP in Turkey. Finally, only a limited number of studies have explored the determinants of MDP. For instance, Said et al. (2020) applied the ordinary least squares (OLS) technique to test the

---

[1] Dr. Asghar Adelzadeh (asghar@adrs-global.com) is Director and Chief Economic Modeller at Applied Development Research Solutions (ADRS) and is Director of Academics at Economic Modelling Academy (EMA). Ludwe Ngangelizwe (ludwe@adrs-global.com) is Economic Analyst at ADRS.

relationship between deprivation indices and a mix of indicators in Pakistan. Similarly, Ribeiro et al. (2014) employed a panel data econometric approach to study the relationship between a multi-country index of multiple deprivation in Europe and macroeconomic variables.

Our study employs a non-index measure to assess poverty across multiple dimensions, aiming for simplicity and transparency. This approach facilitates an intuitive understanding of deprivation in education, health, living conditions and assets, without the complexities associated with formal indexing and weighting. We categorise individuals and households based on the number of dimensions in which they face deprivation, specifically considering education, health, living conditions and assets (i.e. we assess whether individuals experience no deprivation, or deprivation in one, two, three or all four dimensions). To estimate deprivation, we utilise two deprivation lines to represent low and high cut-off deprivations. Low cut-off deprivation includes those with the most severe lack of access to basic services and assets, with indicators' cut-off points set at minimal levels. High cut-off deprivation represents a level of deprivation that is less severe than low cut-offs but still below an acceptable standard of living or quality of life. Here, cut-off points are set to establish whether individuals have adequate access to essential services and assets.[2]

The rest of the paper is organised as follows. Section B provides a brief overview of the linked macro-micro model that has been extended to include the MDP. Section C presents two measurements of MDP for South Africa, explains how MNR techniques have been used to establish the relationship between MDP and macro- and micro-economic indicators, and describes the integration of MDP measures and regression results into the linked macro-micro model. Analysis of model projections of MDP indicators for the period 2024 to 2030 are provided in Section D, followed by the concluding remarks.

B. DYNAMICALLY INTEGRATED MACRO-MICRO MODEL OF SOUTH AFRICA

The dynamically integrated macro-micro model of South Africa (DIMMSIM), built by Applied Development Research Solutions (ADRS), is a linked macro-micro model that includes a multi-sector macro-econometric model component and a full microsimulation of taxes, transfers, poverty and inequality. Its simulation process captures two-way interactions between its macro and micro components as pioneered by Savard (2003) and in more recent time by Adelzadeh (2019).

B.1. DIMMSIM's Macroeconomic Component

The model's macroeconomic component is a bottom-up macro-econometric model with more than 3200 equations that capture the structure of the National Income and Product Account (NIPA) at sector and aggregate levels and produce projections that are consistent with various national accounting identities in nominal and real terms. The model includes more than 400 estimated equations that analytically and empirically capture the behaviour of the private and household sectors as part of capturing the working and dynamics of the economy from its production,

[2] Refer to Table 1 and the model specification section for detailed information.

expenditure and income perspectives.[3] The Macroeconomic Model of South Africa's (MEMSA) equation system can be broken down into a number of blocks, which include:

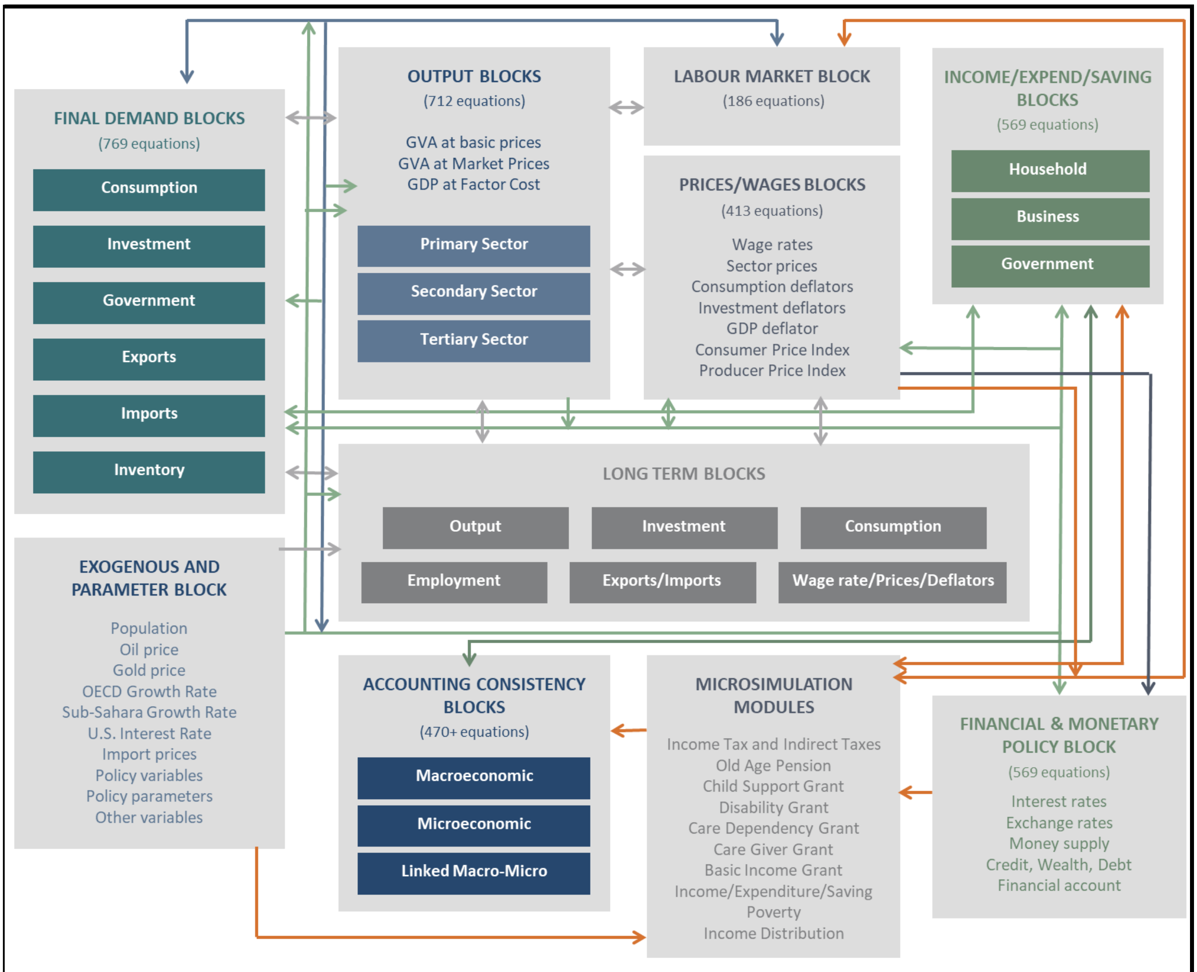
- **The Final Demand Block** encompasses 769 equations. It includes sets of estimated equations that capture the behaviour of the private sector as it relates to sectoral-level investment, exports and imports in 45 sectors; households in terms of expenditure on 27 categories of consumption goods and services; and the public sector in terms of final consumption expenditure and investment. The expenditure block of equations therefore produces projections of various components of aggregate demand in the economy that facilitate the model's projection of real and nominal GDP from the expenditure side.
- **The Production Block** includes 712 equations that represent sector and aggregate production-related activities in the economy. It includes sets of equations that produce projections of sector outputs, potential outputs, capital stock and capital productivity, all in nominal and real terms. Private sector decisions on how much to produce in various sectors of the economy are captured through 40 estimated equations that link the decisions to various demand, supply and price factors in the economy. Therefore, the equations of the Production Block generate consistent projections of nominal and real values for sector and aggregate outputs, namely value added at basic prices. The aggregate of sectoral value added at basic prices plus the net taxes and subsidies on products provide the model's annual projections of GDP from the production side.
- **The Price and Wage Block** consists of 413 equations that include time-series estimated behavioural equations for sector output prices (45), consumer prices (30) and investment prices (45). It also includes equations for sector import and export prices, sector- and economy-wide inflation rates and 45 estimated equations for the sector-level real wage rate (i.e. average remuneration rates) and 45 calculated sectoral-level nominal wage rates.
- **The Labour Market Block** consists of 186 equations which include 40 estimated equations that capture factors that determine short- and long-term demand for sector-level employment. In addition, this block includes equations for sectoral labour productivity, labour force, unemployment rate and other labour market indicators.
- **The Income, Expenditure and Savings Block** includes 569 equations that capture a detailed breakdown of income, expenditure and savings of households, incorporated businesses, and government, in both nominal and real terms. A combination of variables from this block, the Labour Market Block, the Price and Wage Block, and the Production Block provides forecasts of the real and nominal GDP from the income side.
- **The Financial Block** embodies 88 equations for indicators related to the financial and monetary side of the economy, such as the interest rate, exchange rates, money supply, credit extensions, household financial assets and liabilities, and foreign direct and portfolio investments. The Financial Block variables are especially important determinants of variables in other equation blocks and include policy variables and time-series estimated variables.

[3] MEMSA uses the Autoregressive Distributed Lag (ARDL) estimation procedure, developed by Pesaran (1997) and Pesaran et al. (1996, 1999).

- **The National Account Block** incorporates more than 470 equations. This block of equations is responsible for ensuring consistency and enforcing NIPA relationships within the economic system captured by the model. For example, it ensures that, in the model, the calculation of GDP, both real and nominal, from the income, production and expenditure sides comprise relevant NIPA components and are consistent with each other at aggregate and sector levels, in nominal and real terms.

The macroeconomic module of DIMMSIM generates annual forecasts of a relatively large number of aggregates and sector-level, nominal and real variables, and indicators. It includes indicators related to production, labour market, prices, wages, financial variables, and incomes and expenditures of households, businesses and government.

Figure 1: Dynamically Integrated Macro-Micro Simulation Model of South Africa (DIMMSIM)



Source: Asghar Adelzadeh, Applied Development Research Solutions (ADRS), www.adrs-global.com

B.2. DIMMSIM's Microsimulation Component

In DIMMSIM, the macroeconomic module is linked to a full microsimulation model of individuals and households to capture the interactions between macroeconomics, industrial structure, household poverty and income distribution in South Africa.

The modelling principle employed to build the South African household model is the microsimulation technique, whose application to socioeconomic modelling was pioneered by Guy Orcutt in the United States in the late 50s and early 60s.[4] The South African microsimulation model, originally built in 2001 as a static model, was subsequently expanded and complemented with dynamic properties to capture the interactions between the macroeconomy and the household sector.

The main components of the model are its database and its tax and social policy modules. The South African model uses a micro-database of individuals and households using official Household Survey, Income Expenditure Surveys, the Census, and quarterly Labour Force Surveys, which are the main sources of countrywide economic and demographic microdata. The model's database is prepared in terms of family units because it relates closely to the definition of the financial unit used by many of the government tax and transfer programmes.[5] The model's database includes 125,830 individuals, making up 61,684 families or 29,800 households. The database includes weights for individuals, families and households which are used to translate each of the three samples to their corresponding populations for a given year. Each unit record includes more than 400 columns of information for each individual in the family – including demographic, labour force, marital status, housing, income and expenditure information. Diagram 1 presents the flowchart of the model.

The South African microsimulation model includes three modules for government's taxation policies (i.e. personal income tax, excise tax and value-added tax), six modules for transfer programmes (i.e. old age grant, child support, disability grant, care dependency grant, caregiver support and the BIG), a public works module for government's Expanded Public Works Programme (EPWP), and two modules for income poverty and income inequality. The model's annual poverty and inequality projections include projections of six poverty indicators and six income inequality indicators.

B.3. Interactions Among Macro and Micro Components of DIMMSIM

The model establishes two-way interactions between its macro and micro components. First, changes in macroeconomic variables (e.g. changes in prices, employment, wage rates, benefits and transfers) influence the welfare of individuals and families. Second, changes in household-level economic conditions (e.g. poverty, inequality, consumption, taxes, eligibility for social grant) influence macroeconomic outcomes. The Gauss-Seidel's iterative method is used to solve the overall system. The procedure runs the two models for a number of interactions, allowing interactions between the macro and micro parts of the model before it converges and generates the final results for each year of the forecast period. This ensures that the results of each period reflect convergence of the macroeconomic variables and household-level variables at the aggregate level. Therefore, the two models are dynamically integrated and generate time-based results that reflect the actual process of policymaking and evaluation.

---

[4] Orcutt (1957); Orcutt et al. (1961).

[5] Since the South African national surveys use "households", the construction of the unit record of the South African model on the basis of family unit required a substantial amount of programming. The relational codes in the October Household Survey were used to break down households into the appropriate number of families.

C. DIMMSIM's MULTIDIMENSIONAL POVERTY MODULE

DIMMSIM has been extended to incorporate low and high cut-off measures of MDP in order to enable the model to produce annual projections of rates of full or partial deprivations for each measure. As pointed out in the introduction, the attempt to develop a forward-looking MDP is relatively new. The process of building DIMMSIM's MDP module is elaborated in the rest of this section.

C.1. Measurement of Multidimensional Poverty in South Africa

The measuring of MDP involves the selection of poverty dimensions and corresponding indicators and their thresholds. For this process, we drew from both the Statistics South Africa (2014) and the global Multidimensional Poverty Index (Alkire & Santos, 2010), and selected education, health, living conditions and assets as the four distinct dimensions of poverty in South Africa.

Next, we selected four sets of indicators to represent the four dimensions of poverty. The selection of the indicators was governed by several factors; namely, all the indicators had to be available in one survey for comparability purposes. Each indicator needed to be dimension-specific and could only be included in one dimension. Each indicator had to measure a major feature of the dimension it represents and experienced by a considerable number of households. Finally, the indicators must be easily updated as data become available.[6] Column 2 of Table 1 provides the list of indicators used for the selected four dimensions of poverty.

To quantify the extent (or degrees) of deprivation across various dimensions experienced by individuals and households, two likely thresholds (i.e. cut-off points) were chosen for each indicator to denote low (acute) and high (moderate) deprivation associated with that indicator. The selection and determination of indicator thresholds were influenced by various factors, including the targets established by the United Nations Development Programme's Millennium Development Goals (United Nations Economic Commission for Africa, 2015), the standard of living goals set by the South African government (National Planning Commission, 2012), and relevant MDP research conducted by Ribeiro et al. (2014), Naveed et al. (2016), Shahateet (2007), Mishra (2017) and Wanka (2014). These sources collectively informed the decision-making process. Columns 3 to 4 of Table 1 present the two specific cut-off points that we used for the selected deprivation indicators.

Finally, the low and high indicator-specific cut-offs were applied to the General Household Survey of 2018 to generate two, acute and moderate, estimates of population cohorts that were deemed deprived of zero (not deprived), one, two, three or four (fully deprived) of the four dimensions of poverty and to codify the deprivation status of individuals in the survey.

[6] Ngangelizwe and Adelzadeh (2024) provide a more detailed presentation of the indicator selection process for the calculation of MDP.

Table 1: Dimensions, Indicators and Deprivation Cut-off Points

Dimensions	Indicators	Cut-off Points	
		Low Deprivation	High Deprivation
EDUCATION	Years of Schooling	Individuals aged 15+ with less than 5 years of school attendance and no current enrolment.	Individuals aged 15+ with less than 9 years of school attendance and no current enrolment.
	School Attendance	If aged between 7 years and 15 years old and not in school.	Any school-aged child who is not attending up to class 12.
HEALTH	General Health	Individuals who perceive their health as fair or poor instead of good, very good or excellent.	Individuals who perceive their health as fair or poor instead of good, very good or excellent.
	Distance to Nearest Healthcare Centre	Not included.	Households who travel between 30-89 minutes and 90 minutes or more with usual means of transport.
	Medical Aid Cover	Not included.	If individual does not have medical aid cover.
LIVING CONDITIONS	Dwelling Type	Households whose main dwelling is informal shack, traditional dwelling, caravan, tent, other.	Households who live in informal dwellings.
	Fuel for Lighting	Households using candles, parafin, none and other unspecified types.	Households who use dung, sand or other.
	Fuel for Cooking	Households using using parafin, wood, coal, dung, none and other unspecified types.	Households who do not have electricity.
	Fuel for Heating	Households using parafin, wood, coal, dung, none and other unspecified types.	Households who use dung, wood, coal, paraffin, and candles.
	Water Source	Households who do not have piped water in dwelling/stand.	Households who use water vendor, flowing water, stagnant water, well and spring.
	Sanitation	Households who do not have a flush toilet.	Households who use pit latrine, bucket toilets, ecological sanitation and open defecation.
ASSETS	Domestic Asset Ownership	If household does not own a radio/TV/telephone/fridge.	If household owns less than 10/20 home assets.
	Car Ownership	Not included.	If household does not own car in working condition.

Source: Authors

C.2. Factors Associated with Multidimensional Poverty in South Africa

The primary focus of the predominant body of research pertaining to MDP is quantifying diverse dimensions of deprivation encompassing living conditions, health and other relevant factors, as well as identifying individuals who are subject to these deprivations. There is a notable scarcity of studies examining the determinants of MDP and the strategies to effectively alleviate it. These studies include Said et al. (2020), who applied the OLS technique to test the statistical relationship between deprivation indices and a mix of determinants that included industrialisation, employment rate, road density, urbanisation and dependency ratio. The results show that industrialisation is the most important contributor to poverty reduction, followed by road intensity and employment, and that the dependency ratio is insignificant in determining poverty deprivation.

Ribeiro et al. (2014) used an econometric panel data approach to investigate the relationship between a multi-country index of multiple deprivation and macroeconomic variables. The use of cross-sections and fixed effects periods was supported by chi-square and F-tests. Macroeconomic variables were grouped by economic growth, macroeconomic stabilisation and institutional framework. Negative relationships were found between all macroeconomic variables and multiple deprivation, except current unemployment and lagged per capita GDP index.[7] Shahateet (2007) and Santos et al. (2016) found similar relationships, although the two authors used a first difference estimator model and a simple OLS regression consecutively. The consistent finding in the literature is that economic growth and variables directly related to economic growth have a positive effect on reducing overall deprivation.

In this study, we have adopted a different approach to establish factors that impact the MDP and to produce projections of likely future values of MDP indicators. We used the MLR techniques to examine the statistical association between the four dimensions of MDP and selected demographic, social and economic factors that are represented in DIMMSIM and whose future annual values the model generates. The use of the MLR approach proved particularly appropriate, given its efficacy as an analytical tool for comprehensively analysing and elucidating the intricate determinants that influence categorical outcomes featuring multiple response options.

Explanatory variables

The specification of the MLR equations included a wide range of demographic, social and economic factors. Correlation approach and q-square were used to identify possible explanatory factors that are associated with the MDP. The final list of variables offers valuable insights into the various aspects of deprivation in South Africa.

Race: Notably, in the South African context, it is widely understood that the black population faces the highest degree of deprivation. As Figure 2 illustrates, according to the General Household Survey 2018, over 60% of the black population experiences severe levels of deprivation (low cut-offs deprivation). In comparison, the Indian/Asian and white populations encounter deprivation at rates of 16% and 17%, respectively. Moreover, when employing the high cut-offs to measure deprivation, a staggering 96% of the black population experience deprivation, whereas less than half of the white population (49%) are deprived. Therefore, the race variable has been included in the specification of the two MLR equations with different cut-offs.

Gender: The inclusion of gender in the assessment of factors that are associated with deprivation warrants consideration. Figure 2 reveals a consistent pattern where women are slightly more susceptible to deprivation compared to men across both deprivation thresholds. These findings align with research conducted by Rogan (2015), indicating a slightly narrower poverty gap between female-headed and male-headed households when employing the Multidimensional Poverty Index (MPI) as opposed to an income-based poverty measurement.

Age Group: Figure 2 illustrates that, according to the GHS 2018, the elderly population experiences the highest levels of deprivation in South Africa when low cut-offs are used. On the other hand, with the high cut-offs, the young adults with a deprivation rate of 93% suffer the highest levels of

[7] GDP per capita multiplied by the GINI coefficient.

deprivation. Therefore, age has been added to the statistical examination of likely factors that are associated with multidimensional poverty in South Africa.

Province: Given the significant provincial disparities within South Africa, the MLR equations test whether MDP indicators are associated with spatial location of individuals and households.

Employment status: The inclusion of employment status in the MLR as a possible predictor of multiple deprivation is informed by its notable influence on poverty, exemplified by studies such as Feder and Yu (2020), Wolf et al. (2022), Vaalavuo and Sirniö (2022) and Ascher (2022), which specifically explore the intricate dynamics between employment and poverty. Figure 2 demonstrates that, with both deprivation cut-offs, employed individuals in South Africa experience lower levels of deprivation compared to the unemployed.

Income poverty: We used the GHS 2018 household spending data as a proxy for household income, and households that spent less than R2500 per month were categorised as being in income poverty, while those spending more were classified as not being in income poverty. Alkire and Santos (2010) and Mitra and Brucker (2015) suggest a weak connection between income poverty and multidimensional poverty. In the case of South Africa, significant shares of both income-poor and not-poor households experience deprivation. For example, 40% of individuals not categorised as income-poor still experience deprivation when a low cut-off for deprivation is applied. At the same time, using the same cut-offs for deprivation, almost 75% of individuals that are classified as income-poor experience deprivation (Figure 2). Therefore, the specification of MNR equations include examination of statistical association between income poverty and multidimensional poverty.

EPWP participation: To evaluate the effectiveness of the government's anti-poverty policy in mitigating multiple deprivation, we included the EPWP variable in our analysis. Figure 2 suggests minimal disparity between individuals who have engaged in the EPWP and those who have not. Surprisingly, those who did not participate exhibit a slightly more favourable situation, as approximately 95% of EPWP participants experience deprivation according to the high cut-off point, compared to 90% among those who did not participate. Additionally, approximately 61% of EPWP participants face acute deprivation, while the corresponding figure for non-participants stands at 51%.

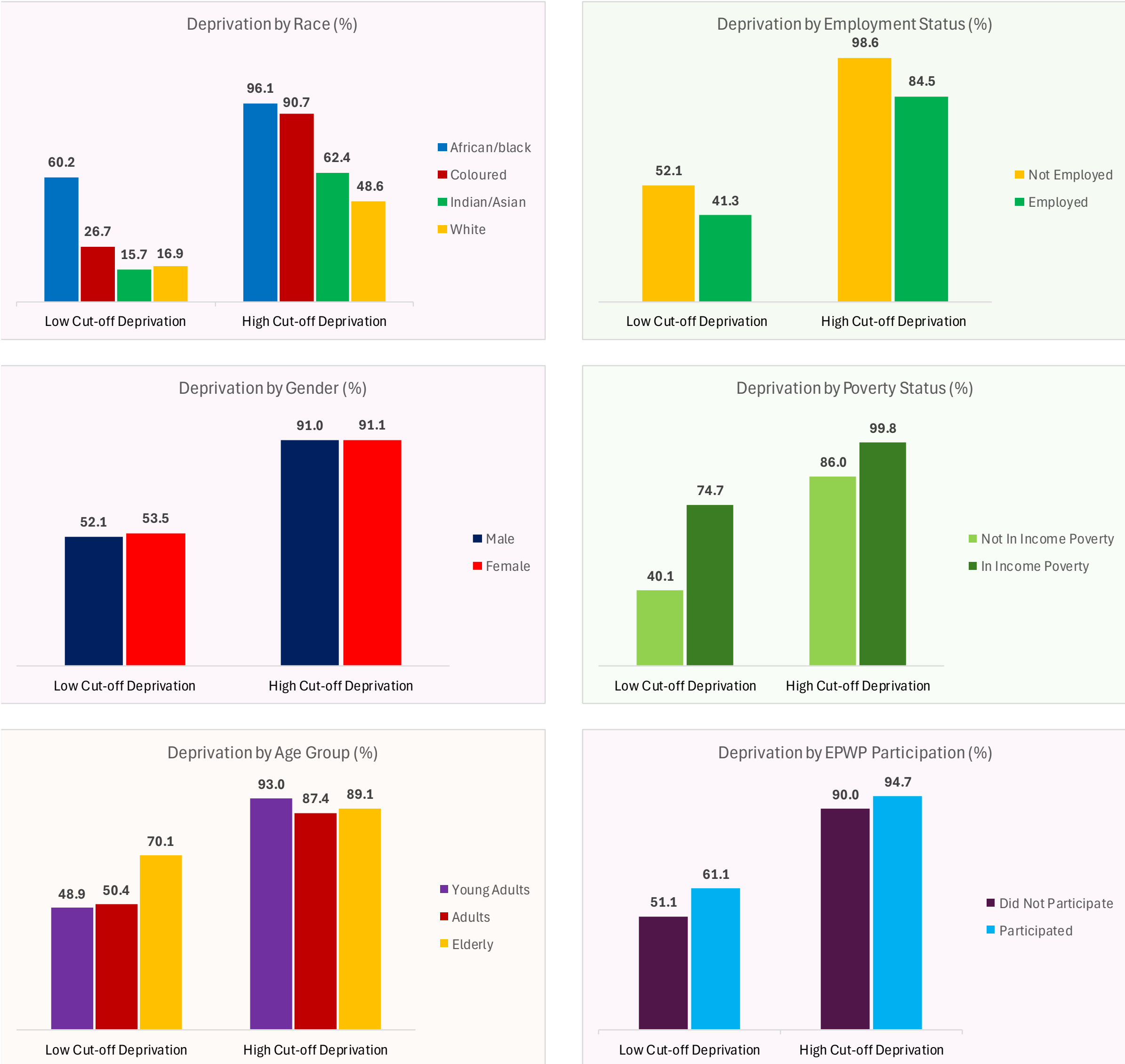
Household income: In the General Household Survey, the household income data are a continuous variable for those earning less than R20 000 per month, excluding rental and interest income. This variable was included in the MLR to investigate the possible influence of income increment on deprivation.

Geographical Income Inequality (GINI): The GINI is a widely used measure of income inequality, highlighting variations and disparities associated with poverty and multiple deprivation. By including the GINI variable as a deprivation predictor, we test the potential role of income inequality in multidimensional poverty. Due to the fact that the GHS does not include an inequality measure or variable, we incorporated the GINI by generating the $zGINI\_Geo$ variable, which was computed from the geographical type[8] variable of the General Household Survey (2018) and geographical

[8] The “geographical type” variable is the classification of individuals according to the settlement characteristics. The geographic area could either be “urban formal”, “traditional” or “farms” (GHS, 2018).

income inequality shares.[9] It was then normalised to prevent severe multicollinearity. We used the STATA statistical software to perform the Z-score normalisation. This method of standardisation is a two-step process, where one centres the data and then re-scales it by normalising it with the standard deviation, $z = \frac{X-\mu}{\sigma}$, where μ is the mean of x and σ is the standard deviation.

Figure 2: Distribution of MDP Measure at Low and High Cut-Off Points



Source: Author's Calculations. Source of Data: Statistics South Africa, General Household Survey, 2018, Metadata.

C.3. Application of Multinomial Logistic Regression (MLR) to Multidimensional Poverty

To determine the association between MDP and socio-economic factors, the multinomial logistic regression technique was employed. *Logistic regression* serves as a counterpart to ordinary linear regression when the dependent variable is categorical. *Binary logistic regressions* are used when the

[9] Geographical income inequality shares were assigned to each geographical area type (as classified in the GHS).

dependent variable has two outcomes, and *MLR* are used as extensions of the binary logistic regression models when the response variable has more than two possible outcomes.

C.3.1. MLR Models

Formally, Binary and multinomial logistic regressions can be expressed as follows.

Binary logistic regression*:* For the probability of a binary categorical response variable y and explanatory variable x, let:

$$\pi(x) = p(y = 1|X = x) = 1 - p(y = 0|X = x) \quad [1]$$

Where the possible outcomes of each observation are either $y = 0$ or $y = 1$ for failure and success, respectively. Equation 1 captures the dependence of y on the value of the explanatory variable, x. A linear probability model is defined as:

$$\pi(x) = \alpha + \beta x \quad [2]$$

Where α is the intercept and β reflects the change in $\pi(x)$ when the independent variable, x, increases by one unit.

With binary data, however, a change in x often has less impact when $\pi(x)$ approaches 0 or 1, rather than when this function is near 0.5. This pattern is observed when the following non-linear probability model is assumed:

$$\pi(x) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} \quad [3]$$

In equation 3, the coefficient β is determined by the rate of increase or decrease of the non-linear S-shaped curve of $\pi(x)$. The β-sign indicates whether the curve is upward ($\beta > 0$) or downward-sloping ($\beta < 0$). The rate of change increases when $|\beta|$increases.

The odds of probability is the ratio of the probability of success divided by the probability of the failure, i.e., $\frac{\pi(x)}{1-\pi(x)}$. Using equation 2, the equation for the odds of probability becomes:

$$\frac{\pi(x)}{1-\pi(x)} = e^{\alpha+\beta x} \quad [4]$$

Equation 4 shows that the odds are an exponential function of x. Hence, the odds increase multiplicatively by e^{β} for every 1-unit increase in x.

The logistic regression model takes the logarithm of the odds as a regression function of the predictors. With one predictor, x, the logit of this probability takes the form:

$$Logit[\pi(x)] = log\frac{\pi(x)}{1-\pi(x)} = \log(e^{\alpha+\beta x}) = \alpha + \beta x \quad [5]$$

Therefore, whereas the odds of probability is represented by a non-linear function (equation 4), the related logistic regression model is a linear function of x (equation 5), where α is the intercept term and β is the regression coefficient, reflecting the change in the logarithm of the odds of the desired outcome with a one unit change in the predictor x.

Multiple logistic regression is the extension of binary logistic models to multiple explanatory variables. For a binary response y, let n denote the number of explanatory variables, $x_1, x_2, \ldots, x_N$, where $n = 1,2, \ldots, N$. The model for log odds is denoted by:

$$Logit\,\pi(x) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_N x_N \qquad [6]$$

In the logistic regression equation 6, the coefficient β_n indicates the effect of x_n on the log odds $y = 1$, at fixed levels of the other explanatory variables, and e^{β_n} is the multiplicative effect on the odds of a 1-unit increase in x_n at fixed levels of other explanatory variables, x_k $(k \neq n)$.

Equation 6 can be transformed to directly represent $\pi(x)$:

$$\pi(x) = \frac{e^{\alpha+\beta_1 x_1+\cdots+\beta_N x_N}}{1+e^{\alpha+\beta_1 x_1+\cdots+\beta_N x_N}} \qquad [7]$$

Multinomial logistic regression is another extension of logistic equations in which the response variable assumes more than two outcomes, that is, for m independent observations with n-explanatory variables, the qualitative response variable y includes J possible categories.

To create the logits in the multinomial case, one of the categories must be considered as the reference category and all the logits are estimated relative to that category. It makes no difference which category is selected as the reference category, because one can always convert one formulation to another. Let π_{ij} denote the multinomial probability of observation i falling in the *jth* category. The relationship between this multinomial probability and the n-explanatory variables, $x_1, x_2, \ldots, x_N$, is found by the following multiple logistic regression:

$$Log\left[\frac{\pi_j(x_i)}{\pi_J(x_i)}\right] = a_{0j} + \beta_{1j} x_{1i} + \beta_{2j}\, x_{2i} + \cdots + \beta_{Nj} x_{Ni} \qquad [8]$$

where $j = 1, 2, \ldots, (J-1)$ and $n = 1,2, \ldots, N$).

Assuming that the last category, J, is the reference category, the model, represented by equation 8, simultaneously estimates the effects of x explanatory variables on the $J-1$ logits computed with respect to the reference category, where $\sum_{j=1}^{J} \pi_j(x_i) = 1$. At the same time, the estimated $J-1$ equations determine the parameters for the logits with other pairs of response categories since:

$$Log\left[\frac{\pi_a(x)}{\pi_b(x)}\right] = log\left[\frac{\pi_a(x)}{\pi_J(x)}\right] - log\left[\frac{\pi_b(x)}{\pi_J(x)}\right] \qquad [9]$$

In the MLR model 8, the coefficient β_{nj} indicates the effect of x_n on the log odds $y = 1$, constraining other explanatory variables x_k $(k \neq j)$. At the same time, given $\sum_{j=1}^{J} \pi_j(x) = 1$, equation 8 directly represents π_{ji} for the $J-1$ categories and for the reference category.

Therefore, the probabilities of the j-th outcome is:

$$\pi_j(x_i) = \frac{e^{a_{0i}+\beta_{1j} x_{1i}+\beta_{2j}\, x_{2i}+\cdots+\beta_{Nj} x_{Ni}}}{1+\sum_{j=1}^{J-1} e^{a_{0i}+\beta_{1j} x_{1i}+\beta_{2j}\, x_{2i}+\cdots+\beta_{Nj} x_{Ni}}} \qquad [10]$$

And the probability of the dependent variable falling within the reference category is defined as: (Liao, 1994).

$$\pi_J(x_i) = \frac{1}{1+\sum_{j=1}^{J-1} e^{a_{0i}+\beta_{1j} x_{1i}+\beta_{2j}\, x_{2i}+\cdots+\beta_{Nj} x_{Ni}}} \qquad [11]$$

C.3.2. MLR Assumptions

MLRs assumptions are different from the traditional OLS regression assumptions and include, first, that dependent variables should be measured on a nominal scale equal to or more than three values. Second, there is one or more independent variable that is continuous, nominal, or ordinal, but ordinal variables should be treated as continuous or categorical. Third, there should be independence of observations and the dependent variable should have exhaustive or mutually exclusive categories.[10] Fourth, there should be no multicollinearity.[11] Fifth, there needs to be a linear relationship between any continuous explanatory variables and the logit transformation of the dependent variable. Finally, sixth, there should be no outliers or highly influential points for the scale or continuous variables.

C.3.3. Specification of the MLR Model

We applied two MLR models to investigate possible associations between individuals' population groups and deprivation levels using low and high deprivation cut-offs, as described in Table 1. Based on the empirical findings of Section C.2, we hypothesised that the following relationship might exist:

$$MDP_{j,i} = \beta_{0,j} + \beta_{1,j}Race_i + \beta_{2,j}Gender_i + \beta_{3,j}Province_i + \beta_{4,j}Agegroup_i + \beta_{5,j}Employment\_status_i + \beta_{6,j}House\_income + \beta_{7,j}Epwp_i + \beta_{9,j}Income\_poverty_i + \beta_{10,j}zGINI\_Geo \quad [12]$$

Where:

MDP represents the dependent variable and includes five categories, namely **not deprived** (denoted as 0), **deprived in one** (denoted as 1), **deprived in two** (2), **deprived in three** (3) and **deprived in four or fully deprived** (4) dimensions of poverty at different levels of deprivation. The four dimensions of poverty refer to education, health, living conditions and assets. The category "not deprived" was used as the reference category.

MDP_{ji} represents individual i's deprivation level j, where j denotes the four deprivation categories other than the reference category.

Race represents four racial categories in South Africa, namely black, Coloured, Indian/Asian and white. The category "black" was used as the reference category. It constitutes the largest racial group in South Africa.

Gender includes two categories: male and female; male is used as the reference category.

Province includes nine South African provinces: Western Cape, Eastern Cape, Northern Cape, Free State, KwaZulu-Natal, North West, Gauteng, Mpumalanga and Limpopo. Gauteng is used as the reference category, as it constitutes the largest population.

---

[10] The Hausman-McFadden and Small-Hsiao tests are usually used to test this assumption. However, various studies, including Fry and Harris (1993) and Cheng and Long (2007), have shown that these tests perform poorly even in large samples.
[11] Multicollinearity occurs when two or more variables are highly correlated with each other.

Agegroup represents the breakdown of the population between three categories: young adults (18–35 years), adults (36–64 years) and elderly (65 years and older). The category "young adults" was used as the reference category.

Employment status represents the labour force status of the working age population (15–64): employed and unemployed, with unemployed used as the reference category.

House income is a continuous variable and represents an estimate of total household income.

Epwp represents participation in the government's public work programme (i.e. EPWP) and includes two categories: "did not participate" and "participated". The "did not participate" category was used as the reference category.

Income_poverty represents the allocation of population between "poor" and "not poor" using income and income poverty line. It therefore includes two categories: "not in income poverty" and "in income poverty". "Not in income poverty" was used as the reference category.

zGini_Geo represents the standardised Geographical Income Inequality Index.

C.3.4. MLR Model Results

MLR estimates $J-1$ models, where *J* is the number of categories for the dependent variable. In this study, the dependent variable is multiple deprivation, with five categories ($J=5$), namely *not deprived, deprived of one, deprived of two, deprived of three,* and *fully deprived.* The MLR coefficients are interpreted relative to the reference category "not deprived"; they can be described as increasing or decreasing odds of falling in the estimated category. Therefore, for a unit change in the predictor variable (in this case, *race, gender, province, age group, employment status, EPWP participation, income poverty, house income* and *GINI Geo*), the logit category *j* relative to the referent group is expected to change by its respective parameter, provided that all other variables remain constant. Tables 2 and 3 present the estimated coefficients of the MLR Equation 12 at two deprivation cut-off points (low and high).

Table 2: MLR Estimation Coefficient Results – Low Cut-off Point Deprivation

Explanatory Variables		Deprived of 1		Deprived of 2		Deprived of 3		Fully Deprived	
		Odds Ratio	Standard Error	Odds Ratio	Standard Error	Odds Ratio	Standard Error	Odds Ratio	Standard Error
Race (Ref. Category: Black)	**Coloured**	-0.776939	0.001968	-0.410377	0.003842	-0.317152	0.008714	-0.300261	0.224119
	Indian/Asian	-1.048700	0.003586	-1.110078	0.008602	-0.184848	0.012602	-22.75561	3,448.17
	Whilte	-0.938672	0.002325	-2.107357	0.009204	-22.43917	602.8049	-21.40254	1,574.88
Gender (Male)	**Female**	-0.060083	0.000975	-0.141449	0.001621	-0.078931	0.003184	-0.503634	0.112591
Province (Gauteng)	**Western Cape**	0.384435	0.001740	0.346005	0.004112	0.210705	0.012402	2.657592	0.058395
	Eastern Cape	0.078430	0.001841	0.350982	0.003220	0.972374	0.007813	3.449283	0.053618
	Northern Cape	0.142423	0.003442	0.655623	0.005507	1.697095	0.010563	4.317176	0.055894
	Free State	0.225590	0.002144	0.555212	0.003872	0.939716	0.009516	2.315859	0.060207
	KwaZulu Natal	0.250825	0.001509	0.534973	0.002884	1.337514	0.007369	3.098843	0.053640
	North West	0.227521	0.002117	0.497932	0.003561	0.941052	0.008442	2.761714	0.055802
	Mpumalanga	0.324460	0.002127	0.513960	0.003602	0.947929	0.008523	2.223354	0.058042
	Limpopo	0.330494	0.002287	0.267080	0.003660	0.219452	0.008838	1.342756	0.060163
Age Group (Young Adults)	**Adults**	0.224065	0.000989	1.618908	0.001769	2.436126	0.004211	1.925439	0.013401
	Elderly	1.023908	0.005057	3.163993	0.007231	4.603887	0.012195	-19.46798	4,717.823
Employment Status (Unemployed)	**Employed**	-0.059068	0.001052	-0.479606	0.001752	-1.059250	0.003763	-0.821573	0.012923
EPWP Participation (Not participated)	**Participated**	-0.097490	0.003501	-0.234765	0.005259	-0.288322	0.009767	0.040604	0.028728
Income Poverty (Not in income poverty)	**In Income Poverty**	0.715017	0.001120	1.035048	0.001788	1.152531	0.003572	1.810294	0.014321
Household Income	**House_income**	-0.000034	0.000000	-0.000060	0.000000	-0.000075	0.000000	-0.000049	0.000001
Income Inequality	**zginigeo**	1.360577	0.000747	1.552957	0.001074	1.698761	0.002025	1.412536	0.006174

Source: Author's Calculations. Source of Data: Statistics South Africa, General Household Survey, 2018, Metadata.

Table 3: MLR Estimation Coefficient Results – High Cut-off Point Deprivation

Explanatory Variables		Deprived of 1		Deprived of 2		Deprived of 3		Fully Deprived	
		Odds Ratio	Standard Error	Odds Ratio	Standard Error	Odds Ratio	Standard Error	Odds Ratio	Standard Error
Race (Ref. Category: Black)	**Coloured**	-0.120128	0.003397	-0.566490	0.003433	-0.699223	0.003559	-1.439499	0.004358
	Indian/Asian	-0.887711	0.003813	-1.761993	0.004206	-2.669721	0.005373	-3.784195	0.010626
	Whilte	-0.928823	0.002207	-2.211415	0.002828	-3.561797	0.004546	-4.450359	0.008658
Gender (Male)	**Female**	-0.186434	0.001819	-0.205047	0.001878	-0.432257	0.001937	-0.591572	0.002104
Province (Gauteng)	**Western Cape**	0.230703	0.002717	0.634618	0.002972	0.863089	0.003165	1.342961	0.003601
	Eastern Cape	0.014851	0.004136	0.050826	0.002972	0.188797	0.004218	0.408965	0.004478
	Northern Cape	-0.001744	0.007403	0.385267	0.007163	0.495094	0.007317	0.525813	0.008036
	Free State	0.165678	0.005142	0.416042	0.005166	0.369981	0.004218	0.290223	0.005664
	KwaZulu Natal	-0.089108	0.003128	0.156963	0.003092	0.243736	0.003179	0.276217	0.003449
	North West	-0.063663	0.005042	0.124458	0.004956	0.205515	0.301171	0.147814	0.005292
	Mpumalanga	0.239559	0.004139	0.149292	0.004350	0.301171	0.004409	0.188549	0.004706
	Limpopo	0.386544	0.005593	0.390002	0.005700	0.350975	0.005763	0.277585	0.005974
Age Group (Young Adults)	**Adults**	-0.206877	0.001907	-0.567374	0.001939	-0.389372	0.002004	-0.091861	0.002173
	Elderly	0.277648	0.005573	-0.608872	0.007500	-0.450367	0.008128	0.201665	0.008695
Employment Status (Unemployed	**Employed**	-1.038119	0.004331	-1.508780	0.004180	-1.434099	0.004230	-1.159441	0.004348
EPWP Participation (Not participa	**Participated**	-0.607624	0.008978	-0.287455	0.008059	-0.072271	0.008047	0.053360	0.008309
Income Poverty (Not in income po	**In Income Poverty**	0.565157	0.009063	2.264631	0.008145	2.924630	0.008133	3.562878	0.008178
Household Income	**House_income**	-0.000036	0.000000	-0.000087	0.000000	-0.000114	0.000000	-0.000144	0.000000
Income Inequality	**zginigeo**	0.458037	0.002537	0.557351	0.002495	1.193297	0.002447	1.697998	0.002484

Source: Author's Calculations. Source of Data: Statistics South Africa, General Household Survey, 2018, Metadata.

C.3.4.1. MLR Results: Demographic Factors

The MLR results (Tables 2 to 3) highlight a significant statistical association between demographic factors and poverty in South Africa, which is in line with other studies (Biyase & Zwane, 2018; Khumalo, 2013; Noble & Wright, 2013).

Race: The results show that for both low and high cut-offs deprivation, *ceteris paribus*, the odds of being deprived (in one, two, three or fully deprived) compared to not being deprived are lower for other racial groups (*Coloured, Indian/Asian and white*) compared to blacks. In other words, Coloured, Asian and whites in South Africa are less likely than blacks to be deprived than not deprived. For example, the odds of experiencing full deprivation rather than no deprivation at all decrease for whites compared to blacks by 21.40 and 4.45 at the low and high cut-offs, respectively. This reflects a well-known finding that the burden of poverty and deprivation is carried by Black South Africans (Khumalo, 2013).[12]

Gender: For both deprivation cut-offs (low and high), holding other factors constant, the odds of women being deprived (*in two, three and fully deprived*) are lower than those of men, compared to not being deprived at all. In other words, females are less likely than males to be deprived than not deprived. For example, with the high cut-offs, the odds of being deprived in one dimension reduce by 0.186 for females than males. Even at full deprivation, with low and high cut-offs, the odds for females relative to males decrease by 0.504 and 0.592, respectively, when the other variables in the models are held constant. These findings align with Rogan's (2015) research, which illustrates that employing the MPI reveals a slightly narrower gap in poverty or deprivation between female- and male-headed households in contrast to the income poverty gap.

Region: For low and high cut-off points, the results verify the geographical dimension of deprivations in South Africa. *Ceteris paribus*, compared to Gauteng, other provinces in the country are more likely to be deprived of one, two, three or fully deprived than not. For instance, with the low and high cut-offs, the odds for the Eastern Cape compared to Gauteng experiencing full deprivation instead of no deprivation are higher by a factor of 3.449 and 0.409, given the other variables in each model are kept constant. These results are in line with expectations and other studies (Mcintyre et al., 2000; Noble & Wright, 2013), given that Gauteng's GDP is equivalent to one-third of the country's GDP and has the largest GDP per capita (STATSSA, 2023). [13]

Age: The MLR results for the age group for both low and high cut-offs provide the odds for the adults and elderly compared to the young adults experiencing deprivation instead of no deprivation, when the other variables are held constant. Therefore, the MLR results show a statistical association between age and deprivation, as posited by Khumalo (2013). The results, for example, show that the odds of being deprived (in two dimensions, three dimensions and fully) compared to not being deprived reduce as age increases. For instance, in the case of the high cut-off deprivation, *ceteris paribus,* the odds of being deprived in three dimensions or being fully deprived compared to not being deprived are lower by 0.389 and 0.092 for adults compared to young adults, respectively.

Thus, in the main, adults and elderly compared to young adults are less likely to be deprived and more likely to not be deprived of low or high cut-offs access to education, healthcare, living services and assets compared to young adults. It is likely that the above association between age group and multidimensional poverty is due to the high rate of youth unemployment in South Africa and lower earnings from job internships and learnerships. Mlatsheni and Leibbrandt (2011) argue that the South

[12] Khumalo (2013) which states that poverty is a challenge that takes a racial, gender, spatial and demographic interpretation in South Africa. Biyase and Zwane (2018) found that blacks are more likely to be poor than other population groups. Noble and Wright (2013) in a multiple deprivation spatial study show that the most deprived individuals are in the former homeland areas of South Africa, where the majority is black.

[13] Mcintyre et al. (2000) also found that Gauteng and Western Cape have the highest population living in the least deprived districts, Noble and Wright (2013) corroborated. StatsSA (2023) "Provincial gross domestic product: experimental estimates, 2013–2022." Discussion Document D0441.1, September. https://www.statssa.gov.za/publications/D04411/D044112022.pdf

African youth's detrimental circumstances and relative deprivation result from policy exclusion; that is, government policies exclude or do not adequately cater to the needs of young South Africans.

C.3.4.2. MLR Results: Economic factors

The MLR estimations of the MDP equation 12 using low and high cut-off indicators capture the statistical relationship between dimensions of deprivation (the MDP) and at least five economic indicators. The five explanatory variables provide direct links between the MDP and the labour market, household income, government public works policies, income poverty and income inequality.

Labour market: Tables 2 and 3 include the MLR results for the relationship between labour market status and various dimensions of poverty. Accordingly, at both low and high deprivation cut-offs, holding other variables in the model constant, the odds of being deprived compared to not being deprived (of one dimension, two dimensions, three dimensions and fully) are lower among employed individuals, in comparison to unemployed individuals. For instance, with the low deprivation cut-offs, holding other factors constant, the odds of being fully deprived, as opposed to experiencing no deprivation, decrease by a factor of 0.822 for employed individuals in comparison to unemployed individuals. For similar circumstances but with the high cut-offs, the corresponding odds decrease by a factor of 1.159. Overall, the MLR results show that being employed compared to not being employed are associated with lessening the chances of being deprived.

Public employment: The EPWP is an important low paid and part-time job creation of the South African government. The MLR estimation at low and high deprivation cut-offs found that the odds of being deprived of one, two, or three dimensions compared to not being deprived reduce for individuals who participated in EPWP in comparison to those who did not participate. For instance, at the low cut-offs, *ceteris paribus*, the odds of being deprived of three dimensions compared to not being deprived reduce by 0.288 for those who participated in EPWP as opposed to those who did not. However, the odds of being fully deprived compared to not being deprived increase amidst EPWP participants compared to non-participants. The corresponding odds increase by a factor of 0.041 and 0.053 with the low and high cut-off deprivations, respectively.

Overall, the MLR results show that the EPWP strategy is mainly effective in reducing poverty at lower deprivation levels than when individuals are deprived of all dimensions. This may be associated with the low and stipend income EPWP offers (Mohapi, 2016).

Income poverty: Notwithstanding the measurement difference between income poverty and multidimensional poverty, the possible relationship between the two can have an important implication for targeted policy interventions; moreover, there may be potent spillover effects in eradicating either one of these challenges. It is worth noting that most empirical research has found weak relations between income poverty and MDP (Alaya & Perez-Mayo, 2011).

In the case of South Africa, the MLR results highlight a significant positive relationship between deprivation and income poverty. Using low and high cut-offs, *ceteris paribus*, the odds of being deprived (in one dimension, two dimensions, three dimensions or fully) than not being deprived increase for a person in income poverty compared to a person who is not in income poverty. The estimation results show that, for example, the odds of being deprived of three dimensions of poverty against not being deprived increase by factors of 1.152 and 2.925 for income-poor compared to not income-poor persons for both low and high cut-off measures of deprivation (Tables 2 and 3).

Household income: Tables 2 to 3 highlight the MLR results (for low and high cut-offs) on whether household income, including income from social grants, has a statistically significant association with MDP. The results show that household income increases have a significant alleviating impact on their deprivation. *Ceteris paribus*, as household monthly income increases, households are less likely to be deprived (of one dimension, two dimensions, three dimensions or fully) and more likely to not be deprived. For example, with low cut-off deprivation, the odds of being deprived of one dimension, two dimensions, three dimensions and fully compared to not being deprived reduce by 0.000034, 0.00006, 0.000075, 0.000049, respectively. For high cut-offs deprivation, the estimated odds ratios convey similar associations between household income and deprivation. Issa Shahateet (2007) also found that a one per cent (1%) reduction in income deprivation, unemployment and education deprivation will result in a 0.7% reduction in the overall deprivation index.

Income inequality: The MLR results (Tables 2 to 3) also affirm that the high inequality levels in South Africa are a contributing factor to deprivation levels thereof. For both deprivation cut-offs, *ceteris paribus,* as income inequality increases, individuals are more likely to be deprived (of one dimension, two dimensions, three dimensions and fully) than not be deprived. At the low cut-off deprivation, for instance, the odds of being deprived of one, two, three and fully compared to not being deprived increase by 1.361, 1.553, 1,699, and 1.412, respectively. Klasen (1997) found that most of the poverty in South African is a direct result of the inequality caused by apartheid policies, policies that denied equal access to education, employment, services and resources to the country's black population.

Overall, the examination of Household Survey data of 2018, using the MLR techniques, establishes statistical association between MDP and demographic and economic indicators. The next section provides a summary of measures that were undertaken to validate the MLR results.

C.3.5. Validation of MLR Results

Prior to integrating the MLR results into DIMMSIM, it is imperative that we undertake relevant tests to verify, as recommended by Peng et al. (2002), the accuracy of the MLR estimates presented in Tables 2 to 3. This section, therefore, encompasses an assessment of the overall relationship between multiple deprivation and all explanatory variables, a test evaluating the significance of explanatory variables in explaining multiple deprivation, as well as an examination of numerical errors and multicollinearity within the MLR solution.

C.3.5.1. Overall test of relationship

According to Peng et al. (2002), "a logistic regression is said to provide a better fit if it demonstrates improvement over the intercept-only model (also called null model)". Table 4 confirms that we may reject the null hypothesis since the log-likelihood of each full model (low and high cut-offs MDP) is greater than that of the corresponding null model, which implies that the full models explain multiple deprivations better than the null models.[14] Furthermore, we tested the overall model fit using the chi-square distribution. The null hypothesis of this test is that there is no difference between the null model (model without explanatory variables) and the full model (model including all the explanatory variables). The alternative hypothesis is that there is a difference. We may reject the null hypothesis if the chi-square p-value is less than 0.05 at a 95% significance level. The estimated p-value of zero for both low and high cut-offs MDP is less than the significant level, which means we can reject the null hypothesis and conclude that there is a statistically significant association between the specified explanatory variables and multiple deprivations with both low and high cut-offs.

Table 4: Model Fit Information for MLR Estimations

Low cut-off Point Deprivation	
Log-likelihood	**Value**
Null Model	-24,242
Full Model	-18,134
Chi-Square	
Deviance (df=25860)	36,268
LR (df=76)	12,216
P-Value	0.0
High Cut-off Point Deprivation	
Log-likelihood	**Value**
Null Model	-35,000,000
Full Model	-26,410,000
Chi-Square	
Deviance (df=25860)	52,820,000
LR (df=76)	17,260,000
P-Value	0.0

C.3.5.2. Testing the Relationship Between Explanatory and Dependent Variables

Peng and Nichols (2003) and Monyai et al. (2015) affirm that even though a significant overall relationship between dependent and independent variables is crucial, it does not necessarily mean all

[14] The multinomial logistic regression employs maximum likelihood estimation, a process characterised by iterative steps. The initial iteration, denoted as iteration 0, represents the log likelihood of the "null" or "empty" model, which contains no predictors. Subsequent iterations involve the inclusion of predictor(s) in the model, with the log likelihood increasing at each step. The objective is to maximise the log likelihood. Convergence occurs when the difference between successive iterations becomes very small, prompting the termination of the iteration process. The results are then provided (Long, 1997).

the explanatory variables included are significant. Therefore, there is a need to test the improvement of the model fit with each of the explanatory variables. The Wald chi-square test[15] method was used to test the significance of each predictor. Although both the likelihood ratio and the Wald methods test similar hypotheses, other studies mostly use the likelihood ratio chi-square method or both methods concurrently.[16] The Wald test method emerges as the most apt for our analysis, particularly given our utilisation of GHS data. Williams (2002) advocates for the use of Wald tests when working with very large data. The null hypothesis of this test is that the categorical variables are independent of each other, and the alternative hypothesis states that they are not. We may reject the null hypothesis if the p-value is less than 0.05 at a 95% significance level. Table 5 presents the results of the significant tests using both deprivation cut-offs. All the p-values are equal to 0, which leads us to conclude that all the predictors included in the model are significant. Thus, there exists a relationship between low and high cut-off multiple deprivation in South Africa and all the predictors used in the two models; each predictor improves the model fit; hence, all predictors should be included in the model.

Table 5: Wald Tests for MLR Estimations

Low Cut-off Point Deprivation			High Cut-off Point Deprivation		
Predictor	Chi-Square	P-Value	Predictor	Chi-Square	P-Value
Race	160,000	0.00	*Race*	140,000	0.00
Gender	9,855	0.00	*Gender*	110,000	0.00
Agegroup	1,100,000	0.00	*Agegroup*	170,000	0.00
Province	52,542	0.00	*Province*	150,000	0.00
Employment_status	140,000	0.00	*Employment_status*	180,000	0.00
EPWP	2,397	0.00	*EPWP*	10,658	0.00
Income_poverty	540,000	0.00	*Income_poverty*	970,000	0.00
House_income	620,000	0.00	*House_income*	2,600,000	0.00
ZGINI_geo	3,600,000	0.00	*ZGINI_geo*	1,600,000	0.00

C.3.5.3. Examining Numerical Errors and Multicollinearity

The standard errors of the coefficient estimates (β)[17] are used to examine multicollinearity or numerical errors related to the solution of the MLR. If the standard error is greater than two, there may be numerical errors, such as multicollinearity, among explanatory variables that are used in a model (Monyai et al., 2015). In logistic regression, multicollinearity occurs as the correlation in independent variables increases. Multicollinearity does not change the estimates of parameters but

[15] The Wald test, also called the Wald chi-square test, is used to test whether explanatory variables are significant in a model. Formula: $W_T = \frac{[\hat{\theta}-\theta]^2}{1/I_n(\hat{\theta})} = I_n(\hat{\theta})\ [\hat{\theta}-\theta]^2$, where $\hat{\theta}$ = maximum likelihood estimator and $I_n(\hat{\theta})$ = evaluated maximum likelihood (Agresti, 1990).

[16] These studies include: Freese and Long (2000), Peng et al. (2002), Peng and Nichols (2003), Monyai et al. (2015), and Etowa et al. (2021), among other studies.

[17] A standard error measures the statistical accuracy of an estimate. Formula: $SE_p = \sqrt{\frac{p(1-p)}{n}} = \sqrt{\frac{pq}{n}}$, where p = proportion estimated from sample, $q = 1 - p$, and n = sample size (Brown, 1982).

indicates their unreliability (EL-Habil, 2012). Tables 2 and 3 illustrate the coefficient results of the two MLR models and thereby the standard errors. Using the low cut-off deprivation dependent variables, 95% of the standard errors are below two, while using the high cut-off deprivations, all the standard errors are below two. This finding suggests that our parameter estimates exhibit minimal numerical errors and are thus reliable.

C.4. Building the MDP Module of DIMMSIM

The process of expanding the DIMMSIM to generate projections of MDP measures involved integrating the estimated MLR equations into the model's system of equations. Specifically, as indicated in Section C.3.1, the MLR technique estimates the log-odds for all other categories relative to the reference category and allows the log-odds to be a liner function of the predictors, where π_{ji} is the probability of observation i falling in category j:

$$\mu_{ji} = log\frac{\pi_{ji}}{\pi_{Ji}}$$

The model estimates $J-1$ multinomial logit equations that contrast each of categories $1, 2, \dots J-1$ with category J. The practical use of the MLR technique in building the forward-looking MDP module of the DIMMSIM relates to the fact that the multinomial logistic regression results in log-odds can be written in terms of the original probabilities, π_{ji}, which add up to one for all J of the probabilities, $\sum_{j=1}^{J}\pi_j(x_i) = 1$:

$$\pi_j(x_i) = \frac{e^{a_{0i}+\beta_{1j}x_{1i}+\beta_{2j}x_{2i}+\cdots+\beta_{Nj}x_{Ni}}}{1+\sum_{j=1}^{J-1}e^{a_{0i}+\beta_{1j}x_{1i}+\beta_{2j}x_{2i}+\cdots+\beta_{Nj}x_{Ni}}} \qquad [10']$$

$$\pi_J(x_i) = \frac{1}{1+\sum_{j=1}^{J-1}e^{a_{0i}+\beta_{1j}x_{1i}+\beta_{2j}x_{2i}+\cdots+\beta_{Nj}x_{Ni}}} \qquad [11']$$

Where β_{jn} represents a regression coefficient related to the nth explanatory variable and the jth outcome, where $n = 1,2, \dots, N$.

DIMMSIM's output includes annual projections of all demographics, economic and social explanatory variables used in the estimated MLR equations, i.e. x_N^{t+1}. Therefore, in the Augmented DIMMSIM, for each forecast period, $t+1$, the MLR probabilities, π_{ji}, are calculated using DIMMSIM generated $t+1$ values for the equation's explanatory variables, thus making the estimated probabilities dynamic. The final model, therefore, uses the dynamic version of the above probability equations represented by:

$$\pi_{ji}^t = \frac{e^{\alpha_{0j}+\beta_{1j}X_{1i}^t+\beta_{2j}X_{2i}^t+\cdots+\beta_{Nj}X_{Ni}^t}}{1+\sum_{j=1}^{J-1}e^{\alpha_{0j}+\beta_{1j}X_{1i}^t+\beta_{2j}X_{2i}^t+\cdots+\beta_{Nj}X_{Ni}^t}} \qquad [10'']$$

$$\pi_{ji}^t = \frac{1}{1+\sum_{j=1}^{J-1}e^{\alpha_{0j}+\beta_{1j}X_{1i}^t+\beta_{2j}X_{2i}^t+\cdots+\beta_{Nj}X_{Ni}^t}} \qquad [11'']$$

Where $t = 1, 2 \dots, t$ is the forecast period.

Therefore, DIMMSIM's projections of rates of deprivation are estimated probabilities that add up to one and represent likely distribution of a population among five dimensions of poverty; that is, not-deprived and deprived of one, two, three or more than three (fully deprived) dimensions of poverty. Currently, the model generates annual rates of deprivation at national and provincial levels and by race and gender for the forecast period.

D. POLICY SCENARIOS AND MDP FUTURE OUTLOOKS (2024–2030)

To demonstrate the utility and outputs of the MDP Augmented DIMMSIM, the model was used to assess the impact of six cumulative economic and social policy scenarios on the evolution of multidimensional poverty indicators for the period 2024 to 2030. Each scenario adds new measures or changes to one or more features of the previous scenario. They include a baseline scenario, two macroeconomic policy scenarios, a private sector investment scenario and two social policy scenarios.

The Baseline Scenario (Scenario 1): The Baseline Scenario envisages government economic policy continuing its current and recent historical path for the rest of the decade. It is assumed that, for example, fiscal policy will continue to prioritise lowering the debt-GDP ratio by restricting the growth of government final consumption expenditure to 6% annually and investments by the public sector (the general government and public corporations) to 4% annually. Under the Baseline Scenario, tax rates will remain unchanged and monetary authorities will continue to set the interest rate to enforce strict adherence to inflation targeting, with a 6% ceiling for the inflation rate.

Macroeconomic Policy Scenarios: The weak performance of the South African economy, at least since 2010, in terms of growth and employment and persistent high poverty and inequality provide the motivation for the inclusion of two "what if" scenarios that consider revisiting the macroeconomic policy approach of the Baseline Scenario. The aim of these scenarios is to highlight the model's utility to provide the impact of macroeconomic policy and performance on MDP measures.

Fiscal Policy Scenario (Scenario 2): The purpose of this scenario is to use the MDP Augmented DIMMSIM to consider what will be the likely impact on MDP measures if the government considers increasing its current and capital spending during the next seven years, 2024 to 2030. The scenario considers:

- "What if" the government and public corporations systematically increased their investment in economic infrastructure (e.g. roads, bridges, dams, electricity and water supply), social infrastructure (e.g. schools, hospitals, parks and administrative services) and economic services (e.g. business enterprises) by 10% annually between 2024 and 2030.
- "What if" the government spending on goods and services (i.e. government final consumption expenditure) annually increased by 8% to provide necessary funding to expand the delivery of individual and collective social services.

Monetary Policy Scenario (Scenario 3): This scenario is designed to demonstrate the indirect link between monetary policy and the MDP. It therefore considers:

- "What if" the Reserve Bank's current solitary mandate under inflation targeting were upgraded to a dual mandate of targeting 6 per cent real GDP growth and price stability with the upper limit of 8% for the inflation rate.
- "What if" monetary authorities adopted necessary measures to raise the annual growth of credit extension to the private sector to 15%.

Private Sector Investment Scenario (Scenario 4): Using the Public-Private Growth Initiative (PPGI) in South Africa, which was established in early 2018, this scenario uses the model to quantitatively show the potential role of private sector investment to reduce MDP. It therefore considers:

- "What if" the PPGI increased investments in the South African economy by R500 billion over the next seven years.

Public Employment Scenario (Scenario 5): This scenario uses the South African government's public employment programme to quantify its impact on MDP. It therefore considers:

- "What if" the number of job opportunities that are offered under the government's Expanded Public Works Programme were annually increased by 10 per cent so that by 2030, the size of the programme doubled.
- "What if" the daily remuneration rate for the government public works programme were increased to R160 in 2024 and annually increased by 6 per cent afterward.
- "What if" the duration of all EPWP works were set at 120 days.

Social Grant Scenario (Scenario 6): This scenario is used to highlight the model's ability to assess the implication of changes to the social security programme for the MDP measures. It considers:

- "What if" the current monthly child support grant were increased to the official Food Poverty Line from 2024.
- "What if" the government introduced in 2024 a caregiver grant for the family member that takes care of a person who receives a child support grant, a care dependency grant, a disability grant or an old age pension grant. The monthly caregiver grant amount set at the Food Poverty Line will annually increase by six per cent and be limited to one caregiver grant per family.

Model results

Table 6 summarises the impact of the scenarios on five key macroeconomic indicators. In addition, the table presents the model's projections for an additional five variables that we found to have statistically significant associations with MDP in Section C.3.4. These include Household Gross Disposable Income, Public Works Employment, Social Benefits and Transfers Paid by Government, Income Poverty rate, and Income Inequality (GINI-Coefficient Index). The main focus of this section is to present the model results, including its projections of MDP indicators under alternative policy scenarios, for 2024 to 2030.

The simulation of the Baseline Scenario shows (Table 6, Baseline column) that during the next seven years, 2024–2030, GDP growth will be on average 1.4% per annum, which is consistent with the current official projections for the period 2023 to 2026 of 1.5 per cent (World Bank 2021). Moreover, the average annual unemployment rate (narrow definition) for the period will be 31.2%. The average debt-GDP ratio is projected at 76.5% and the average annual inflation rate at 6.9%. During 2024 to 2030, under the Baseline Scenario, the government is expected to annually spend an equivalent of 7.64% of GDP on the social benefits and transfers, and, the national income poverty rate and Gini-coefficient will be on average annually 43.2% and 0.709, respectively.

The model's simulation results for the five alternative policy scenarios (scenarios 2 to 6) show that the scenarios will expand macroeconomic outcomes during the next seven years in terms of cumulative increases in GDP growth, employment and household disposable income (Table 6). At the same time, given the model's linked macro-household architecture, the scenarios' expected positive economic outcomes are projected to help reduce income poverty and inequality during the rest of the decade

(Table 6). For example, the sixth scenario's cumulative policy measures are expected to help reduce the average annual unemployment rate by 5.7% points and reduce the average annual poverty rate by almost 4% points (Table 6).

Table 6: South Africa's Outlook Scenarios (Key Indicators)

Indicators: Average Annual, 2024-2030	Baseline (Scen. 1)	Fiscal Policy (2)	Monetary Policy (3)	Private Investment (4)	Public Employment (5)	Social Grant (6)
GDP Growth (%)	1.4	2.8	3.1	3.5	3.5	3.9
Unemployment rate (%)	31.2	28.5	27.7	26.4	26.3	25.5
Employment	17,598,000	18,315,322	18,512,850	18,860,955	18,873,036	19,086,190
Debt-GDP Ratio (%)	76.5	73.9	63.0	58.5	58.4	60.7
Inflation (%)	6.87	6.82	7.01	6.78	6.90	6.95
Household Gross Disposable Income (Rand, millions)	6,304,372	6,653,861	6,722,735	6,798,346	6,826,239	7,051,758
Public Works Employment	1,007,000	1,007,000	1,007,000	1,007,000	1,506,000	1,506,000
Social Benefits and Transfers Paid by Government (Rand, millions)	700,506	661,008	650,022	639,453	639,625	834,300
Income Poverty rate (%)	43.2	40.8	40.2	39.5	38.7	38.3
Income Inequality (GINI Coefficient)	0.709	0.697	0.694	0.690	0.684	0.681

Source: ADRS Dynamically Integrated Macro-Micro Simulation Model of South Africa (DIMMSIM)

Moreover, the novel outcome of this study is the model's projections of the likely impact of various economic and social policy scenarios on the outlook for MDP indicators. Table 7 presents the likely impact of the six socioeconomic scenarios on the low and high cut-off measures of multidimensional poverty during the rest of the decade, represented by reductions in the shares of population that are deprived of one, two, three, and more than three (fully deprived) dimensions of poverty. For example, the results for the period 2024 to 2030 show that, relative to the low cut-offs Baseline Scenario, scenarios 2 to 6 are expected to reduce the average annual shares of population that are deprived of all four dimensions of poverty by between 0.9% (deprived of one dimension) and 20.4% (deprived of three dimensions). For the high cut-offs MDP, the comparable average annual declines will be between 17.9% (deprived of one dimension) and 32.7% (fully deprived).

Table 7 also depicts the extent to which the selected policy scenarios are likely to lower poverty within population groups. For example, relative to the low cut-off Baseline Scenario's average annual results for the next seven years, the not-deprived average annual share of the male population is projected to increase between 13.3% (Scenario 2) and 26% (Scenario 6). The corresponding average annual increases for the female portion of the population are 8.2% (Scenario 2) and 19.5% (Scenario 6). When employing the high cut-offs, policy scenarios 2 to 6 are expected to help move males and females out of poverty at much higher rates than the low cut-off (Table 7).

Table 7 includes the likely impact of policy scenarios on deprivation among the racial groups in South Africa. For the period 2024 to 2030, the average share of the not deprived among the white population is projected at 57.6% and 65.5% for the low and high cut-offs, respectively, for the Baseline Scenario. The corresponding shares for the black population are estimated at 13.8% (low cut-offs) and 7.4% (high cut-offs), which are 4.2 (low cut-offs) and 8.8 (high cut-offs) times lower than the shares for the white population. The model results show that the expansionary policy scenarios (scenarios 2 to 6) will reduce, relative to the Baseline Scenario, deprivation among all racial groups.

However, the scenarios are not effective in reducing the gap between the rates of deprivation among black and white populations; that is, the deprivation inequality. Consequently, for the period 2024 to 2030, using the low cut-offs and under the Baseline Scenario, the average deprivation rate among blacks, namely the percentage of black population who are deprived of one, two, three and more than three (fully) dimensions of poverty is projected to be almost twice the rate of deprivation among the white population (86.2% compared to 42.4%). The inequality in deprivation between the two population groups will be even higher under high cut-offs (92.6% compared to 34.5%). Even though lower deprivation rates are projected for the four racial groups under policy scenarios 2 to 6, the deprivation inequalities are expected to grow. For example, the average deprivation rate for the African population is projected to be 2.4 (low cut-offs) and 3.2 (high cut-offs) times more than the corresponding rates for the white population.

At regional level, the model's projections for the rest of the decade reflect the initial variations and additional variations in terms of the impact of the scenarios. Overall, with the high cut-offs Baseline Scenario, the average annual deprivation rate among the nine provinces is expected to range between 74.7% for Gauteng and 94.4% for Limpopo during the rest of the decade (Table 7). Between 2023 and 2030, policy scenarios 2 to 6 are expected to increase the average annual share of the not-deprived population across the nine provinces by between 13% (Northern Cape) and 30.8% (Limpopo), using the low cut-offs.

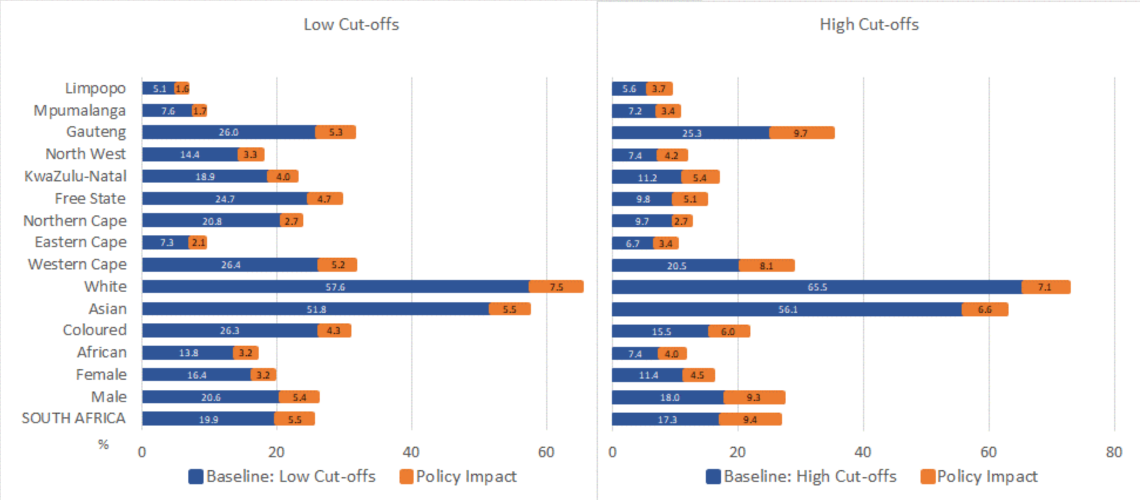
Figure 3 further expands the findings of Table 7 by decomposing the Social Grant Scenario projections of the not-deprived shares of population groups between the impact of the Baseline Scenario and the impact of additional policy measures that are included in the Social Grant Scenario.

Table 7: Policy Scenarios and MDP Future Outlooks (Annual Average, 2024:2030, %)

Dimensions/ Variables	**Baseline** (Scen. 1)	**Fiscal Policy** (2)	**Monetary Policy** (3)	**Private Investment** (4)	**Public Employment** (5)	**Social Grant** (6)	**Baseline** (Scen. 1)	**Fiscal Policy** (2)	**Monetary Policy** (3)	**Private Investment** (4)	**Public Employment** (5)	**Social Grant** (6)
	Low Cut-offs						**High Cut-offs**					
	MDP: NATIONAL DISTRIBUTION											
One Dimension	45.9	45.8	45.8	45.6	45.5	45.5	17.9	19.7	20.2	20.6	20.7	21.1
Two Dimensions	29.5	27.4	26.8	26.1	25.9	25.3	34.3	32.0	31.3	30.4	30.1	29.6
Three Dimensions	3.87	3.46	3.34	3.22	3.18	3.08	25.9	22.6	21.6	20.6	20.3	19.5
Fully Deprived	0.86	0.80	0.79	0.77	0.76	0.75	4.7	3.9	3.6	3.4	3.4	3.2
Not Deprived	19.9	22.5	23.4	24.3	24.7	25.4	17.3	21.9	23.3	24.9	25.5	26.7
	MDP BY GENDER: NOT DEPRIVED											
Male	20.6	23.4	24.2	25.1	25.4	26.0	18.0	22.8	24.2	25.8	26.3	27.3
Female	16.4	17.7	18.2	18.7	19.1	19.6	11.4	13.3	14.0	14.7	15.2	15.9
	MDP BY RACE: NOT DEPRIVED											
African	13.8	15.2	15.6	16.2	16.5	17.0	7.4	9.2	9.7	10.5	10.9	11.4
Cloured	26.3	28.5	29.0	29.6	30.0	30.6	15.5	18.5	19.3	20.2	20.7	21.5
Asian	51.8	55.1	56.2	57.0	57.1	57.3	56.1	60.1	61.5	62.5	62.6	62.7
White	57.6	62.7	64.3	65.4	65.1	65.2	65.5	70.4	71.9	72.9	72.6	72.6
	MDP BY PROVINCE: NOT DEPRIVED											
Western Cape	26.4	29.3	30.1	30.8	31.1	31.6	20.5	25.1	26.3	27.4	27.9	28.6
Eastern Cape	7.3	8.0	8.3	8.5	9.0	9.4	6.7	8.1	8.5	9.1	9.5	10.1
Northern Cape	20.8	22.9	23.6	24.2	22.9	23.5	9.7	11.9	12.8	13.3	11.8	12.4
Free State	24.7	26.8	27.3	28.0	28.7	29.4	9.8	12.1	12.6	13.4	14.1	14.9
KwaZulu Natal	18.9	20.6	21.2	21.8	22.2	22.8	11.2	13.6	14.4	15.3	15.9	16.6
North West	14.4	16.0	16.4	16.9	17.2	17.8	7.4	9.3	9.8	10.5	10.9	11.6
Gauteng	26.0	28.7	29.5	30.5	30.9	31.3	25.3	30.2	31.7	33.5	34.2	35.0
Mpumalanga	7.6	8.3	8.6	8.9	9.1	9.3	7.2	8.5	9.1	9.7	10.1	10.6
Limpopo	5.1	5.9	6.1	6.4	6.5	6.7	5.6	7.4	7.8	8.4	8.7	9.3

Source: ADRS Dynamically Integrated Macro-Micro Simulation Model of South Africa (DIMMSIM)

Figure 3. Projections of Not-Deprived Population Shares (2024-2030)



Source: ADRS Dynamically Integrated Macro-Micro Model of South Africa (DIMMSIM)
Note: For the policy impact, the figure uses the results from the Social Grant Scenario that is a cumulative scenario

E. SUMMARY AND FINAL REMARKS

The aim of this study was to extend the research on MDP, which began with the seminal works of Sen and Anand (1997), Alkire and Foster (2007, 2009) and Alkire and Santos (2010), by developing a forward-looking approach that enables the quantitative examination of likely impact of economic performance, policy measures and shocks on the future values of MDP indicators. The paper shows how a linked macro-micro economic model that already includes a full microsimulation of individuals and households can be extended to generate projections of MDP indicators for a country and its population groups.

In this study, we have therefore gone beyond using statistical techniques to identify factors that explain deprivation and proposed an approach to produce forward-looking projections of multidimensional poverty indicators. The proposed MDP Augmented linked macro-micro model can be used as a policy tool for designing anti-poverty policies and producing ex-ante assessment of their impact on MDP, which is a more multifaceted measure of poverty.

We used a full General Household Survey of South Africa as the database to measure deprivation using education, healthcare, living conditions and assets as four dimensions of poverty, each measured through four indicators with low and high cut-offs. We then specified and estimated two MLR models, for the two cut-offs, each with five deprivation outcomes as its categorically distributed dependent variable and a set of independent variables composed of demographic, economic and social indicators. The two estimated equations, for low and high cut-offs, provided the probabilities of the different poverty outcomes given the independent variables used. The estimated MLR equations were used to build the MDP module of DIMMSIM, which is a South African linked macro-micro model, built by the ADRS. In each period, the model's projections of demographic, economic and social variables that were used in the estimation of the MLR equations are used by the MDP module to generate projections of deprivation indicators at national level and by gender, race and region.

The final MDP Augmented model was used to establish the current trajectory for deprivation of various population groups in South Africa and to test the direct and indirect effects of five cumulative policy measures (i.e. fiscal policy, monetary policy, private investment, public employment and social grant scenarios) on dimensions of deprivation. Therefore, the model links the likely evolution of deprivation measures to the dynamic of the economy, the country's demographic evolution and socioeconomic policy interventions.

Since the multidimensional poverty measures are built using several indicators that relate to the Sustainable Development Goals (SDGs) (e.g. good health, inclusive education, zero hunger, clean water), they provide an integrated understanding of the SDGs (Alkire & Santos, 2010). The innovation to use an empirical economic model for the MDP provides, by extension, the possibility to systematically link SDGs to the economy, making it possible to design and test targeted economic and social policy interventions that have a better chance of meeting the SDGs.

F. REFERENCES

Adelzadeh, A. (2019). *ADRS' Dynamically Integrated Macro-Micro Simulation Model of South Africa (DIMMSIM).* https://adrsglobal.com/resources/static/downloads/A_Technical_Introduction_to_DIMMSIM.pdf

Alkire, S., & Santos, M. E. (2010). *Multidimensional poverty index*. https://www.ophi.org.uk/wp-content/uploads/OPHI-MPI-Brief.pdf

Alkire, S. and Foster, J. (2007, revised in 2008). *Counting and multidiemnsional poverty measurement.* https://www.ophi.org.uk/wp-content/uploads/ophi-wp7_vs2.pdf

Ascher, W. (2022). *Coping with the ambiguities of poverty-alleviation programs and policies: A policy sciences approach*. https://web.p.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=8&sid=9fb6b666-e25d-4c9e-b577-72cafba462f8%40redis

Ayala, L., Jurado, A., & Perez-Mayo, J. (2011). *Income poverty and multidimensional deprivation: Lessons from cross-regional analysis*. http://roiw.org/2011/n1/40-60.pdf

Biyase, M., & Zwane, T. (2018). *An empirical analysis of the determinants of poverty and household welfare in South Africa*. https://web.a.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=7&sid=bdbd5c51-c714-4cd0-aec0-3e475937085d%40sessionmgr4008

Burger, R., van der Berg, S., van der Walt, S., & Yu, D. (2016). *The long walk: Considering the enduring spatial and racial dimensions of deprivation two decades after the fall of apartheid*. https://link.springer.com/article/10.1007/s11205-016-1237-1

Cheng, S., & Long, J. S. (2007). *Testing for IIA in the Multinomial Logit Model*. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.951.3160&rep=rep1&type=pdf

EL-Habil, A. M. (2012). *An application on Multinomial Logistic Regression Model*. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=An+Application+on+Multinomial+Logistic+Regression+Model&btnG=

Etowa, J., Hannan, J., Etowa, E. B., Babatunde, S., & Phillips, C. J. (2021). *Determinants of infant feeding practices among Black mothers living with HIV: A multinomial logistic regression analysis*. https://web.a.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=2&sid=bdbd5c51-c714-4cd0-aec0-3e475937085d%40sessionmgr4008

Feder, J., & Yu, D. (2020). *Employed yet poor: Low-wage employment and working poverty in South Africa*. https://web.p.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=5&sid=9fb6b666-e25d-4c9e-b577-72cafba462f8%40redis

Fransman, T., & Yu, D. (2019). *Multidimensional poverty in South Africa in 2001–16*. https://www.tandfonline.com/doi/full/10.1080/0376835X.2018.1469971?scroll=top&needAccess=true

Fry, T. R. L., & Harris, M. N. (1993). *A Monte Carlo study of tests for the independence of irrelevant alternatives property*. file:///C:/Users/cool/Downloads/monash-156%20(3).pdf

Gradin, C. (2011). *Race, poverty, and deprivation in South Africa*. https://ideas.repec.org/p/inq/inqwps/ecineq2011-224.html

Jackson, S., & Yu, D. (2023). *Re-examining the Multidimensional Poverty Index of South Africa*. https://repository.uwc.ac.za/bitstream/handle/10566/8761/Jackson_Re%E2%80%91examining%20the%20Multidimensional_2023.pdf?sequence=1

Khumalo, P. (2013). *The dynamics of poverty and poverty alleviation in South Africa*. https://web.a.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=4&sid=bdbd5c51-c714-4cd0-aec0-3e475937085d%40sessionmgr4008

Klasen, S. (1997). Poverty, inequality and deprivation in South Africa: An analysis of the 1993 SALDRU Survey. *Social Indicators Research, 41*(1–3), 51–94. https://doi.org/10.1023/A:1006892216864

Long, J. S., & Freese, J. (2001). *Regression models for categorical dependent variables using STATA*. https://is.muni.cz/el/1423/podzim2010/VPL454/Regression_Models_For_Categorical_Dependent_Variables_USING_STATA.pdf

McIntyre, D., Muirhead, D., Gilson, L., Govendor,V., Mbatsha, S., Goudge, J., Wadee, H., & Ntutela, P. (2000). *Geographic patterns of deprivation and health inequities in South Africa: Informing public resource allocation strategies*. https://www.researchgate.net/publication/241191819_Geographic_patterns_of_deprivation_and_health_inequities_in_South_Africa_Informing_public_resource_allocation_strategies

Mishra, P. K. (2017). Multidimensional poverty in Uttar Pradesh: Trends and patterns. *Indian Journal of Economics and Development, 5*(11). https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Multidimensional+poverty+in+Uttar+Pradesh%3A+trends+and+patterns&btnG=

Mitra, S., & Brucker, D. L. (2015). *Income poverty and multiple deprivations in a high-income country: The case of the United States*. https://www.researchgate.net/profile/Sophie-Mitra/publication/293806637_Income_Poverty_and_Multiple_Deprivations_in_a_High-Income_Country_The_Case_of_the_United_States/links/572a002d08ae2efbfdbc1338/Income-Poverty-and-Multiple-Deprivations-in-a-High-Income-Country-The-Case-of-the-United-States.pdf

Mlatsheni, C., & Leibbrandt, M. (2011). *Youth unemployment in South Africa: Challenges, concepts and opportunities*. https://www.researchgate.net/profile/Murray-Leibbrandt/publication/49119531_Youth_unemployment_in_South_Africa_Challenges_concepts_and_opportunities/links/568fbd6208ae78cc05198c64/Youth-unemployment-in-South-Africa-Challenges-concepts-and-opportunities.pdf

Mohapi, J. B. (2016). *The social sector of the Expanded Public Works Programme as a strategy to alleviate poverty amongst vulnerable groups in Gauteng*. https://www.researchgate.net/profile/Boitumelo-Mohapi/publication/305744531_The_social_sector_of_the_Expanded_Public_Works_Programme_as_a_strategy_to_alleviate_poverty_amongst_vulnerable_groups_in_Gauteng/links/5aa79b7e0f7e9bbbff8cfc5d/The-social-sector-of-the-Expanded-Public-Works-Programme-as-a-strategy-to-alleviate-poverty-amongst-vulnerable-groups-in-Gauteng.pdf

Monyai, S. Lesoana, M., Darikwa,T., & Nyamugure, P. (2015). *Application of multinomial logistic regression to educational factors of the 2009 General Household Survey in South Africa*. https://www.tandfonline.com/doi/full/10.1080/02664763.2015.1077941

National Planning Commission. (2012). *Our future – Make it work: National Development Plan 2030*. https://www.gov.za/sites/default/files/gcis_document/201409/ndp-2030-our-future-make-it-workr.pdf

Naveed, A., Wood, G., & Ghaus, M. U. (2016) *Geography of poverty in Pakistan – 2008–09 to 2012−13: Distribution, trends and explanations*. https://www.think-asia.org/bitstream/handle/11540/7074/PPAF_SDPI_Report_Geography_of_Poverty_in_Pakistan.pdf?sequence=1

Ngangelizwe, L., & Adelzadeh, A. (2024). *The Impact of COVID-19 on South African Multidimensional Poverty*. ADRS Working Paper, Forthcoming.

Noble, M., & Wright, G. (2013). *Using indicators of multiple deprivation to demonstrate the spatial legacy of apartheid in South Africa*. https://www.jstor.org/stable/pdf/24719179.pdf?casa_token=OzwbAjm6DdsAAAAA:mFKx1XgahN6dxaOAGGlAOb6XGkUjOyjlt18jsgNWs-7htcr_UWO6FDn7lW7SlkGVPTKsW1KBWmfDDOl_WgUKBtNLEaCT3LNW4q_4aT4nTZHQqJMhLhof

Ntsalaze, L., & Ikhide, S. (2018). *Rethinking dimensions: The South African multidimensional poverty index*. https://link.springer.com/article/10.1007/s11205-016-1473-4

Orcutt, G.H. (1957). *A new type of socio-economic system*. https://www.jstor.org/stable/1928528

Orcutt, G.H., Greenberger, M., Korbel, G. & Rivlin, A.M. (1961). Microanalysis of socioeconomic systems: A simulation study. https://api.semanticscholar.org/CorpusID:160357907

Peng, C., Lee, K. L., & Ingersoll, G. M. (2002). *An introduction to logistic regression analysis and reporting*. https://www.jstor.org/stable/27542407?seq=1#metadata_info_tab_contents

Peng, C. J., & Nichols, R. N. (2003). *Using multinomial logistic models to predict adolescent behavioral risk*. https://digitalcommons.wayne.edu/jmasm/vol2/iss1/16/

Pesaran, M.H. (1997). *The role of economic theory in modelling the long run*. https://academic.oup.com/ej/article-abstract/107/440/178/5144300

Pesaran, M.H., Shin, Y. & Smith, R.P. (1999). *Pooled mean group estimation of dynamic heterogeneous panels*. https://www.jstor.org/stable/2670182

Pesaran, M.H. & Shin, Y. (1996). *Cointegration and speed of convergence to equilibrium*. https://www.sciencedirect.com/science/article/abs/pii/0304407694016976

Ribeiro, A. P., Silva, T. S., & Guimarães, D. (2014). *Macroeconomic fundamentals of poverty and deprivation: An empirical study for developed countries*. https://repositorio-aberto.up.pt/bitstream/10216/70994/2/25382.pdf

Robinson, M., Vollmer, F., Doğan, B., & Grede, N. (2022). *Distributional impacts of cash transfers on the multidimensional poverty of refugees: The ESSN programme in Turkey*. https://ophi.org.uk/wp-142/

Rogan, M. (2015). *Gender and multidimensional poverty in South Africa: Applying the global Multidimensional Poverty Index (MPI)*. https://link.springer.com/article/10.1007/s11205-015-0937-2

Said, F., Musaddiq, T., & Mahmud, M. (2020). *Macro level determinants of poverty: Investigation through poverty mapping of districts of Pakistan*. https://www.jstor.org/stable/23617741

Santos, M. E., Dabus, C., & Delbianco, F. (2016). *Growth and poverty revisited from a multidimensional perspective*. https://www.ophi.org.uk/wp-content/uploads/OPHIWP105.pdf

Savard, L. (2003). *Poverty and income distribution in a CGE-Household Micro-Simulation model: Top-down/bottom up approach.* https://www.researchgate.net/publication/5165229_Poverty_and_Income_Distribution_in_a_CGE-Household_Micro-Simulation_Model_Top-DownBottom_Up_Approach

Sen, A. & Anand, S. (1997). *Concepts of human development and poverty: a multidimensional perspective*. https://scholar.harvard.edu/sen/publications/concepts-human-development-and-poverty-multidimensional-perspective

Shahateet, M. I. (2007) *The determinants of deprivation in Jordan: Empirical study*. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.855.9643&rep=rep1&type=pdf

Song, S., & Imai, K. S. (2019). *Does the hunger safety net programme reduce multidimensional poverty? Evidence from Kenya*. https://www.tandfonline.com/doi/full/10.1080/21665095.2019.1582347

Statistics South Africa. (2023). *Gross domestic product third quarter*. https://www.statssa.gov.za/publications/P0441/P04413rdQuarter2023.pdf

Statistics South Africa. (2014). *The South African MPI: Creating a multidimensional poverty index using census data*. http://www.statssa.gov.za/publications/Report-03-10-08/Report-03-10-082014.pdf

United Nations Economic Commission for Africa. (2015). *Assessing progress in Africa toward the Millennium Development Goals*. https://www.afdb.org/fileadmin/uploads/afdb/Documents/Publications/MDG_Report_2015.pdf

Vaalavuo, M., & Sirniö, O. (2022). *Jobs against poverty: A fixed-effects analysis on the link between gaining employment and exiting poverty in Europe*. https://web.p.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=11&sid=9fb6b666-e25d-4c9e-b577-72cafba462f8%40redis

Wanka, F. A. (2014). *The impact of educational attainment on household poverty in South Africa: A case study of Limpopo province*. http://etd.uwc.ac.za/xmlui/bitstream/handle/11394/4286/Wanka_MECO_2014.pdf

Williams, R. (2002). *Post-estimation commands for MLogit*. https://www3.nd.edu/~rwilliam/stats3/Mlogit2.pdf

Wolf, F., Lohmann, H., & Böhnke, P. (2022). *The standard of living among the poor across Europe: Does employment make a difference?* https://web.p.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=9&sid=54af0165-1b0b-48a5-8aed-92194941baca%40redis

World Bank. (2021). *South Africa COVID-19 Response Development Policy Loan.* December, P174246. https://documents1.worldbank.org/curated/en/385961640281217498/pdf/South-Africa-South-Africa-COVID-19-Response-Development-Policy-Operation.pdf

G. ANNEXURE A TO D: SAMPLE OF DIMMSIM'S DETAIL MDP RESULTS

A. Baseline Scenario (Scenario 1)

Low Cut-offs

Table A1. Multidimensional Poverty: Deprivation Level: Two Dimension (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Afri	33.65	33.93	32.19	31.28	29.31	28.19	26.75	24.78	29.49
Male	33.62	33.75	31.99	31.00	28.83	27.50	25.89	23.65	28.94
Female	34.39	34.77	33.86	33.42	32.62	32.35	31.80	31.06	32.84
African	38.81	39.09	38.05	37.45	36.29	35.74	34.94	33.77	36.48
Coloured	15.43	15.58	14.76	14.38	13.46	13.06	12.45	11.70	13.63
Asian	8.57	8.37	7.36	6.74	5.66	4.86	4.05	3.12	5.74
White	6.65	6.51	5.17	4.52	3.27	2.49	1.76	1.09	3.54
Western Cape	16.84	16.95	16.03	15.60	14.43	13.72	12.79	11.59	14.44
Eastern Cape	47.86	48.16	47.71	47.26	46.52	46.23	45.72	45.04	46.66
Northern Cap	32.42	32.56	31.56	30.68	29.84	29.68	28.65	27.67	30.09
Free State	26.13	26.35	25.52	24.74	23.98	23.70	23.08	22.36	24.25
KwaZulu-Nata	37.23	37.48	36.42	36.03	34.59	34.03	33.06	31.69	34.76
North West	41.61	41.76	40.82	40.32	39.42	38.89	38.26	37.24	39.53
Gauteng	19.48	19.73	18.22	17.61	16.08	15.19	14.15	12.70	16.24
Mpumalanga	46.62	47.15	46.26	45.42	44.59	44.16	43.59	42.74	44.84
Limpopo	60.84	61.10	60.71	60.53	60.00	59.64	59.22	58.52	59.96

Table A2. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Afri	1.00	1.00	0.94	0.90	0.85	0.81	0.77	0.72	0.86
Male	0.94	0.95	0.91	0.88	0.84	0.81	0.78	0.73	0.84
Female	1.09	1.07	1.01	0.96	0.90	0.87	0.83	0.79	0.92
African	1.57	1.52	1.42	1.33	1.23	1.17	1.10	1.02	1.26
Coloured	1.44	1.41	1.30	1.23	1.12	1.07	1.00	0.92	1.15
Asian	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	0.21	0.21	0.21	0.20	0.19	0.19	0.18	0.17	0.19
Eastern Cape	2.27	2.17	2.02	1.87	1.73	1.63	1.53	1.43	1.77
Northern Cap	1.59	1.53	1.39	1.28	1.20	1.16	1.05	0.98	1.23
Free State	1.17	1.17	1.11	1.03	0.98	0.95	0.90	0.85	1.00
KwaZulu-Nata	1.31	1.30	1.23	1.20	1.13	1.12	1.08	1.02	1.15
North West	2.37	2.33	2.21	2.11	1.99	1.90	1.82	1.71	2.01
Gauteng	0.14	0.15	0.14	0.14	0.14	0.13	0.13	0.12	0.14
Mpumalanga	1.78	1.74	1.65	1.57	1.51	1.48	1.45	1.38	1.54
Limpopo	1.86	1.82	1.74	1.67	1.60	1.54	1.48	1.39	1.61

High Cut-offs

Table A3. Multidimensional Poverty: Deprivation Level: Two Dimensions (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	37.05	37.02	36.60	36.13	34.81	33.76	32.16	29.52	34.29
Male	36.93	36.88	36.42	35.86	34.38	33.09	31.21	28.08	33.70
Female	37.23	37.17	37.16	37.07	36.79	36.62	36.32	35.79	36.70
African	39.27	39.19	39.63	39.81	39.96	39.93	39.82	39.42	39.68
Coloured	40.23	40.22	39.36	38.74	37.22	36.35	34.88	32.98	37.11
Asian	19.55	18.81	15.75	13.74	10.60	8.35	6.27	4.11	11.09
White	12.05	11.38	7.75	6.07	3.53	2.24	1.26	0.57	4.69
Western Cape	37.21	37.14	36.03	35.41	33.32	31.89	29.78	26.68	32.89
Eastern Cape	34.99	34.90	35.24	35.56	35.97	36.09	36.34	36.58	35.81
Northern Cape	39.41	39.33	39.24	39.05	38.69	38.62	37.70	36.87	38.50
Free State	43.09	43.04	43.04	42.72	42.51	42.23	41.74	41.10	42.34
KwaZulu-Natal	39.69	39.66	39.75	39.73	39.44	39.34	38.95	38.10	39.28
North West	37.85	37.76	38.21	38.39	38.57	38.57	38.50	38.24	38.32
Gauteng	40.94	41.10	38.92	37.54	34.44	32.25	29.58	25.49	34.19
Mpumalanga	32.66	32.44	32.92	33.24	33.44	33.47	33.48	33.35	33.19
Limpopo	20.88	20.75	21.11	21.30	21.66	21.91	22.15	22.42	21.61

Table A4. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
South Africa	7.07	7.18	6.08	5.53	4.47	3.92	3.27	2.51	4.71
Male	7.14	7.16	6.07	5.48	4.36	3.73	3.04	2.23	4.58
Female	7.76	7.94	7.25	6.89	6.30	6.08	5.69	5.18	6.48
African	8.91	9.01	8.19	7.72	6.92	6.52	6.01	5.31	7.10
Coloured	5.22	5.26	4.58	4.22	3.54	3.23	2.80	2.34	3.71
Asian	0.71	0.66	0.45	0.35	0.21	0.13	0.08	0.04	0.27
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	4.24	4.26	3.66	3.37	2.70	2.33	1.90	1.42	2.81
Eastern Cape	13.10	13.22	12.55	11.85	10.94	10.49	9.83	9.06	11.13
Northern Cape	8.22	8.22	7.33	6.66	6.11	5.92	5.16	4.61	6.29
Free State	6.48	6.55	6.01	5.51	5.04	4.84	4.44	4.04	5.20
KwaZulu-Natal	8.09	8.18	7.42	7.15	6.25	5.92	5.38	4.66	6.42
North West	10.76	10.81	9.88	9.40	8.61	8.14	7.62	6.84	8.76
Gauteng	2.84	2.89	2.31	2.07	1.58	1.31	1.05	0.74	1.71
Mpumalanga	11.06	11.39	10.47	9.69	8.91	8.50	8.02	7.29	9.18
Limpopo	13.14	13.34	12.72	12.36	11.66	11.11	10.52	9.61	11.62

B. Macroeconomic Policy Scenario (Scenario 3)

Low Cut-offs

Table B1. Multidimensional Poverty: Deprivation Level: Two Dimensions (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	33.65	33.34	30.90	28.65	26.35	24.90	22.69	20.44	26.75
Male	33.62	33.16	30.62	28.23	25.88	24.16	21.73	19.33	26.16
Female	34.39	34.46	33.21	32.10	30.89	30.48	29.61	28.56	31.33
African	38.81	38.71	37.25	35.80	34.27	33.50	32.20	30.67	34.63
Coloured	15.43	15.40	14.18	13.13	12.17	11.60	10.77	10.02	12.47
Asian	8.57	8.09	6.65	5.58	4.61	3.80	2.81	2.11	4.81
White	6.65	6.11	4.32	3.13	2.18	1.51	0.87	0.49	2.66
Western Cape	16.84	16.66	15.33	13.88	12.62	11.61	10.28	9.19	12.80
Eastern Cape	47.86	47.90	47.01	46.17	44.96	44.67	43.80	42.67	45.31
Northern Cape	32.42	32.00	30.51	29.33	27.29	26.81	25.81	24.55	28.04
Free State	26.13	26.06	24.52	23.22	22.27	21.70	20.80	19.95	22.65
KwaZulu-Natal	37.23	37.11	35.64	34.04	32.45	31.59	30.05	28.30	32.74
North West	41.61	41.48	40.01	38.70	37.21	36.55	35.55	34.14	37.66
Gauteng	19.48	19.23	17.30	15.61	14.16	13.03	11.49	10.02	14.41
Mpumalanga	46.62	46.72	45.17	44.35	43.31	42.52	41.57	40.35	43.43
Limpopo	60.84	60.92	60.15	59.43	57.94	57.76	56.98	55.93	58.44

Table B2. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	1.00	0.98	0.91	0.84	0.77	0.73	0.67	0.61	0.79
Male	0.94	0.94	0.87	0.82	0.76	0.73	0.68	0.62	0.77
Female	1.09	1.06	0.98	0.91	0.84	0.81	0.77	0.72	0.87
African	1.57	1.50	1.38	1.26	1.15	1.09	1.02	0.93	1.19
Coloured	1.44	1.40	1.24	1.11	1.01	0.95	0.87	0.80	1.05
Asian	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	0.21	0.21	0.20	0.18	0.17	0.16	0.15	0.14	0.17
Eastern Cape	2.27	2.15	1.98	1.82	1.66	1.57	1.47	1.34	1.71
Northern Cape	1.59	1.47	1.34	1.24	1.04	1.00	0.94	0.86	1.13
Free State	1.17	1.16	1.04	0.95	0.89	0.85	0.80	0.74	0.92
KwaZulu-Natal	1.31	1.28	1.20	1.12	1.06	1.04	0.98	0.92	1.09
North West	2.37	2.31	2.15	2.00	1.85	1.76	1.67	1.56	1.90
Gauteng	0.14	0.14	0.14	0.13	0.12	0.12	0.11	0.10	0.12
Mpumalanga	1.78	1.72	1.60	1.53	1.46	1.40	1.36	1.29	1.48
Limpopo	1.86	1.82	1.67	1.58	1.47	1.44	1.38	1.31	1.52

High Cut-offs

Table B3. Multidimensional Poverty: Deprivation Level: Two Dimensions (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	37.05	36.95	36.02	34.37	31.96	30.03	26.77	22.98	31.30
Male	36.93	36.80	35.74	33.95	31.39	29.09	25.42	21.36	30.54
Female	37.23	37.18	37.07	36.69	36.06	35.72	34.98	33.85	35.94
African	39.27	39.35	39.84	39.99	39.79	39.50	38.84	37.67	39.28
Coloured	40.23	40.09	38.53	36.70	34.62	33.13	30.83	28.48	34.63
Asian	19.55	18.00	13.67	10.54	7.85	5.76	3.53	2.23	8.80
White	12.05	10.30	5.81	3.39	1.85	1.01	0.42	0.17	3.28
Western Cape	37.21	36.89	35.18	32.36	29.63	26.95	23.28	20.09	29.20
Eastern Cape	34.99	35.05	35.65	36.06	36.48	36.58	36.62	36.32	36.11
Northern Cape	39.41	39.24	39.08	38.73	36.76	36.30	35.30	33.62	37.00
Free State	43.09	43.07	42.72	42.07	41.43	40.77	39.68	38.50	41.18
KwaZulu-Natal	39.69	39.71	39.76	39.39	38.73	38.26	37.04	35.25	38.31
North West	37.85	37.92	38.41	38.55	38.27	38.03	37.57	36.61	37.91
Gauteng	40.94	40.50	37.36	33.84	30.20	27.05	22.66	18.20	29.97
Mpumalanga	32.66	32.65	33.29	33.49	33.54	33.36	33.08	32.48	33.13
Limpopo	20.88	20.88	21.49	21.93	22.50	22.56	22.67	22.65	22.10

Table B4. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	7.07	6.82	5.36	4.19	3.19	2.62	1.91	1.32	3.63
Male	7.14	6.81	5.30	4.10	3.09	2.45	1.72	1.15	3.52
Female	7.76	7.72	6.81	6.04	5.30	5.00	4.50	3.94	5.62
African	8.91	8.74	7.66	6.69	5.79	5.32	4.64	3.92	6.11
Coloured	5.22	5.13	4.11	3.34	2.71	2.36	1.91	1.55	3.02
Asian	0.71	0.60	0.34	0.20	0.12	0.07	0.03	0.01	0.20
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	4.24	4.09	3.27	2.46	1.87	1.46	1.02	0.73	2.13
Eastern Cape	13.10	12.95	11.78	10.76	9.45	9.07	8.19	7.14	9.91
Northern Cape	8.22	7.69	6.64	5.90	4.53	4.25	3.77	3.19	5.14
Free State	6.48	6.38	5.41	4.64	4.13	3.81	3.36	2.96	4.38
KwaZulu-Natal	8.09	7.94	6.96	6.01	5.18	4.73	4.02	3.30	5.45
North West	10.76	10.55	9.21	8.13	7.07	6.57	5.91	5.09	7.50
Gauteng	2.84	2.71	2.00	1.47	1.09	0.84	0.56	0.36	1.29
Mpumalanga	11.06	11.00	9.55	8.77	7.89	7.17	6.49	5.67	8.08
Limpopo	13.14	13.14	11.93	10.99	9.47	9.24	8.43	7.49	10.10

C. Combined Macroeconomic and Private Investment Scenario (Scenario 4)

Low Cut-offs

Table C1. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	1.00	0.98	0.90	0.83	0.75	0.71	0.64	0.58	0.77
Male	0.94	0.93	0.87	0.81	0.74	0.71	0.64	0.58	0.75
Female	1.09	1.06	0.98	0.91	0.83	0.80	0.75	0.69	0.86
African	1.57	1.50	1.37	1.25	1.13	1.07	0.98	0.89	1.17
Coloured	1.44	1.38	1.24	1.10	1.00	0.93	0.85	0.76	1.04
Asian	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	0.21	0.21	0.20	0.18	0.17	0.16	0.14	0.13	0.17
Eastern Cape	2.27	2.15	1.97	1.81	1.65	1.54	1.42	1.30	1.69
Northern Cape	1.59	1.47	1.34	1.21	1.04	0.97	0.91	0.84	1.11
Free State	1.17	1.15	1.03	0.94	0.87	0.83	0.77	0.70	0.90
KwaZulu-Natal	1.31	1.28	1.19	1.12	1.05	1.01	0.96	0.88	1.07
North West	2.37	2.30	2.15	2.00	1.83	1.75	1.64	1.49	1.88
Gauteng	0.14	0.14	0.14	0.13	0.12	0.12	0.10	0.10	0.12
Mpumalanga	1.78	1.72	1.60	1.53	1.42	1.39	1.32	1.25	1.46
Limpopo	1.86	1.82	1.67	1.56	1.46	1.41	1.36	1.27	1.51

Table C2. Multidimensional Poverty: Deprivation Level: Not Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	15.37	15.76	18.38	20.98	24.41	26.39	30.16	33.72	24.26
Male	15.58	16.10	18.77	21.57	25.02	27.29	31.43	35.34	25.07
Female	14.53	14.56	16.09	17.35	19.17	19.78	21.16	22.59	18.67
African	11.42	11.62	13.08	14.56	16.46	17.32	19.09	20.94	16.15
Coloured	22.25	22.65	25.00	27.69	30.00	31.49	33.98	36.63	29.63
Asian	40.71	42.42	47.62	51.74	56.77	61.28	67.31	72.20	57.05
White	41.09	43.50	51.72	58.19	66.31	72.48	80.38	85.38	65.42
Western Cape	21.73	22.13	24.64	27.44	30.75	33.14	37.08	40.67	30.84
Eastern Cape	6.22	6.27	6.91	7.63	8.66	9.19	10.12	11.02	8.54
Northern Cape	17.58	18.20	20.31	22.36	24.98	26.02	27.76	29.44	24.15
Free State	21.83	21.95	24.46	26.47	28.71	29.52	31.36	33.65	28.02
KwaZulu-Natal	16.03	16.27	17.94	19.66	22.03	23.24	25.48	28.08	21.81
North West	12.21	12.43	13.95	15.32	17.33	18.03	19.60	21.68	16.91
Gauteng	20.76	21.26	24.24	27.04	30.52	32.68	36.93	40.55	30.46
Mpumalanga	6.40	6.44	7.40	8.02	9.04	9.52	10.47	11.38	8.90
Limpopo	4.47	4.47	4.97	5.75	6.58	6.94	7.53	8.29	6.36

High Cut-offs

Table C3. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	7.07	6.76	5.25	4.10	2.93	2.37	1.59	1.08	3.44
Male	7.14	6.75	5.21	4.00	2.85	2.23	1.44	0.94	3.35
Female	7.76	7.68	6.71	5.98	5.08	4.75	4.14	3.57	5.42
African	8.91	8.71	7.56	6.59	5.53	5.05	4.24	3.54	5.89
Coloured	5.22	5.01	4.07	3.24	2.61	2.25	1.75	1.32	2.89
Asian	0.71	0.59	0.33	0.20	0.11	0.06	0.02	0.01	0.19
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	4.24	4.05	3.22	2.42	1.76	1.36	0.89	0.60	2.04
Eastern Cape	13.10	12.93	11.68	10.61	9.23	8.58	7.54	6.66	9.60
Northern Cape	8.22	7.67	6.56	5.61	4.43	4.02	3.46	3.00	4.96
Free State	6.48	6.37	5.31	4.60	3.92	3.63	3.12	2.58	4.22
KwaZulu-Natal	8.09	7.90	6.87	5.97	4.96	4.44	3.67	2.95	5.25
North West	10.76	10.47	9.15	8.10	6.82	6.34	5.48	4.50	7.27
Gauteng	2.84	2.67	1.94	1.45	0.97	0.75	0.44	0.28	1.21
Mpumalanga	11.06	10.92	9.52	8.69	7.46	6.93	5.97	5.23	7.82
Limpopo	13.14	13.13	11.89	10.54	9.27	8.72	7.93	6.96	9.78

Table C4. Multidimensional Poverty: Deprivation Level: Not Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	9.49	10.17	14.13	18.45	24.65	28.61	35.88	42.66	24.94
Male	9.39	10.21	14.29	18.90	25.13	29.63	37.50	44.71	25.77
Female	8.47	8.66	10.58	12.39	15.13	16.26	18.73	21.47	14.75
African	4.64	4.88	6.35	8.00	10.40	11.71	14.42	17.49	10.46
Coloured	10.17	10.72	13.50	16.85	20.18	22.49	26.44	30.98	20.17
Asian	39.69	42.54	50.65	56.38	63.18	68.77	75.41	80.25	62.45
White	45.85	49.33	59.77	67.07	75.22	80.76	87.15	90.88	72.88
Western Cape	13.06	13.78	17.16	21.78	26.92	31.06	37.71	43.68	27.44
Eastern Cape	4.60	4.76	5.96	7.15	9.11	10.16	12.15	14.29	9.08
Northern Cape	6.20	6.98	8.74	10.71	13.99	15.41	17.68	19.86	13.34
Free State	6.72	6.94	9.28	11.27	13.66	14.91	17.34	20.74	13.45
KwaZulu-Natal	7.33	7.67	9.68	11.94	15.12	17.14	20.78	25.01	15.33
North West	4.83	5.12	6.59	8.10	10.61	11.71	13.98	17.47	10.51
Gauteng	14.99	15.97	21.37	26.47	33.65	37.93	46.22	52.77	33.48
Mpumalanga	4.81	4.96	6.52	7.66	9.73	10.81	13.11	15.31	9.73
Limpopo	3.96	3.99	5.13	6.76	8.67	9.65	11.24	13.60	8.43

D. Combined Macroeconomic, Private Investment, Public Employment and Social Security Scenario (Scenario 6)

Low Cut-offs

Table D1. Multidimensional Poverty: Deprivation Level: Three Dimensions (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	4.32	4.23	3.76	3.43	2.94	2.80	2.36	2.04	3.08
Male	4.03	3.95	3.48	3.15	2.69	2.52	2.09	1.77	2.81
Female	4.87	4.85	4.65	4.52	4.26	4.27	4.10	3.92	4.37
African	5.37	5.20	4.79	4.46	4.04	3.91	3.57	3.27	4.18
Coloured	2.83	2.69	2.36	2.11	1.83	1.74	1.53	1.32	1.94
Asian	1.46	1.35	1.00	0.82	0.58	0.47	0.28	0.19	0.67
White	0.34	0.30	0.19	0.13	0.07	0.05	0.02	0.01	0.11
Western Cape	1.85	1.87	1.72	1.57	1.36	1.30	1.09	0.95	1.41
Eastern Cape	7.51	7.46	7.10	6.78	6.41	6.36	6.05	5.82	6.57
Northern Cape	5.65	5.58	5.07	5.08	4.65	4.56	4.28	4.06	4.75
Free State	5.87	5.82	5.41	5.13	4.73	4.79	4.47	4.13	4.93
KwaZulu-Natal	5.38	5.23	4.83	4.55	4.13	4.03	3.65	3.34	4.25
North West	8.04	7.88	7.44	7.02	6.44	6.35	5.94	5.50	6.65
Gauteng	1.42	1.46	1.31	1.23	1.05	1.01	0.84	0.73	1.09
Mpumalanga	6.21	6.12	5.72	5.56	5.24	5.20	4.91	4.65	5.34
Limpopo	7.13	7.06	6.78	6.43	6.10	6.03	5.81	5.56	6.25

Table D2. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	1.00	0.97	0.88	0.81	0.73	0.69	0.62	0.55	0.75
Male	0.94	0.92	0.85	0.79	0.72	0.69	0.62	0.56	0.74
Female	1.09	1.04	0.95	0.89	0.81	0.78	0.73	0.67	0.84
African	1.57	1.48	1.34	1.23	1.11	1.05	0.96	0.87	1.15
Coloured	1.44	1.35	1.19	1.07	0.96	0.91	0.82	0.72	1.00
Asian	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	0.21	0.21	0.19	0.18	0.16	0.16	0.14	0.13	0.17
Eastern Cape	2.27	2.14	1.94	1.78	1.62	1.52	1.41	1.28	1.67
Northern Cape	1.59	1.52	1.32	1.21	1.04	0.99	0.93	0.86	1.12
Free State	1.17	1.12	1.01	0.91	0.82	0.80	0.74	0.66	0.87
KwaZulu-Natal	1.31	1.25	1.16	1.10	1.02	1.00	0.93	0.86	1.05
North West	2.37	2.28	2.12	1.94	1.78	1.71	1.59	1.45	1.84
Gauteng	0.14	0.14	0.13	0.13	0.11	0.11	0.10	0.09	0.12
Mpumalanga	1.78	1.70	1.58	1.51	1.40	1.38	1.30	1.21	1.44
Limpopo	1.86	1.81	1.66	1.54	1.45	1.40	1.35	1.25	1.49

High Cut-offs

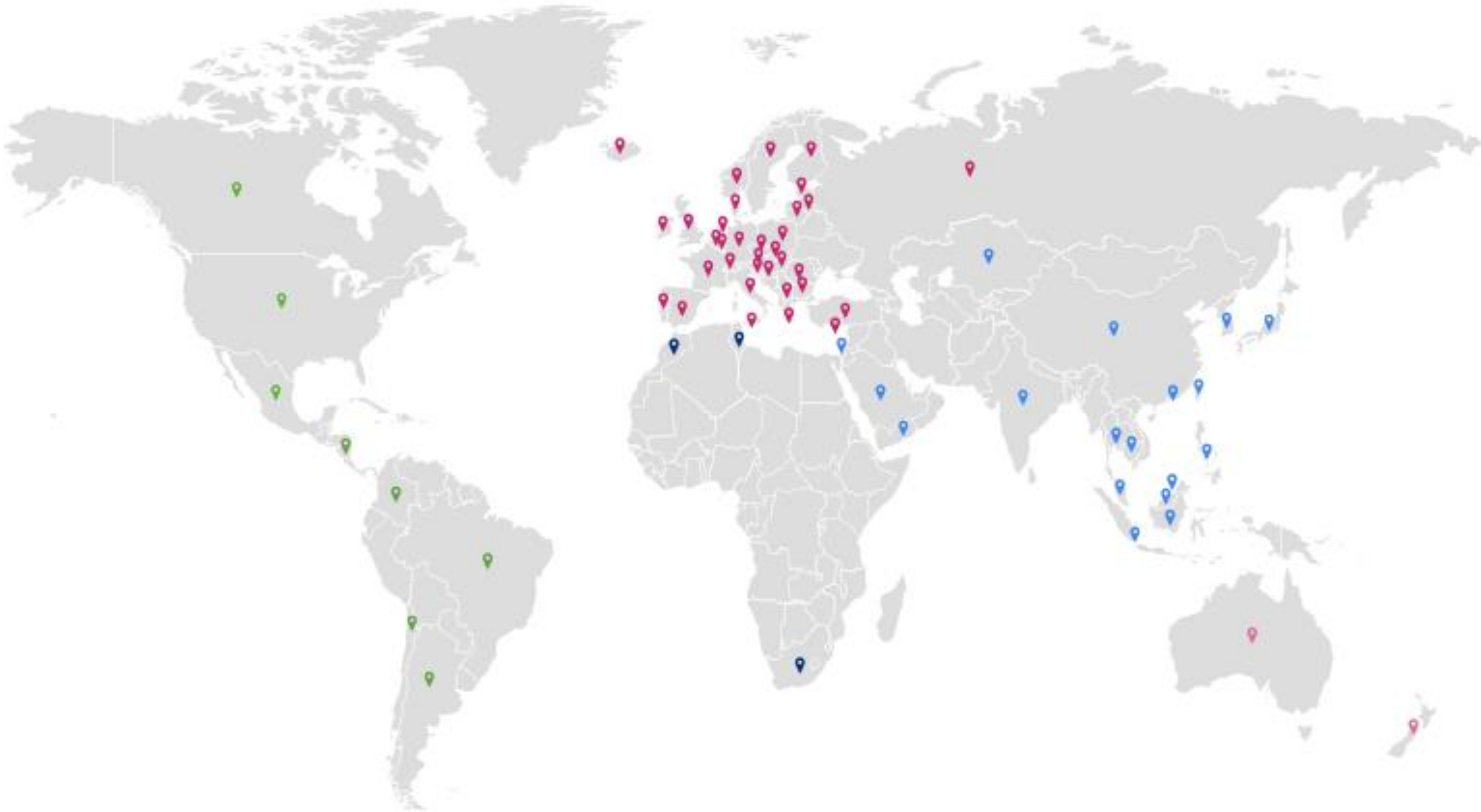
Table D3. Multidimensional Poverty: Deprivation Level: Three Dimensions (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	33.15	31.46	26.86	23.21	18.19	16.19	11.88	8.77	19.51
Male	33.01	31.47	26.65	22.84	17.77	15.53	11.03	7.94	19.03
Female	34.32	33.20	30.76	28.74	25.95	25.12	22.86	20.50	26.73
African	38.44	37.34	34.65	32.30	29.12	27.90	24.96	22.04	29.76
Coloured	25.64	24.32	20.99	18.34	15.54	14.39	11.99	9.71	16.47
Asian	8.90	7.83	4.91	3.54	2.02	1.37	0.59	0.30	2.94
White	2.45	1.95	0.83	0.45	0.14	0.07	0.02	0.00	0.49
Western Cape	24.94	23.69	20.26	16.89	13.21	11.48	8.26	6.13	14.27
Eastern Cape	40.11	39.41	37.35	35.20	32.64	31.68	29.25	27.07	33.23
Northern Cape	32.41	31.55	28.04	27.17	23.80	22.96	21.04	19.34	24.84
Free State	32.67	31.33	28.39	25.96	23.05	22.56	20.11	17.33	24.10
KwaZulu-Natal	35.79	34.63	31.91	29.67	26.28	25.08	21.79	18.85	26.89
North West	37.53	36.46	34.16	31.71	28.62	27.70	25.11	22.15	29.42
Gauteng	22.83	21.37	17.20	14.33	10.50	8.89	5.92	4.09	11.76
Mpumalanga	41.85	41.01	38.27	36.73	33.47	32.65	29.58	26.67	34.05
Limpopo	54.64	54.19	51.79	49.12	46.12	45.02	42.67	39.12	46.86

Table D4. Multidimensional Poverty: Deprivation Level: Fully Deprived (%)

	2023	2024	2025	2026	2027	2028	2029	2030	Ave. 24-30
All South Africa	7.07	6.40	4.84	3.81	2.61	2.19	1.40	0.92	3.17
Male	7.14	6.51	4.86	3.77	2.56	2.09	1.28	0.81	3.13
Female	7.76	7.27	6.32	5.62	4.73	4.47	3.84	3.24	5.07
African	8.91	8.34	7.13	6.22	5.13	4.76	3.92	3.21	5.53
Coloured	5.22	4.76	3.74	3.02	2.35	2.09	1.59	1.18	2.68
Asian	0.71	0.60	0.32	0.21	0.10	0.06	0.02	0.01	0.19
White	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Western Cape	4.24	3.90	3.02	2.28	1.58	1.29	0.81	0.54	1.92
Eastern Cape	13.10	12.53	11.10	9.75	8.37	7.90	6.79	5.94	8.91
Northern Cape	8.22	7.81	6.28	6.01	4.82	4.55	3.94	3.45	5.27
Free State	6.48	5.96	4.98	4.26	3.49	3.36	2.79	2.23	3.87
KwaZulu-Natal	8.09	7.56	6.45	5.65	4.56	4.21	3.34	2.67	4.92
North West	10.76	10.07	8.76	7.58	6.29	5.92	4.99	4.08	6.81
Gauteng	2.84	2.54	1.81	1.37	0.88	0.69	0.39	0.24	1.13
Mpumalanga	11.06	10.53	9.07	8.34	6.98	6.66	5.59	4.71	7.41
Limpopo	13.14	12.79	11.35	10.03	8.75	8.32	7.47	6.39	9.30

ADRS INTERNATIONAL COUNTRY MODELS



AFRICA

Morocco | Tunisia | South Africa (IO-Model, Suite of Macro and Micro Models)

ASIA

Brunei | Cambodia | China | Hong Kong | India | Indonesia | Israel | Japan | Kazakhstan | South Korea | Malaysia | Philippines | Saudi Arabia | Singapore | Taiwan | Thailand | Yemen

EUROPE

Austria | Belgium | Bulgaria | Croatia | Cyprus | Czech Republic | Denmark | Estonia | Finland | France | Germany | Greece | Hungary | Iceland | Ireland | Italy | Latvia | Lithuania | Luxembourg | Macedonia | Malta | Netherlands | Norway | Poland | Portugal | Romania | Russian | Federation | Slovakia | Slovenia | Spain | Sweden | Switzerland | Turkey | United Kingdom

NORTH & CENTRAL AMERICA

Canada | Mexico | United States of America

SOUTH AMERICA

Argentina | Brazil | Chile | Colombia | Costa Rica

OCEANIA

Australia | New Zealand

APPLIED DEVELOPMENT RESEARCH SOLUTIONS (ADRS)

ORGANISATIONAL PROFILE

Our vision: a world of people empowered to advance human development.

Our mission: helping people gain economic insight and foresight to shape policy that matters.

Applied Development Research Solutions (ADRS) is an economic consultancy organization registered in South Africa and the United States, driven by the idea that successful economic development relies on good policy design. We are an independent, forward thinking specialized consultancy committed to economic development through high quality quantitative analysis, evidence-based policy research, expert advice and innovative training. ADRS proudly offers state-of-the-art economic modelling tools and services that provide the insight and foresight needed to make informed policy choices. We view ourselves as partners with our clients and the constituencies they serve.

ADRS offers expertise in economic modelling, policy research, advisory services, training and capacity building to assist our clients in government, non-governmental organizations, development agencies, and the private sector. ADRS services in economic analysis, policy analysis, economic modelling, innovative web-based modelling interface, and capacity building equip policymakers and others with the tools to design policies that go to the heart of development challenges. To date, ADRS has built economic models for more than 60 countries, exemplifying expertise that enables users to design and test the effectiveness of wide-ranging policy choices.

In South Africa, ADRS has extensive experience in economic research, policy analysis, economic model building and capacity building. Since 1994, ADRS members have worked closely with the South African government at national and provincial levels. ADRS has exclusively built ten web-based user-friendly economic models for South Africa, at national, provincial, district and municipal levels, that researchers and policy analysts use to design macroeconomic, industrial, poverty, income distribution, education, and energy-emissions policies.

The Economic Modelling Academy (EMA) uses ADRS economic models as part of its executive certificate courses in various economic modelling topics (e.g., macroeconomic, poverty and inequality, skills demand and supply, and green economy modelling) that are offered in partnership with the GIBS Business School. For the upcoming courses visit the course pages on GIBS or EMA websites.

ADRS
P.O. Box 948
Folsom, CA 95630
United States
T: +1-916-505-4874

ADRS
P.O. Box 413232
Craighall 2024
South Africa
T: +27-(0)11-083-6474

Email: info@adrs-global.com
Website: www.adrs-global.com
LinkedIn: ADRS