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MEASURING MULTIDIMENSIONAL POVERTY IN KENYA ACROSS TIME AND SPACE

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Measuring multidimensional poverty in Kenya across time and space

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Abstract
This study aims to assess Kenya's progress in the reduction of poverty in the context of achieving sustainable development goals (SDGs). We start with a standard set of indicators from the Alkire-Foster (AF) multidimensional framework which encompasses multiple facets of the SDGs but begin by interrogating their appropriateness. We start by assessing the reliability of the indicators using the item response theory and the reliability of the overall model using McDonald's Omega statistic. We find that the overall model is not reliable. In particular, we find that the child mortality indicator is not reliable thus we drop it from the analysis. We introduce indicators measuring child schooling gaps, household overcrowding, and financial inclusion which make the poverty measurement model reliable. We assess the validity of the AF framework using the confirmatory factor analysis. We find that the most valid model is one with equal non-normalized weighting of the indicators which excludes the child mortality indicator. This is in contrast to the standard AF framework which uses equal weights per domain and equal weights for the dimensions within each domain. We thus estimate the multidimensional model AF framework with additional indicators, with equal weights and without the child mortality indicator. We use the finite mixture model, latent class analysis and negative binomial frameworks to estimate an optimal poverty threshold and find the negative binomial framework fits the data best. The optimal threshold classifies an individual as poor if they are deprived in 7 or more of the 12 indicators. This contrasts with the standard AF framework in which an individual is considered poor if they are deprived of a third or more of the weighted indicators. Using our index, we then go on to profile multidimensional poverty over the period 2014 to 2022. The results show that Kenya has experienced remarkable improvements in the poverty situation as shown by significant reductions in the poverty headcount and multidimensional poverty index (MPI) at the national, sub-group and spatial levels between 2014 and 2022. A decomposition of the MPI shows that the largest contributor to multidimensional poverty is the living standards dimension while the education dimension makes the least contribution. The provision of cheaper clean cooking fuel, electricity and low-cost housing is imperative since the lack of access to these indicators is the largest contributor to the MPI.

Classification JEL
I32, B41, C38, R12, O1

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1. Background

The members of the United Nations ratified 17 sustainable development goals (SDGs) in 2015. They envisaged that attaining these goals would improve the standards of living of their population. The first SDG goal aims at eradicating extreme poverty. The SDGs were adopted by Kenya in September 2015. As of 2023, Kenya was ranked 123rd out of 166 countries in the achievement of the SDG goals. However, the percentage of SDG achievement increased from 56.3% in 2014 to 60.71% in 2021. Despite being a lower-middle-income country (LMIC), Kenya has a higher poverty rate than other LMICs. Kenya has made great strides in reducing poverty and performs better than Sub-Saharan Africa (SSA). The chief driver of poverty reduction is growth in the agricultural sector. Nevertheless, Kenya is not on track to achieve the SDG goal of halving poverty by 2030 given that the reduction of poverty both at the $2.15/day and $3.65/day poverty lines has seemingly stagnated.[1]

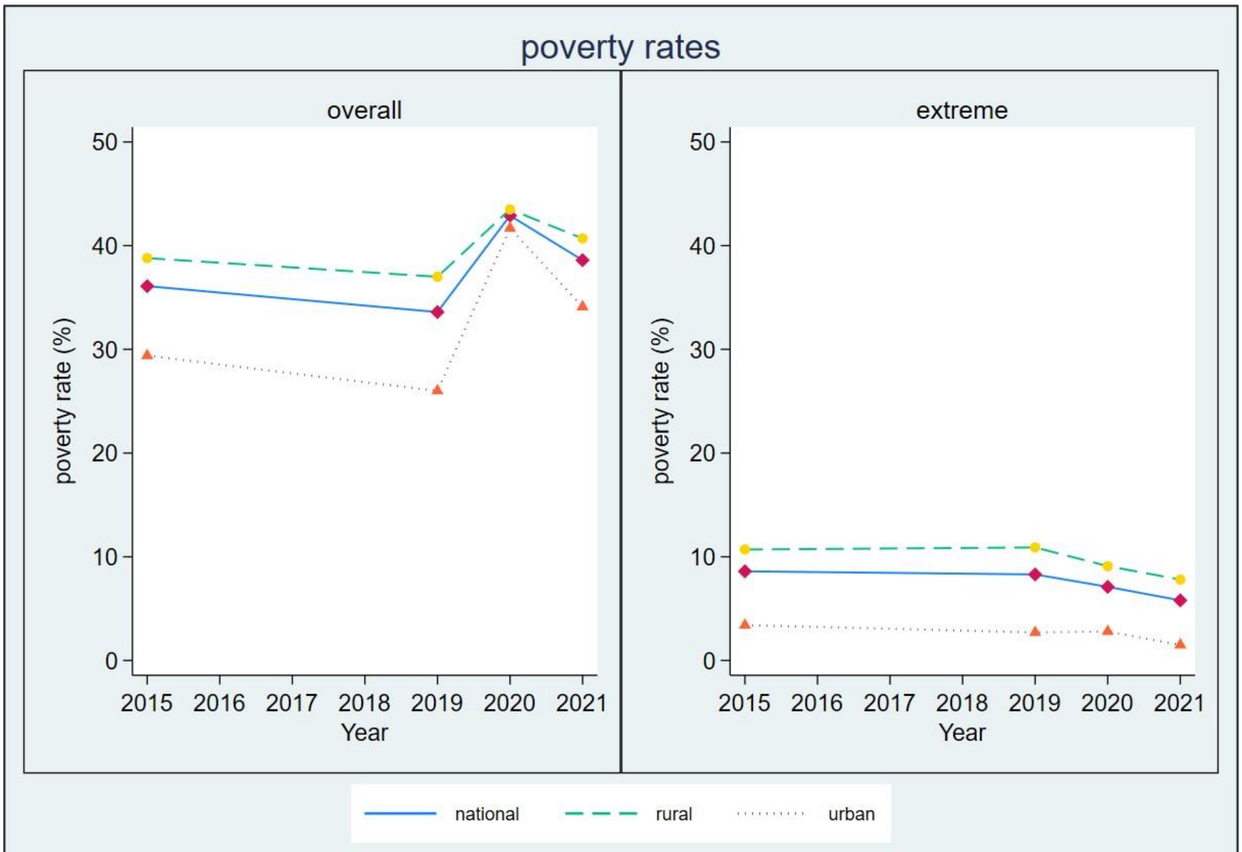
According to the latest Kenya poverty report, an individual is considered poor if their consumption per adult equivalent is less than Kshs. 3,947 per month if living in a rural area and Kshs. 7,193 per month if living in an urban area. The individual is considered extremely poor if their consumption per adult equivalent is less than Kshs. 2,331 and Kshs. 2,905 per month if living in a rural and urban area, respectively. These thresholds for poverty and extreme poverty are determined using the cost of basic needs (CBN) approach which determines a basic consumption bundle and estimates the cost of purchasing said consumption bundle. Figure 1 shows the poverty rates in 2015, 2019, 2020 and 2021.[2, 3, 4]

The overall poverty rates were on a downward trajectory between 2015 and 2019. However, the poverty rates increased in 2020 due to the effects of the COVID-19 pandemic which led to the closure of most economic activities. The locust infestation in 2020 also affected agriculture negatively thus explaining the increase

1 (The United Nations, 2015; World Bank Group, 2018; Sachs et al.*, 2023)*
2 (Ravallion, 1998; Kenya National Bureau of Statistics, 2023)
3 Food basket and poverty lines based on the Kenya Integrated Household and Budget Survey (KIHBS) 2015/16 survey. Prices are adjusted across surveys to reflect inflation over time.
4 2015 data is extracted from the KIHBS. 2019, 2020 and 2021 data is extracted from the Kenya Continuous Household Survey (KCHS).

in poverty rates in 2020. The extreme poverty rates remained constant between 2015 and 2019 with slight decreases thereafter. For both the overall and extreme poverty rates, rural poverty rates remain higher while urban poverty remains consistently lower than the national averages.

Figure 1: Poverty headcount in Kenya between 2015 and 2021



Source: Own illustration using poverty rates given in the KNBS 2023 poverty report

The measurement of poverty using a monetary poverty line does not take into account the lower living conditions that come with low income. Poor people also tend to be disadvantaged in education attainment, health, and access to basic services. Thus, they have a lower living standard. Most surveys are also lacking in data on incomes and expenditures thus making it difficult to assess poverty. This necessitates the use of more inclusive poverty measures. Asset-based and deprivation-based measures fill this gap. Asset-based measures use household ownership of assets and access to public services to assess their socioeconomic ranking. Therefore, asset-based measures have been used in various studies as an alternative to measuring poverty.[5]

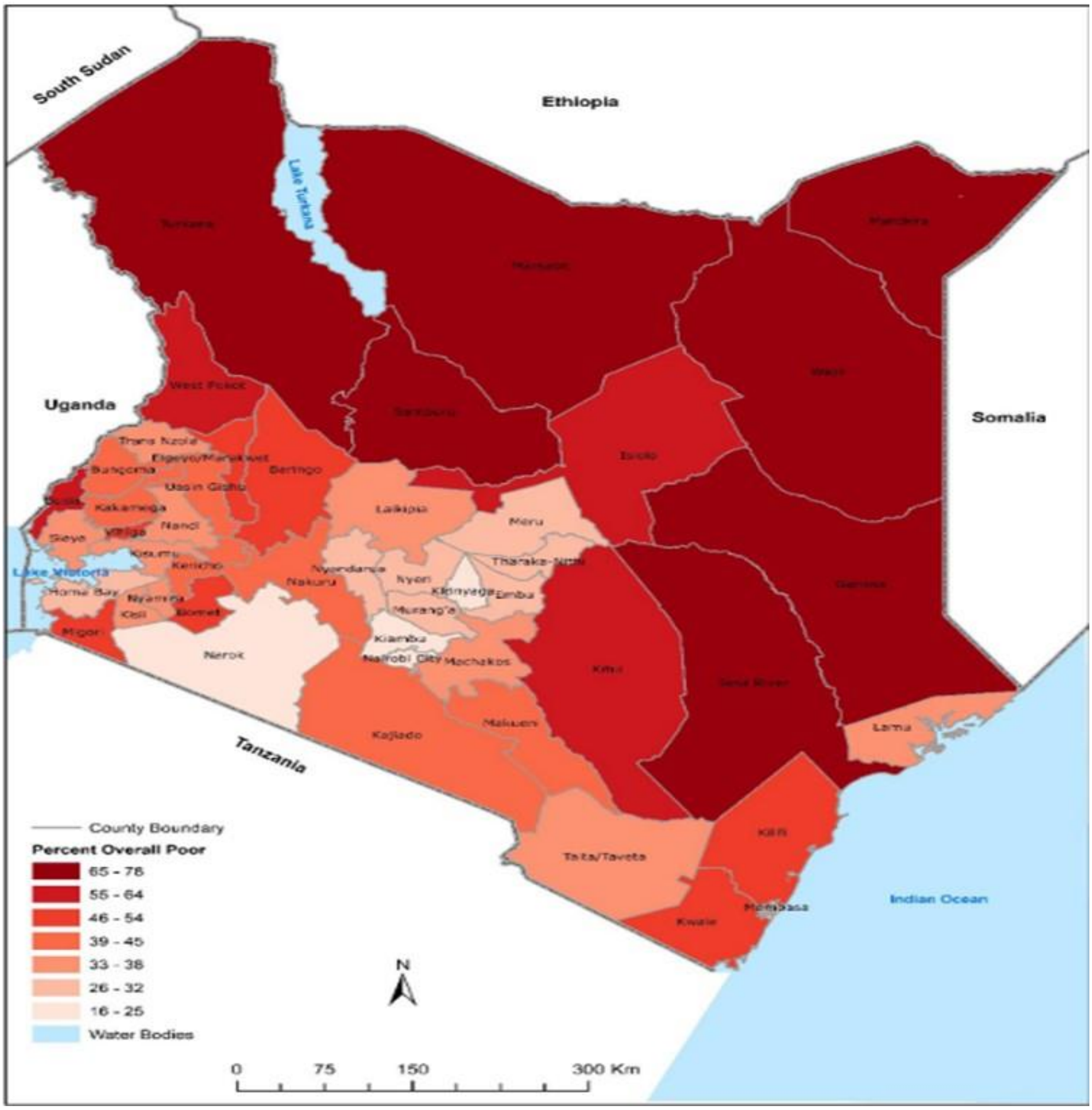
Deprivation-based measures of poverty such as the multidimensional poverty index (MPI) further extend the asset-based measures. The global MPI includes indicators of health, education and household living standards in the calculation of multidimensional poverty. It combines the poverty headcount and poverty intensity in the calculation of poverty. The higher the MPI, the worse off the country/unit of analysis is. As of 2024, the global MPI in Kenya was calculated as 0.113 with higher poverty experienced in rural areas.[6]

The spatial aspect of poverty also cannot be ignored. While rural-urban differences have been widely studied, spatial differences have not been given adequate attention.[7] The poverty rate in urban areas is lower compared to rural areas. Poverty in rural areas is largely attributed to lower access to public services such as electricity, improved water and improved flooring while urban poverty largely arises from deprivations in school attendance, child mortality and malnutrition. As of 2024, the areas in northern Kenya have the highest MPI levels while Nairobi and central Kenya had the lowest MPI. Figure 2 shows the individual poverty headcount in Kenya as per the latest poverty report (2023).[8] The highest poverty headcount is seen to be concentrated towards the north and northeast of the country thus lending credence to the hypothesis that poverty depends on the location of the individual. The within and between-county inequalities in consumption expenditures are substantially high. The consumption in the richest counties is skewed towards the households in the top 20th percentile. For Nairobi and Mombasa counties, consumption in the richest households accounts for 82.9% and 72.2% of the consumption, respectively while consumption of the poor in the poorest county; i.e., Turkana, accounts for 34.6% of the total consumption in the county. Between the

5 *(Foster, 1998; Sahn and Stifel, 2000; Vyas and Kumaranayake, 2006; Booysen* et al.*, 2008; Kabubo-Mariara, Karienyeh and Mwangi, 2008; Filmer and Scott, 2012; Davila* et al.*, 2014; Wittenberg and Leibbrandt, 2017; Ngo and Christiaensen, 2018; Shifa and Ranchhod, 2019)*
6 *(Oxford Poverty & Human Development Initiative and United Nations Development Programme, 2019; Oxford Poverty & Human Development Initiative, 2024)*
7 *(Shifa and Leibbrandt, 2017)*
8 *(Kenya National Bureau of Statistics, 2023)*

counties, the highest median per adult expenditure per month is observed in Nairobi County (Kshs 10,925) which is approximately 4 times that observed in Turkana County (Kshs 2,629).[9]

Figure 2: Overall individual poverty headcount at the county level



Source:[10]

9 (Alkire and Housseini, 2017; Oxford Poverty & Human Development Initiative, 2022b; Kenya National Bureau of Statistics, 2023)

10 (Kenya National Bureau of Statistics, 2023)

In this study, we sought to evaluate the progress Kenya has made in poverty reduction since the adoption of the SDGs. We used the multidimensional poverty index (MPI), which incorporates the dimensions of education, health and living standards into poverty measurement. We first determined the soundness of the dimensions and indicators used in the global MPI poverty measurement. This was done by assessing the reliability of the indicators used in the global MPI calculation and the validity of the dimensions and weights used. Secondly, we investigated the evolution of poverty pre and post-2015 using the validated MPI. Thirdly, we evaluated poverty at sub-group and sub-national levels and assessed poverty pre and post-adoption of the SDGs.

The paper is organized as follows. The data and methodology used is presented in section 2. Section 3 discusses aspects of poverty measurement starting from the definition of indicators, the cut-offs that determine whether one is deprived or not, testing of reliability and validity of the deprivation measures and calculation of the poverty cut-off to define the multidimensionally poor and the non-poor. Section 4 presents the calculation of poverty measures such as the headcount and intensity of poverty, the multidimensional poverty index and subgroup decompositions over different population groups and across spatial units. We then conclude in section 5 by discussing the results observed and offering policy recommendations that arise from our study.

2. Data and Methodology

The Kenya Demographic and Health Surveys (DHS) collected in 2014 and 2022 were used in this study. The DHS is representative at the national and county level.[11] The sample consisted of 145,902 and 147,116 individuals, which comprise 96.56% and 96.35% of the individuals in the 2014 and 2022 DHS surveys, respectively. The reduction in the sample arose due to missing data for some of the individuals. We used the multidimensional poverty index (MPI) to profile the changes in poverty between 2014 and 2022. The MPI incorporates a set of household and individual living standards indicators, thus giving a more holistic measurement of an

11 (Kenya National Bureau of Statistics and ICF International, 2015; Kenya National Bureau of Statistics, Ministry of Health and The DHS program ICF, 2023) individual's deprivation apart from income. We used the M_0 measure of poverty, also referred to as the adjusted headcount ratio which accounts for the intensity of poverty. Secondly, we conducted the analysis described above from a spatial lens. This builds on previous research [12] that explored multidimensional poverty at sub-national levels; i.e., counties and constituencies, in Kenya.

3. Poverty measurement: Construction of the MPI

We followed the MPI construction steps outlined in existing literature for our analysis.[13,14]

3.1. Indicators used in the calculation of the multidimensional poverty index

Traditionally, health, education and living standards are the broad dimensions included in the global MPI calculation. The global MPI includes 10 indicators in the measurement of poverty.[15] The indicators are similar to those in literature which use the dimensions of health, water, sanitation, education, food, shelter and information access in the measurement of child poverty.[16] Figure 3 shows the indicators used to measure these dimensions and an indication of the SDG goal under which they fall.

In terms of the health dimension, Kenya has achieved the target of reducing wasted children under the age of 5 and is on track to reduce mortality and the prevalence of stunting for the same age group. However, the prevalence of undernourishment has been on the increase since 2013. As for the education dimension, the literacy rate is quite high and on an upward trajectory from 86.53% in 2014 to 88.7% in 2021. The most promising indicator in the living standards dimension is access to electricity which increased from 36% in 2014 to 71.4% in 2021. Access to clean cooking fuel, basic drinking water and sanitation services is on the increase, albeit too slowly to achieve the SDG targets by 2030.[17]

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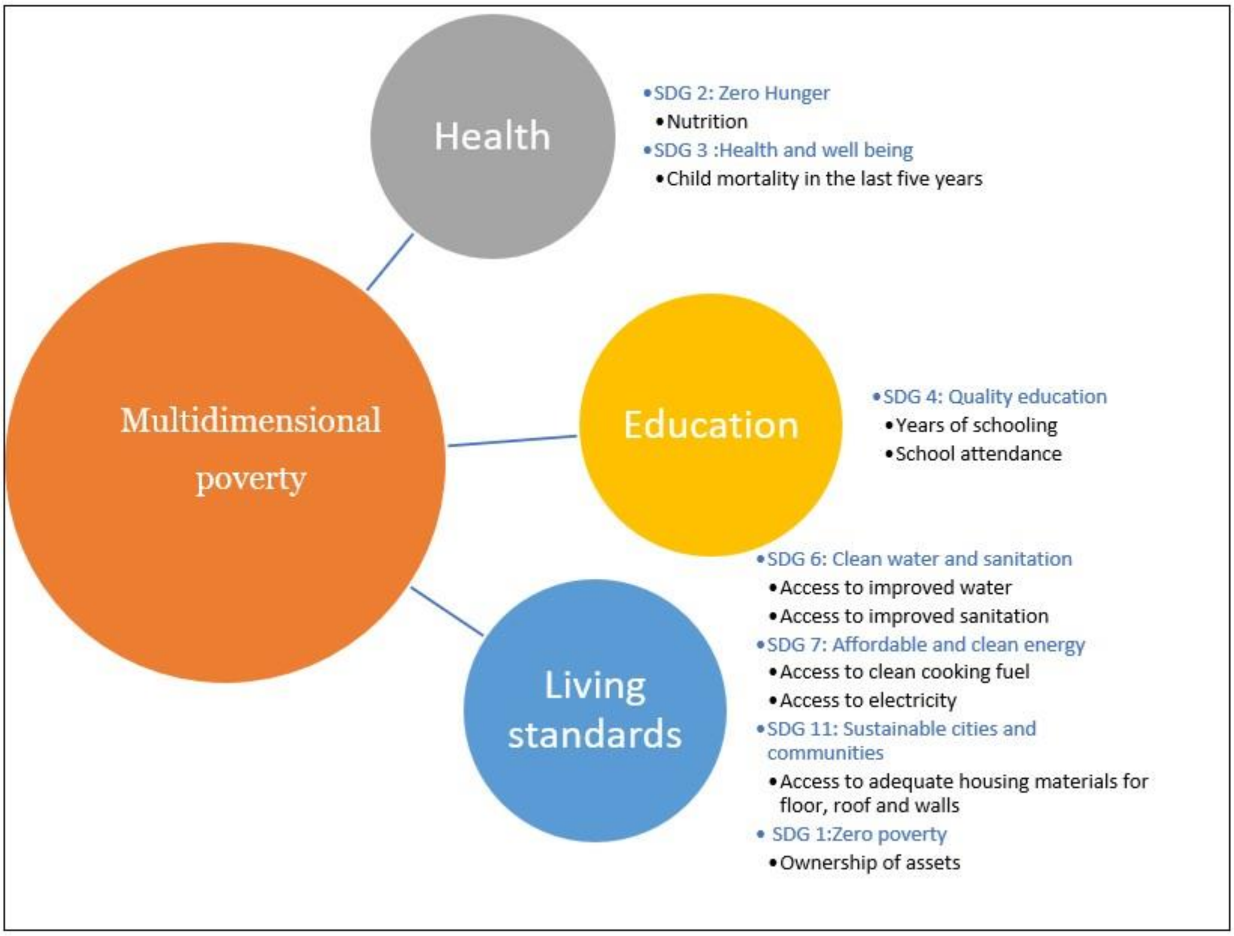
12 *(Shifa and Leibbrandt, 2017)*
13 *(Alkire* et al.*, 2015; Oxford Poverty & Human Development Initiative and United Nations Development Programme, 2019)*
14 *The construction of indicators done in this chapter is done using do-files adapted from (Oxford Poverty & Human Development Initiative, 2022a)*
15 *(Oxford Poverty & Human Development Initiative and United Nations Development Programme, 2019)*
16 *(Gordon* et al.*, 2003)*
17 *(Sachs* et al.*, 2023)*

Figure 3: Indicators included in the global MPI and their respective sustainable development goals



Source:[18]

3.2. Defining the deprivation cut-off for each indicator

An individual is considered deprived if the household they belong to is deprived. Let z_j represents the minimum achievement for an indicator j and x_{ij} be the household x's achievement of indicator j. An individual is considered deprived if their household achievement is lower than the minimum achievement; i.e.,

$$deprivation\ status\ matrix\ (g_{ij}^{0}) = \begin{cases} 1\ if\ x_{ij} < z_j \\ 0\ otherwise \end{cases}$$

18 (Oxford Poverty and Human Development Initiative, 2018; Alkire, Kanagaratnam and Suppa, 2020)

Table 1 presents the deprivation cut-offs as used in literature in the calculation of the global MPI.[19]

Table 1: Indicator deprivation cut-offs

Dimension	Indicator	Specifics of deprivation cut-off
Health	Nutrition	The household has a member who is malnourished. This is defined depending on the individual age groups. Age 0-5: z-score for height for age or weight for age is more than 2 s.d below the median. Age 5-19: Age-specific BMI is more than two s.d below the median. Age 20-54: BMI is less than 18.5kg/m2.
	Child mortality	The household has a child aged 18 years and below who died in the 5 years preceding the survey.
Education	Years of schooling	The household has individuals who are in an age group where they should have completed 6 years of education, but they have not. Individuals aged 10 years and above with 6 years of education are not considered deprived.
	School attendance	A school-aged child in the household is not in school up to the age they should complete class 8 (age 14).

19 *(Alkire, Kanagaratnam and Suppa, 2020)*

Living standards	*Drinking water*	The household does not have access to improved drinking water, or it takes more than 30 minutes to access safe drinking water.
	Sanitation	The household uses unimproved sanitation facilities or improved sanitation that is shared with other households.
	Cooking fuel	The household uses solid fuels and solid biomass fuels for cooking.
	Electricity	The household has no access to electricity.
	Housing	The household does not have access to improved roofing, improved floors or improved walls.
	Asset ownership	The household does not own more than one of the following: radio, TV, telephone, computer, animal cart, bicycle, motorcycle, or refrigerator, and does not own a car or truck.

An important consideration to make before using these indicators for poverty measurement is whether they are reliable and whether the model used is valid. Reliability rests on the indicators being internally consistent such that the ranking of individuals is systematic for all indicators. Validity ensures that the indicators measure the phenomena they intend to measure, in this case, poverty. [20] We therefore started by conducting this appraisal.

20 (Nájera Catalán and Gordon, 2020)

3.3. Reliability

We used the McDonald's Omega statistic as a measure of the reliability of the overall model. The ω statistic measures how well the combination of indicators relates to the latent construct being measured, in this case, multidimensional poverty.[21]

$$\omega = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum V(e_i)}$$

Where λ_i is the factor loading of item i

$V(e_i)$ is the variance in the poverty measure emanating from item i

Table 2 presents the results of the McDonald's Omega statistics.

Table 2: Omega statistic test for overall model reliability

Survey	***Global MPI specification***	***Expanded specification***	***Expanded specification without unreliable indicators***
2014	0.6924	0.9085	0.9520
2022	0.7592	0.9057	0.8816

Source: Authors' calculations

The reliability of the indicators for the global MPI specification was lower than the recommended threshold of 0.8 as shown in the first column of table 2. Thus, the model was lacking in reliability.[22] We, therefore, introduced variables which have been used in other contexts in an attempt to improve the model's reliability. The key literature that informed the additional variables is drawn from country specific national MPIs.[23] We incorporated indicators of household overcrowding, financial inclusion and the schooling gap. Table 3 presents the additional indicators introduced into the model and the specifics of the deprivation cut-offs. The second

21 *(Hayes and Coutts, 2020; Nájera Catalán and Gordon, 2020)*
22 *(Nájera Catalán and Gordon, 2020)*
23 *(Santos* et al.*, 2015; Mensah* et al.*, 2020; National Bureau of Statistics, 2022)*

column of table 2 shows that the inclusion of additional indicators increases the model reliability to the required threshold.

Table 3: Additional indicators included in MPI analysis

Dimension	***Indicator***	***Specifics of deprivation cut-off***
Education	*Schooling gap*	A household is deprived if it has a child who is of school-going age who is more than two years delayed in the expected grade level in school.
Living standards	*Overcrowding*	A household is deprived if has three or more people per sleeping room.
	Financial inclusion	A household is deprived if no household member owns a bank account.

We also conducted an assessment of the individual indicator reliability. The reliability of the individual indicators was tested using the item response theory (IRT). The IRT measures whether the indicators provide valuable information in the construction of the multidimensional poverty index. The 2-parameter IRT produces two results. First is the discrimination coefficient which measures how well an indicator differentiates between the individuals with high deprivations from those with the least deprivations. Second is the difficulty coefficient which measures the acuteness of the deprivation relative to the deprivation of the average individual.[24] The results of these two statistics are presented in table 4.

An indicator is considered reliable if the discrimination statistic is above 0.4 and the difficulty statistic is between -3 and +3.[25] It can be seen in table 4 that the child mortality indicator does not meet both the difficulty and discrimination thresholds for both the 2014 and 2022 surveys. The low discrimination statistic shows that the indicator does not discriminate well between the poor and the non-poor. The high

24 (Hambleton and Jodoin, 2003; Nájera Catalán and Gordon, 2020)
25 (Nájera and Gordon, 2023)

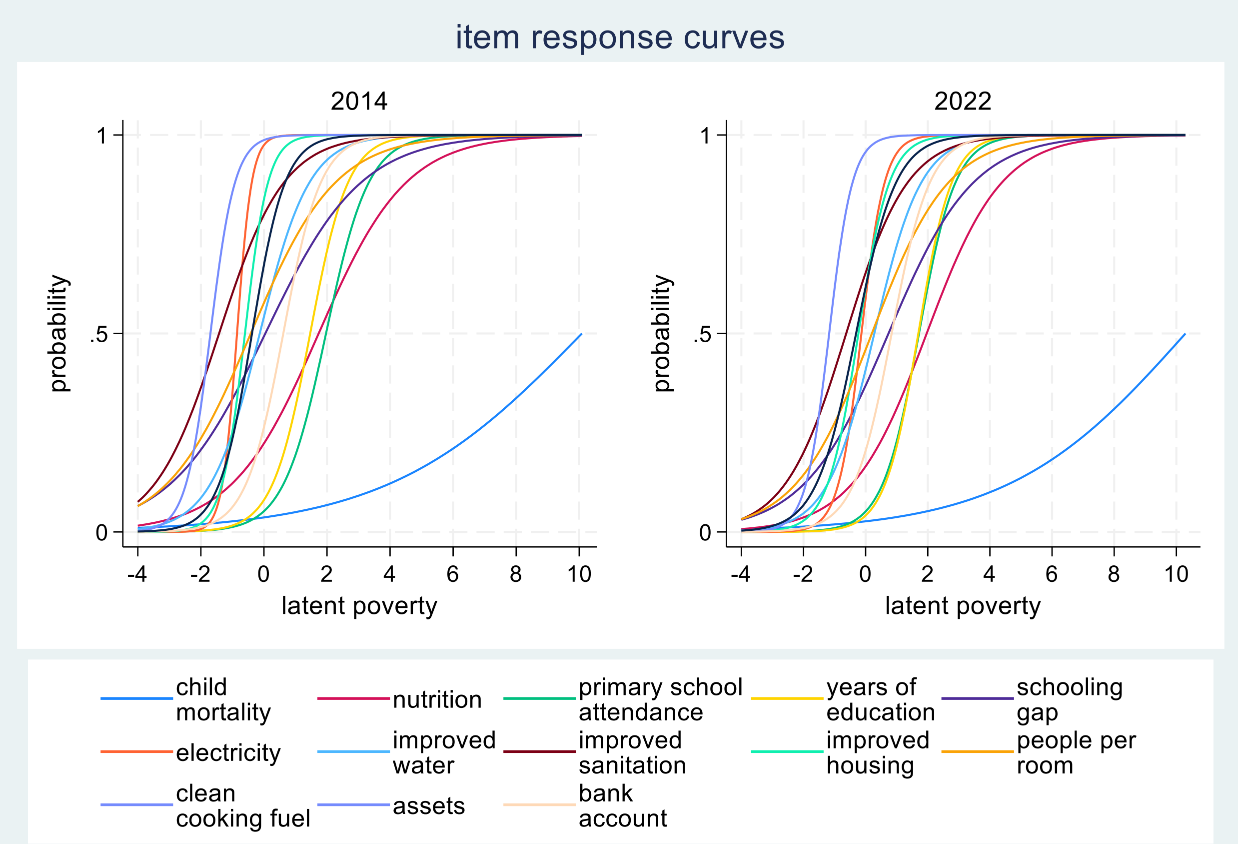
difficulty statistic shows that a low proportion of individuals are deprived of this indicator. The indicators' responses to latent poverty are also illustrated in figure 4. The item probability function plots the probability of being deprived in an indicator against the latent construct that is being measured, in this case, multidimensional poverty.

Table 4: Item response theory statistics

Indicator	**2014**		**2022**	
	Discrim.	***Diff***	***Discrim.***	***Diff***
Child mortality	0.3242	10.0859	0.3489	10.2954
Nutrition	0.7193	1.7366	0.8243	1.9652
School attendance	1.4709	1.9702	1.6959	1.7170
Years of education	1.6610	1.4679	1.8522	1.6965
Schooling gap	0.6571	0.0444	0.7294	0.7361
Electricity	4.2696	-0.8530	2.6709	-0.1350
Improved water	1.2667	-0.1315	1.3192	0.2802
Improved sanitation	0.9699	-1.4216	1.0086	-0.6253
Improved housing	2.7259	-0.6015	1.9988	-0.2325
Overcrowding	0.7436	-0.4163	0.8092	0.2017
Clean cooking fuel	2.5600	-1.6963	2.6515	-1.1734
Household assets	1.6756	0.6149	1.6214	0.8374
Bank account	1.8999	-0.3776	1.5486	-0.3074

Source: Authors' calculations

Figure 4: Deprivation indicators response to latent poverty



Source: Own estimation using Kenya 2014 and 2022 DHS survey data

The location of the indicator plot depends on the severity of poverty and the slope of the indicator plot depends on how well the indicator discriminates between the poor and the non-poor. As indicated earlier, the child mortality indicator does not discriminate well between the poor and the non-poor as shown by the flatter curve. Therefore, increases in latent poverty do not significantly increase the probability of a child in the household dying before their 18th birthday possibly because the proportion of individuals who experience this deprivation is small; i.e., 3.8% in 2014 and 2.78% in 2022. Therefore, given the indicators listed in table 4, we dropped the child mortality indicator as it does not meet the reliability criterion for both surveys. We used 12 deprivation indicators for analysis for the rest of this paper. The McDonald Omega statistic remains above the required threshold after dropping the child mortality indicator as shown in table 2.

3.4. Validity

The structure of the global MPI model is presented in figure 3. The 10 indicators are divided into three dimensions, namely education, health and living standards. In the global MPI specification, the importance of each dimension is assumed to be the same since each dimension is given the same weight. The importance of the indicators also is assumed to be the same within the dimensions as each indicator is weighted the same within the dimensions. However, the weights vary for indicators across dimensions since the health and education dimensions have fewer indicators and as such, the indicators in these dimensions have higher weights compared to those in the living standards dimension.

In testing for the validity of the global MPI model, we utilized confirmatory factor analysis (CFA) which tests relationships that have been defined apriori between the indicators and the latent construct.[26] We compared a unidimensional model, to the multidimensional model, with non-normalized weights; i.e., $P_j w_j = d$ and with normalized global MPI weights; i.e., $P_j w_j = 1$.[27] The CFA analysis produces three goodness of fit statistics which are relevant to our validity assessment. The Comparative Fit Index (CFI) and the Tucker Lewis Index (TLI) test the fit of the model compared to a baseline model with the worst possible fit where the components are not correlated. The threshold of the CFI and TLI is at least 0.9. The Root Mean Square Error of Approximation (RMSEA) tests the error of a given model given a perfect model with perfect correlation among the indicators. It has a maximum threshold of 0.06. The results of the validity tests are presented in table 5.

Table 5: Validity statistics

	2014			***2022***		
	CFI	**TLI**	**RMSEA**	**CFI**	**TLI**	**RMSEA**
	Expanded unidimensional model					
	0.9605	0.9526	0.0433	0.9543	0.9452	0.0450
	Expanded MPI specification					

26 (Flora, 2020)
27 (Alkire and Foster, 2011; Alkire et al.*, 2015; Nájera Catalán and Gordon, 2020)*

MPI weights	0.8611	0.8495	0.0772	0.8739	0.8633	0.0710
Equal weights	0.9607	0.9506	0.0442	0.9554	0.9438	0.0455
	Expanded MPI specification without child mortality indicator					
MPI weights	0.8643	0.8507	0.0834	0.8771	0.8648	0.0767
Equal weights	0.9612	0.9498	0.0484	0.9557	0.9427	0.0499

Source: Authors' calculations

The expanded multidimensional specification with the global MPI weights is the least valid while the expanded multidimensional specification with non-normalized weights is the most valid among the three models.[28] Taking into account the reliability statistics and removing the child mortality indicator, the outcome remains the same as before with the MPI model with non-normalized weights meeting the thresholds for the CFI, TLI and RMSEA. The expanded specification with global MPI weights still does not meet the validity threshold even after dropping the child mortality indicator. The global MPI model therefore is not valid in the Kenyan context. Subsequently, we used the expanded multidimensional model without the child mortality indicator and with non-normalized weights for the analysis done henceforth.

3.5. Calculating the deprivation score

Table 6 shows the proportion of individuals who are classified as being deprived according to the definitions given in tables 1 and 3 which give the deprivation cutoffs for the respective indicators. Except for the schooling gap, all the other MPI indicators show a reduction in the proportion of individuals who are deprived.

Table 6: Proportion of individuals who are deprived in the MPI indicators

	2014		***2022***	
Indicator	***mean***	***se.***	***mean***	***se.***
Nutrition	0.2189	0.0042	0.1588	0.0034

28 (Hu and Bentler, 1999)

School attendance	0.0559	0.0027	0.0543	0.0026
Years of education	0.1023	0.0032	0.0622	0.0023
Schooling gap	0.4496	0.0054	0.3328	0.0050
Electricity	0.7164	0.0075	0.4934	0.0083
Improved water	0.4737	0.0078	0.3796	0.0072
Improved sanitation	0.7520	0.0074	0.5932	0.0088
Improved housing	0.6433	0.0087	0.5375	0.0089
Overcrowding	0.5371	0.0058	0.4142	0.0055
Clean cooking fuel	0.8452	0.0056	0.7413	0.0068
Household assets	0.2717	0.0051	0.2199	0.0042
Bank account	0.5525	0.0063	0.5315	0.0063

Source: Authors' calculation

The deprivation score is defined as the sum of the deprivations for each individual.

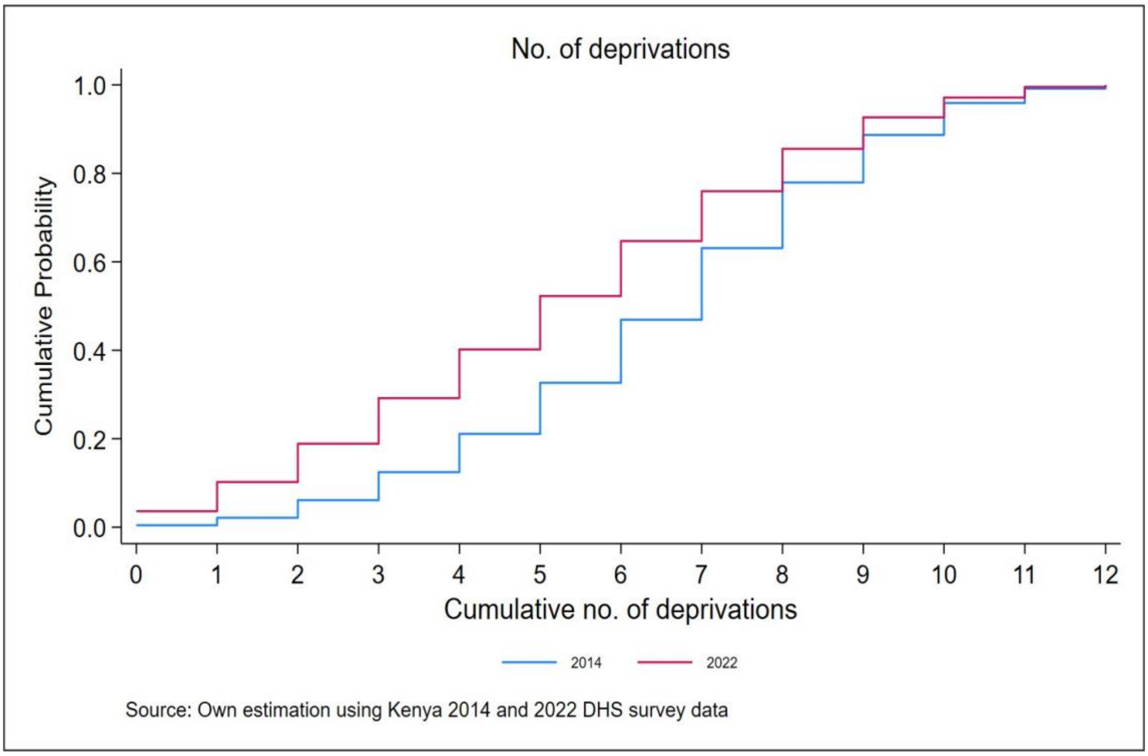
$$c_i = \sum_{j=1}^{d} g_{ij}^{0}$$

where:

g_{ij}^{0} is the deprivation of individual i in indicator j

The higher the deprivation score, the more dire the poverty status of the individual; i.e., individuals with a zero-deprivation score are not deprived in any of the indicators and the ones with a deprivation score of 12 are deprived in all the indicators. Individual deprivations were reduced between the 2014 and 2022 surveys as evidenced by the proportion of the individuals who are classified as being deprived in 2022 being lower compared to the 2014 survey at all the deprivation scores. Figure 5 shows the cumulative deprivation scores for the 2014 and 2022 surveys.

Figure 5: Cumulative deprivation scores



3.6. Determining the poverty cut-off

A poverty line serves to distinguish between the poor and the non-poor depending on the total number of indicators in which one is deprived. While the global MPI has a poverty line set at $^{1}/_{3}$; i.e., in which an individual lacking in more than a third of the weighted sum of indicators is considered poor, setting similar poverty lines across countries assumes that deprivations in all countries mean the same thing. However, this construct might not be valid given the differences in the standard of living in these contexts. Being deprived of even one indicator in a high income country might imply an individual is poor while an individual with multiple deprivations above the $^{1}/_{3}$ poverty line might not be considered poor in a low income country context. [29]

To overcome this challenge several solutions have been proposed. The Bristol optimal method uses income and deprivation levels to determine the threshold at which the split between the deprived and the non-deprived is best. The individual

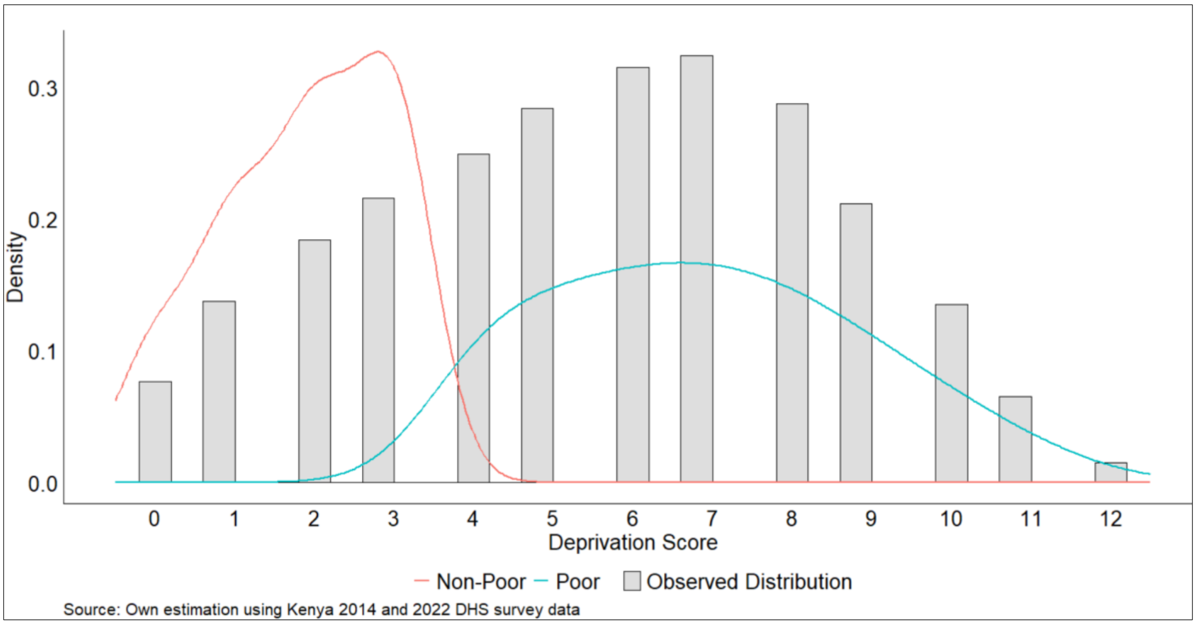
29 *(Babones, Simona Moussa and Suter, 2016)*

is considered poor if they are deprived of k or more indicators This is achieved using ANOVA and logistic regressions. In the absence of an income variable in our dataset, we explore other methods of determining the optimal poverty line which depend only on the deprivation status. These are finite mixture models (FMM), latent class analysis (LCA) and the Poisson/negative binomial frameworks.

Finite mixture models (FMM) assume that the data generation process is driven by the combination of different subpopulations with different distributions. In our case, the poor and the non-poor are assumed to have different distributions, each with a weight that is equal to the share of the population that is nested within each class.[30] The probabilities of being classified as either poor or non-poor are shown in figure 6. The results show that there is no probability of an individual who is deprived of 0 or 1 items being classified as poor. Conversely, the probability of an individual deprived of 5 or more items being classified as non-poor is also zero. The optimal threshold lies at the point of intersection between the distribution of the poor and non-poor groups. The FMM predicts that 24.58% of individuals are classified as non-poor with an optimal threshold of 3; i.e., an individual is poor if they are deprived in 3 or more indicators.[31]

30 (Benaglia et al.*, 2009; Chen, 2017; Nájera and Gordon, 2023)*
31 (Benaglia *et al.*, 2009)

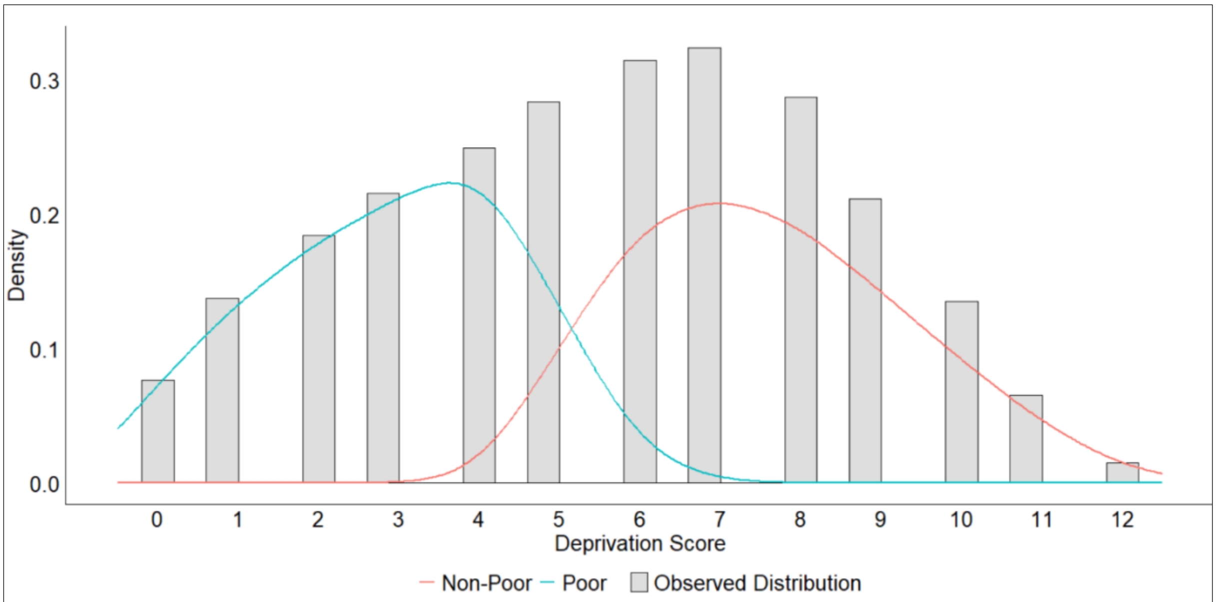
Figure 6: Predicted probabilities of belonging in the poor and non-poor groups as calculated using FMM



Latent class analysis (LCA) assumes the existence of unobserved sub-groups within the population. LCA estimates the probability of an individual belonging to a latent class, in this case, the poor or non-poor group, using the observed indicator deprivation status as the predictor variables. The classes are assumed to be mutually exclusive and exhaustive. However, LCA assumes local independence with the severity of deprivation being assumed to be constant within classes. This implies that the performance of LCA models improves with increases in the number of classes.[32] The results presented in figure 7 show that the probability of an individual who is deprived of 8 or more indicators of multidimensional poverty being classified as non-poor is zero. The same applies to an individual who is deprived in 3 or fewer indicators being classified as poor. The LCA determines the optimal threshold to be 5 with 59.39% of individuals being classified as non-poor.[33]

32 *(Najera Catalan, 2017; Acconcia* et al.*, 2020; Weller, Bowen and Faubert, 2020)*
33 (Linzer and Lewis, 2022)

Figure 7: Predicted probabilities of belonging in the poor and non-poor groups as calculated using LCA



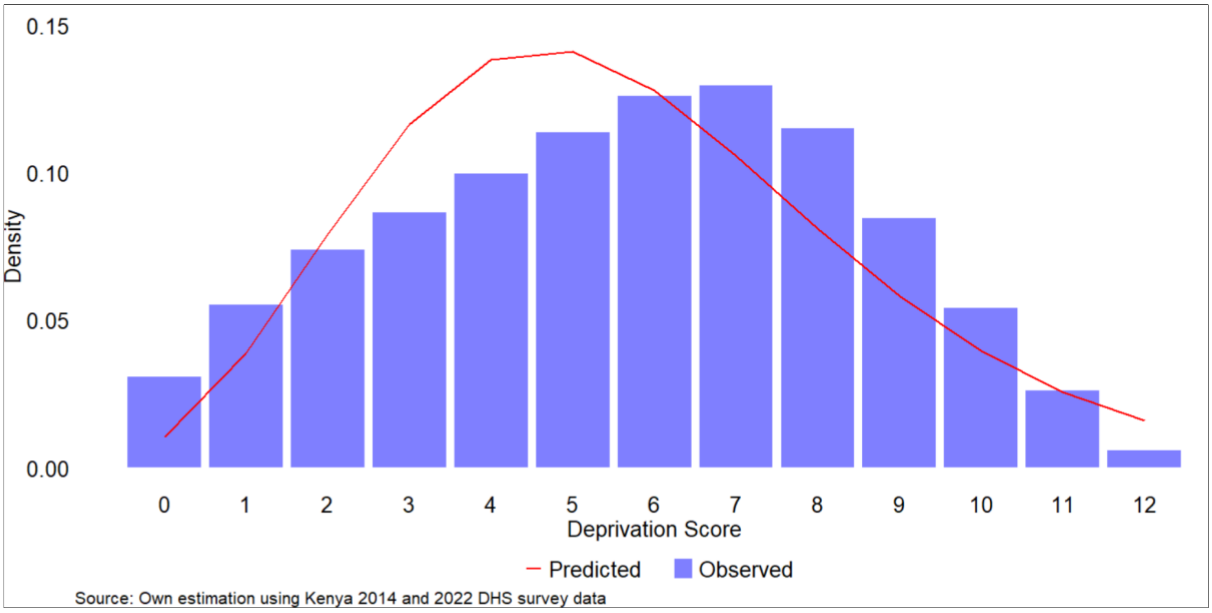
Source: Own estimation using Kenya 2014 and 2022 DHS survey data

The Poisson and negative binomial frameworks assume that there is a theoretical counterpart for every observed level of deprivation. The poverty threshold is calculated at the k above which the empirical incidence of deprivations exceeds the expected distribution given λ; i.e., at the point at which the actual number of the deprived exceeds the theoretical expectation. The method compares the actual distribution of deprivations against the expected distribution of deprivations given the average number of deprivations; i.e., λ=average deprivation.[34] Since we are estimating the poverty statistics across different periods, we used a pooled dataset for the 2014 and 2022 DHS to ensure comparability.[35] The distributions are plotted in figure 8. The observed deprivations exceed the expected deprivations at k>6. Therefore, we set the poverty line at k=7. This implies that an individual is considered poor if they are deprived of 7 or more indicators.

34 (Babones, Simona Moussa and Suter, 2016; Nájera and Gordon, 2023)

35 The choice between the Poisson and the negative binomial framework is informed by the mean and variance of the deprivation score. The Poisson model assumes equality between the mean and variance while the negative binomial model relaxes this assumption. For our case, the deprivation score has a mean of 5.66 with a variance of 7.92 thus the suitability of the negative binomial framework model.

Figure 8: Observed vs. predicted negative binomial distributions



Since the 3 methodologies produced different optimal thresholds, it was thus pertinent to determine which model fits our data best. We used fit statistics to make this assessment. The log-likelihood gives the probability of the data given the model parameters with higher values indicating a better fit. The Akaike and Bayesian information criterion with lower values indicate a better fit. The goodness of fit statistics; chi-square and G-information test measure the differences between the predicted and expected frequency of deprivations. Lower X^2 and G^2 indicate a better model fit. We compare these fit statistics in table 7 to the extent to which it is possible since the different estimation methods do not produce all the fit statistics.[36]

Table 7: Fit statistics across methodologies

	FMM	*LCA*	*Negative binomial*
Log Likelihood	-711129.8	-1809847	-
AIC	1422270	3619744	1456535.19
BIC	1422260	3620009	1456556.36
G^2	-	165072	29148.63
χ^2	-	300906.5	33483.14

Source: Authors' calculations

[36] (Nájera and Gordon, 2023)

The FMM produces the highest log likelihood and the lowest AIC and BIC statistics. The implementation of the FMM however assumes a univariate normal distribution which is not ideal for the deprivation scores. Nevertheless, it offers an initial starting point in exploring the optimal threshold.[37] The LCA produces the highest AIC, BIC, G^2 and X^2 statistics. The negative binomial framework has a better fit compared to the LCA. Consequently, we define individuals as being poor if they are deprived in 7 or more indicators as derived from the negative binomial framework.

Comparing this to the global MPI framework which sets the poverty line at k=$^1/_3$, the empirical determination of the poverty line makes a substantial difference in the poverty assessment. Using the global MPI poverty line would imply that the individuals deprived of 4 or more indicators would be considered poor. This means that individuals who are deprived in 4, 5 or 6 indicators, who make up 32.54% and 35.29% of the individuals in the 2014 and 2022 DHS surveys respectively, would be classified as poor under the global MPI framework thus giving higher poverty statistics.

Having determined the poverty line, we apply this to our data and use it to censor the non-poor. The poverty identification function is defined as:

$$\rho_k(x_i; z) = \begin{cases} 1 \; if \; c_i \geq k \\ 0 \; otherwise \end{cases}$$

The poverty identification function ensures that the poverty and deprivation focus of the MPI is maintained; i.e., an increase in the individual achievement of a non-poor individual does not change the MPI since it does not result in a change in the identification function.[38]

37 (Nájera and Gordon, 2023)
38 (Alkire et al.*, 2015)*

4. MPI results for Kenya

4.1. The headcount ratio (H), intensity of deprivation (A) and multidimensional poverty index (MPI)

The headcount ratio refers to the proportion of multidimensionally poor individuals. This is equal to the proportion of the individuals identified as poor in section 3.4 as a fraction of the total population.

$$H(X; z) = {}^{q}/_{n}$$

Where:

q is the number of poor people. In our context, these are individuals deprived in 7 or more of the 12 indicators under consideration

n is the total number of individuals

The proportion of individuals who are classified as poor dropped significantly between the 2014 survey and the 2022 survey as shown in table 8.[39] This presents an optimistic trajectory for poverty reduction in Kenya.

Table 8: Overall multidimensional poverty

	2014				**2022**			
measure	*b*	*se*	*95% CI*		*b*	*se*	*95% CI*	
H	0.4200	0.0067	0.4069	0.4333	0.2562	0.0057	0.2452	0.2675
A	0.6832	0.0016	0.6800	0.6864	0.6712	0.0020	0.6673	0.6752
M_0	0.2869	0.0048	0.2776	0.2964	0.1720	0.0039	0.1644	0.1799

Source: Authors' calculations

While the headcount ratio succeeded in presenting the poverty picture, it does not show how acute the deprivations of the poor are. To achieve this, we calculate the intensity measure which is the average number of indicators for which the poor are deprived. The poverty intensity is estimated as the average deprivation experienced by the poor.

39 The analysis conducted from this point is conducted using the mpitb toolbox (Suppa, 2022, 2023)

$$A = \sum_{i=1}^{q} c_i(k) \Big/ q$$

Where $\sum_{i=1}^{q} c_i(k)$ are the total deprivations experienced by the poor

The poverty intensity reduced slightly between the two time periods as shown in table 8. While the statistics show a statistically significant reduction in poverty intensity, the poor are deprived of approximately 8 indicators in both surveys. We use the MPI/adjusted headcount ratio (M_0) to measure poverty. The headcount ratio is adjusted by the poverty intensity (A). The MPI is calculated as

$$MPI = H \times A$$

The MPI measures the weighted deprivations of the poor as a proportion of the total population. [40] The reduction in the MPI between 2014 and 2022 was substantial. The reduction in the MPI arises from changes in either the poverty headcount or the poverty intensity. [41] In our case, we conclude that this reduction in the MPI is attributable to the significant reductions in the poverty headcount since there is no reduction in the poverty intensity between the two time periods.

We also conducted a sensitivity analysis of the H, A and MPI to different poverty cut-offs to determine how they change when the poverty cut-offs change. The results are presented in figure A1 in the appendix. Both the H and MPI reduce as k increases while A increases as k increases. This also emphasizes the importance of the exercise in section 3.6 of determining the optimal poverty cut-off since different cut-off points give different poverty figures. As per the global MPI framework, an individual is considered poor if they are deprived of $1/3$ or more indicators which translates to 4 or more out of 12 indicators. This is in contrast with our methodology which yields a poverty line that classifies an individual as being poor if they are deprived in 7 or more indicators.

4.2. Decomposition of the MPI over dimensions and indicators

One of the favourable properties of the MPI is its decomposability across dimensions, indicators, population subgroups and geographical units. This rests on

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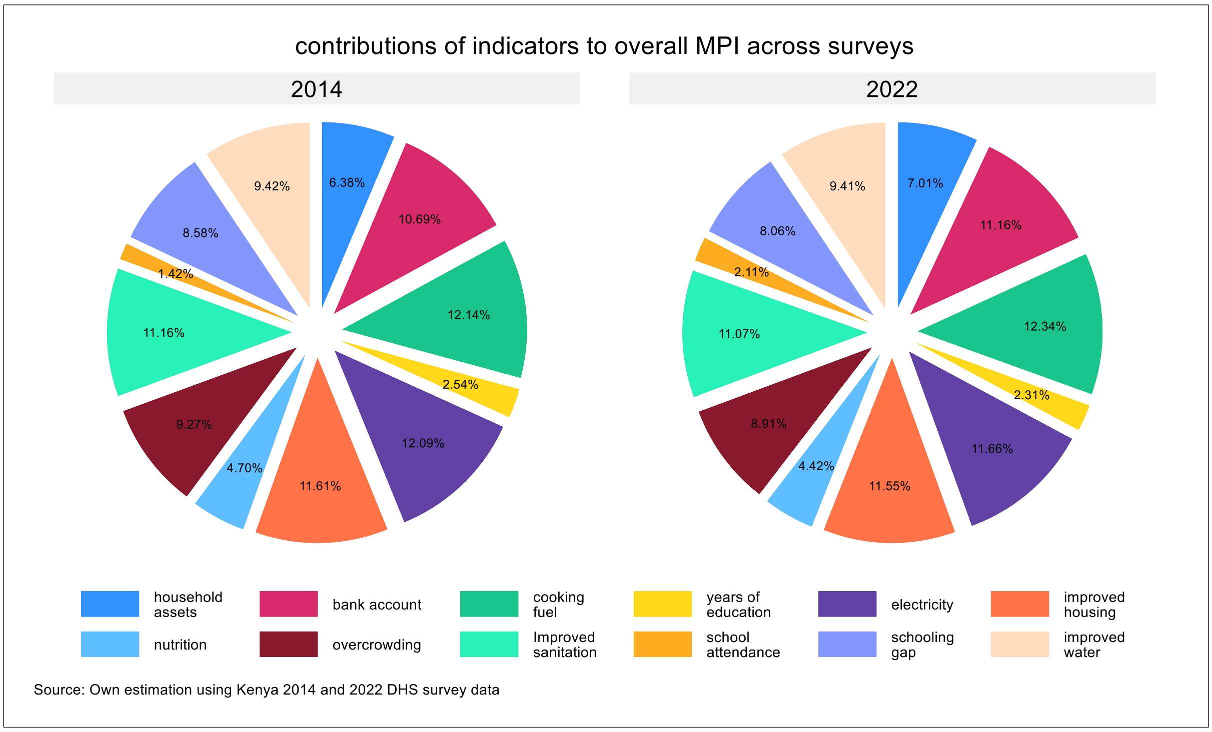
40 (Alkire et al.*, 2015)*
41 (Apablaza and Yalonetzky, 2013)

the assumption that overall poverty is the summation of the weighted poverty levels of the constituent components.[42] We started by decomposing the MPI across its constituent indicators. Figure 9 presents the relative contributions of the indicators to the MPI.

Figure 9: Relative contributions of indicators to the MPI



In terms of the indicators, the leading contributors to the MPI are clean cooking fuel, electricity and improved housing. These fall under the living standards dimension which is the dominant contributor to the MPI. The contributions of the indicators and dimensions are similar to those given in the Oxford Poverty and Human Development Initiative 2024 report which has the living standards indicator as the leading contributor to the MPI in 2022, followed by the health dimension and lastly the education dimension.

4.3. Subgroup decompositions of poverty

We then disaggregated the MPI into the rural vs. urban profiles.[43] Figure A2 in the appendix presents the indicator deprivation across the subgroups over time. It is

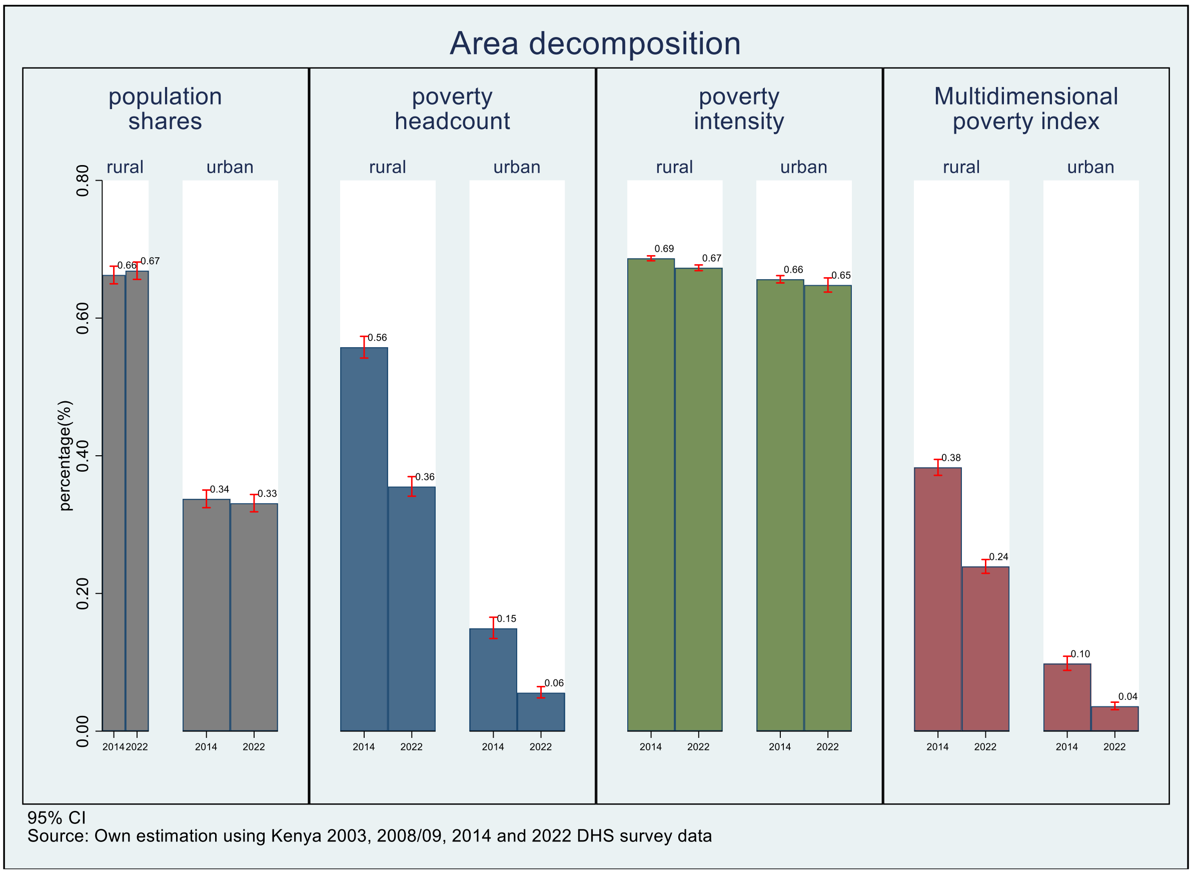
42 *(Alkire* et al.*, 2015)*
43 *(Alkire* et al.*, 2015; Shifa and Leibbrandt, 2017)*

evident that individuals living in rural areas tend to have more deprivations in all, except the overcrowding indicator, compared to their counterparts in urban areas. This especially stems from substantial differences in access to clean cooking fuel, electricity, access to bank accounts, schooling gap and improved water. This is similar to previous literature that has linked the higher poverty levels in rural areas to poor infrastructure, lower education levels and lower incomes in rural compared to urban areas.[44]

Figure 10 presents the poverty decompositions for the area sub-groups. The poverty headcount and the MPI reduced between the 2014 and 2022 surveys. However, the poverty intensity showed no significant differences between the two surveys. Approximately 2/3 of the population lives in rural areas. Nonetheless, the rural areas still have a larger proportion of their population being poor compared to the urban areas; i.e., the MPI in rural areas were around three and six times that in urban areas in 2014 and 2022, respectively. The poverty intensity in both rural and urban areas is approximately the same at 8 out of 12 indicators for both surveys.

44 (United Nations Development Programme, 2018)

Figure 10: Poverty headcount, intensity and multidimensional poverty index disaggregated by area of residence



4.4. Spatial decomposition of poverty

So far, we managed to give the national and rural-urban picture of poverty and its evolution over time. While we presented a picture of multidimensional poverty reducing over time, the rural-urban profiles show marked differences and there is a possibility that some regions within Kenya might have a different narrative. We thus do a decomposition from a subnational lens, using counties as our unit of analysis. Kenya currently has 47 counties, which also serve as the second administrative tier of government. We started by assessing which counties are most deprived in each of the indicators under consideration and how the deprivations have changed in the respective counties between the 2014 and 2022 surveys.[45]

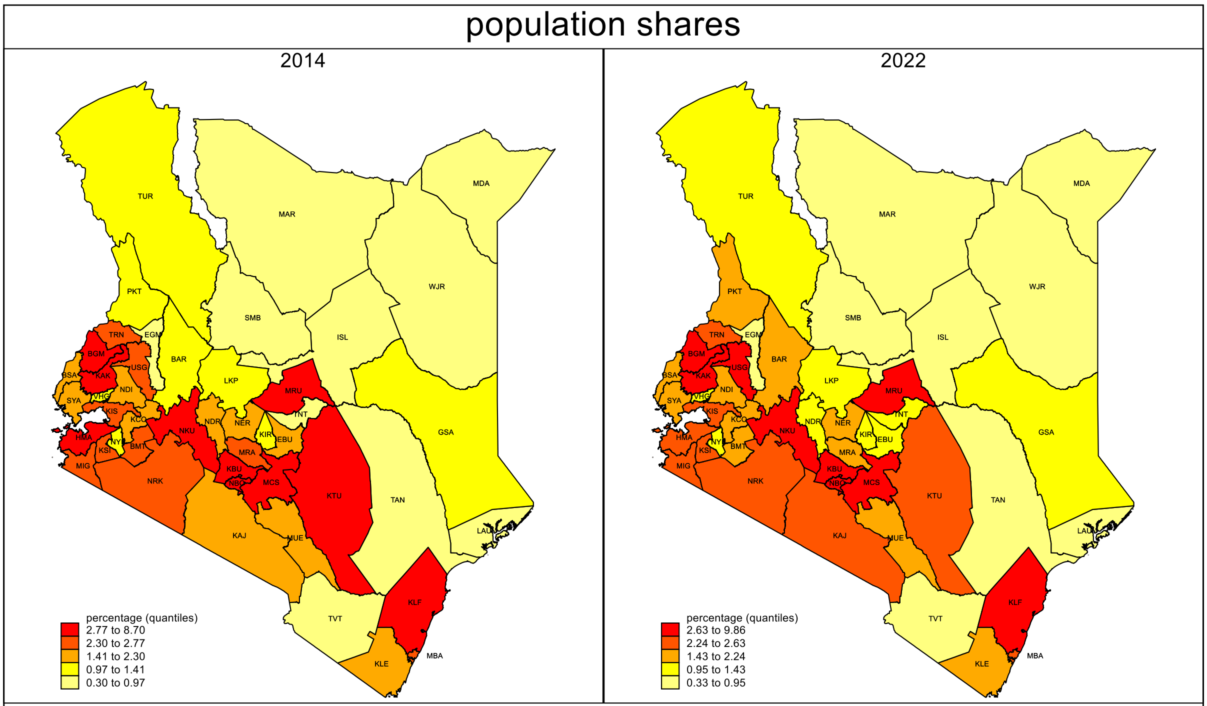
45 Full county names and short codes are presented in table A1 in the appendix

The results of this assessment are presented in figures A3 to A14 in the appendix. Several things are evident. First, the deprivations are lower in 2022 compared to 2014 as evidenced by the lower averages of the deprivations in most indicators in 2022 compared to 2014. Secondly, the counties which were highly deprived in 2014 are also highly deprived in 2022 as shown by the upward trend of the plots. Lastly, most Kenyan counties are seemingly doing well in the education dimension as shown by the high number of counties clustered around the lower left parts of the years of education and school attendance plots. However, most counties still have high schooling gaps. The deprivations in nutrition, household assets, the schooling gap, overcrowding and bank accounts are distributed from low to high deprivation between the counties. On the other hand, most Kenyan counties are highly deprived of electricity, improved water, improved sanitation, improved housing and clean cooking fuel as shown by most counties being clustered towards the upper parts of their respective plots.

We then decomposed the poverty headcount, intensity and MPI at sub-national levels.[46] The country demographics are quite similar between 2014 and 2022. In terms of population shares per county, high-density counties are mainly concentrated in the western, central, southern and southeastern parts of Kenya as shown in figure 11.

46 Kenya county shapefiles are sourced from The Demographic and Health Surveys Program (2019).

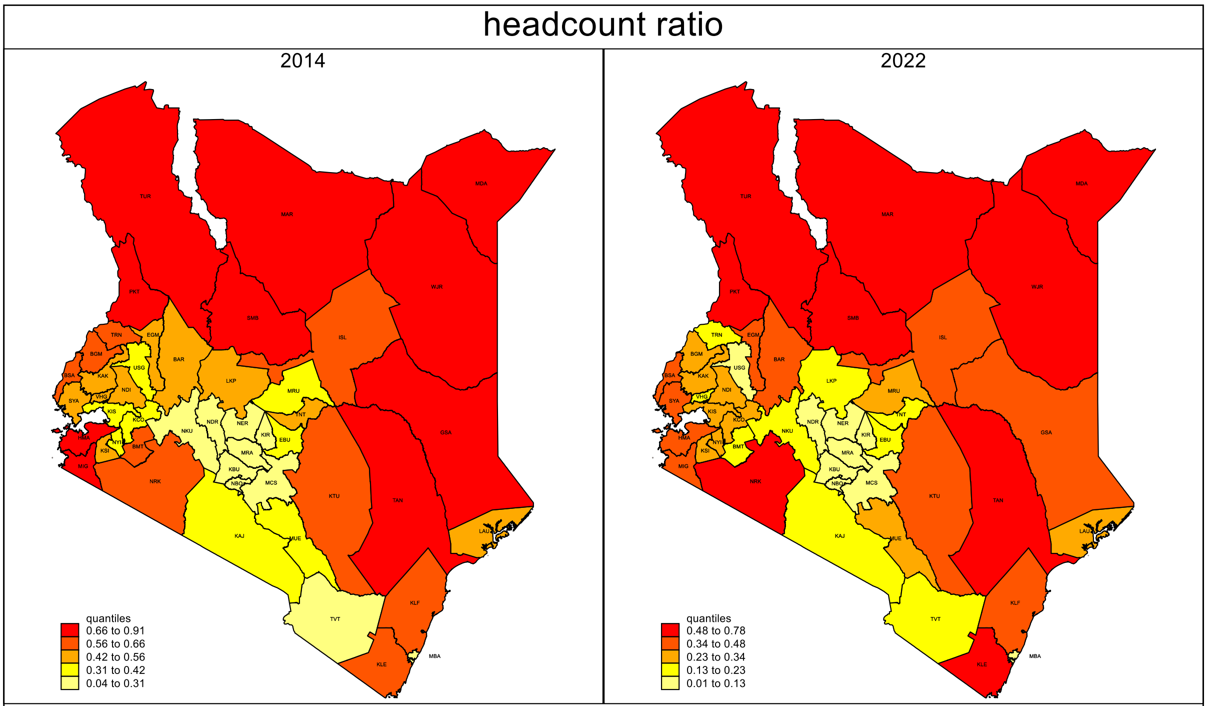
Figure 11: Population shares across counties in Kenya in 2014 and 2022



Source: Own estimation using Kenya 2014 and 2022 DHS survey data

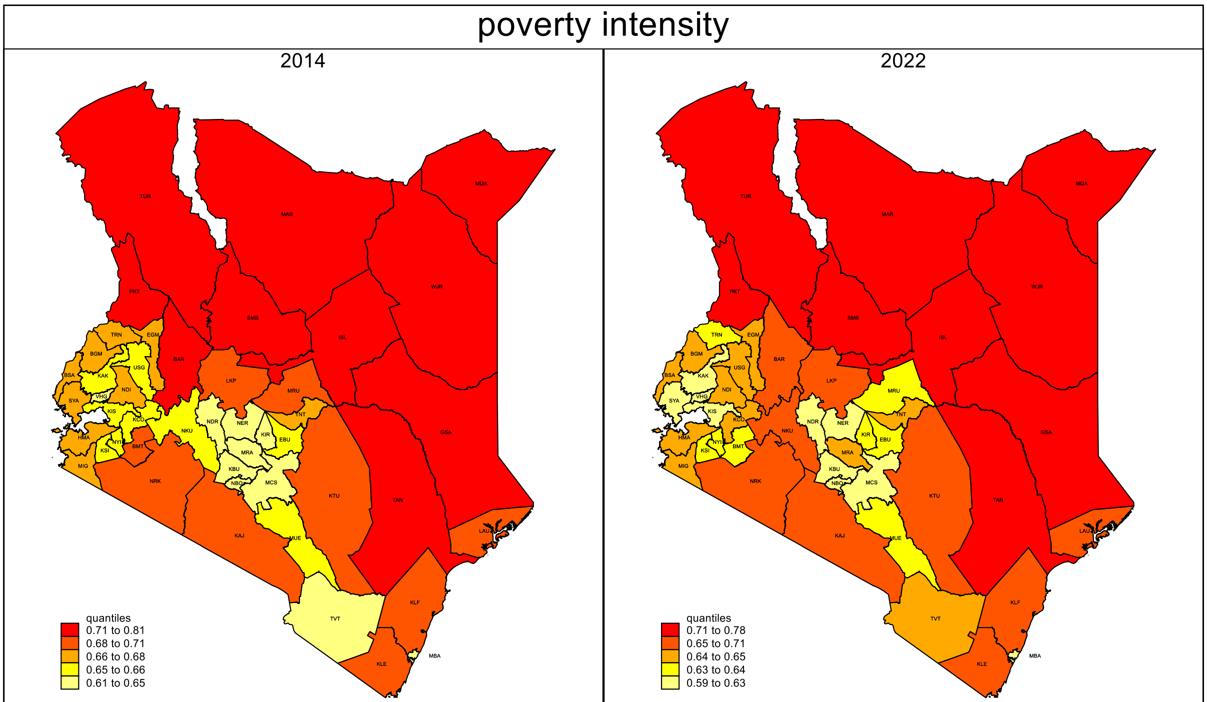
The population density reduces towards the north, northeastern and some of the southeastern counties. The poverty situation in 2014 and 2022 is similar as shown in figures 12 to 14. Most counties with low population densities also have a high proportion of individuals classified as poor as shown by the high poverty headcount in figure 12. The poor in these counties also experience high deprivations as indicated in figure 13. These counties also have high poverty levels as indicated by the multidimensional poverty index in figure 14. Comparing the 2022 poverty headcounts and MPI to the monetary poverty headcount as shown in figure 2, it is clear that multidimensional poverty is highly correlated with monetary poverty.

Figure 12: Poverty headcount ratios across counties in Kenya in 2014 and 2022



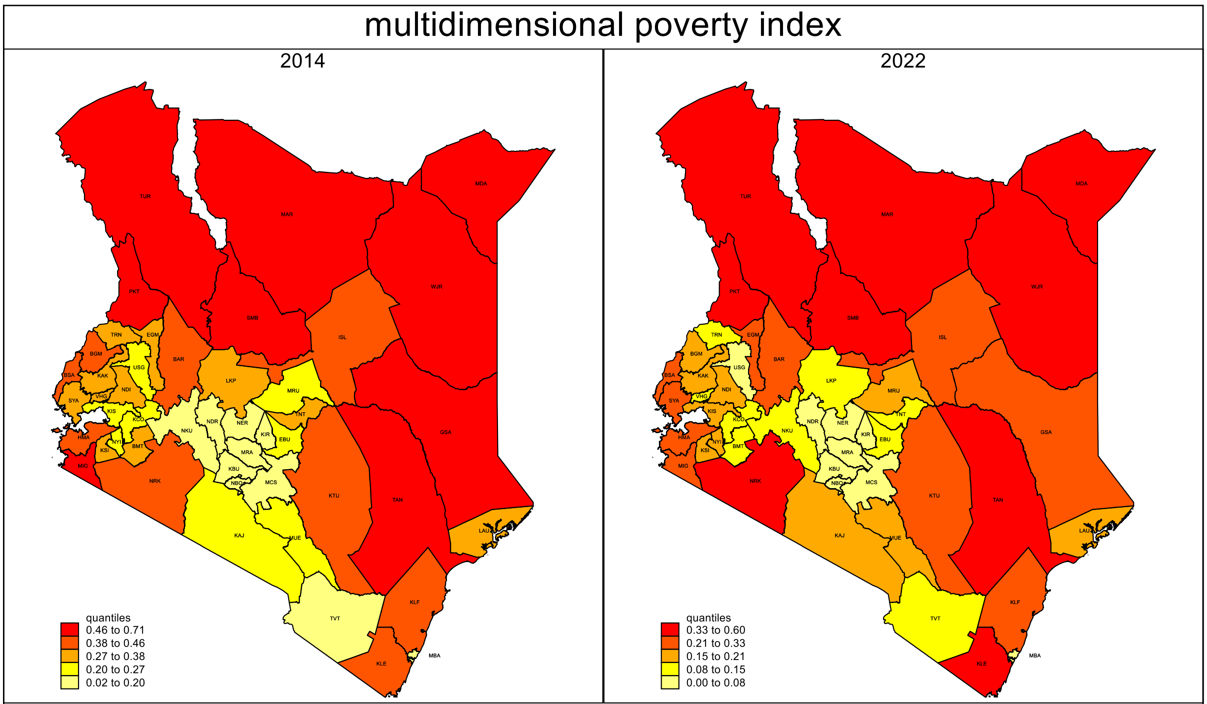
Source: Own estimation using Kenya 2014 and 2022 DHS survey data

Figure 13: Poverty intensity across counties in Kenya in 2014 and 2022



Source: Own estimation using Kenya 2014 and 2022 DHS survey data

Figure 14: Multidimensional poverty index across counties in Kenya in 2014 and 2022

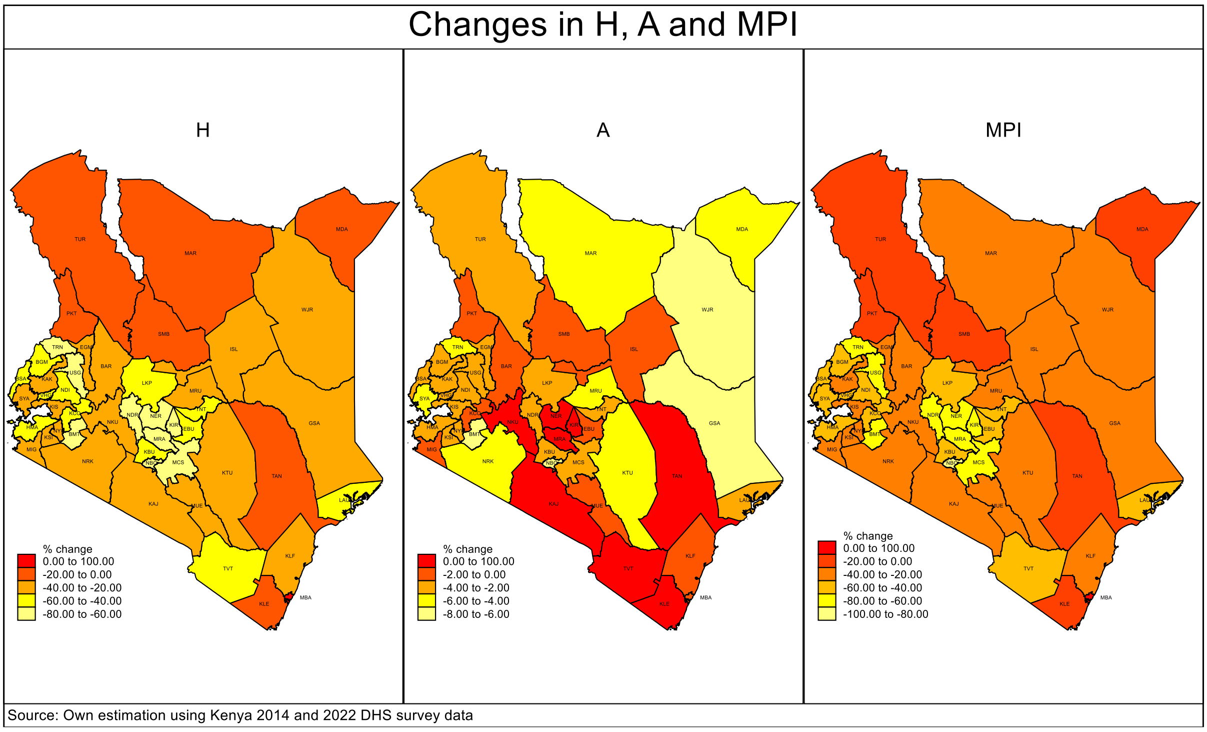


Source: Own estimation using Kenya 2014 and 2022 DHS survey data

The overall poverty picture for the counties is optimistic. Figure 15 presents the changes in poverty between 2014 and 2022. Only Mombasa County experienced an increase in the poverty headcount and the MPI However, it should be noted that Mombasa is one of the counties with the lowest poverty statistics in the country. The reductions in the poverty intensity are minimal with 8 out of 47 counties experiencing an increase in the poverty intensity. These increases are minimal at less than 2.5%. The reduction in the MPI is driven by the changes in the poverty headcount as the changes in the poverty intensity are experienced at a smaller scale compared to the poverty headcount. This takes us back to the argument that the MPI will only reduce if there is a significant reduction in either H, A or both.[47] However, it is also important to note that while the reductions in poverty intensity are not substantial, some of the highest reductions are observed in the poorest counties.

47 *(Apablaza and Yalonetzky, 2013)*

Figure 15: *Changes in the poverty headcount, poverty intensity and the MPI across counties in Kenya between 2014 and 2022*



5. Discussion, Conclusion and Policy Recommendations

The first SDG aims to end poverty in all its forms everywhere by 2030. Monetary measures of poverty are often correlated to non-monetary deprivations thus necessitating the use of more inclusive indicators in the measurement of poverty. Non-monetary indicators of poverty, however, have to be reliable and valid in that, they can discriminate well between the poor and the non-poor and also measure the latent construct which they are endeavouring to estimate. We used the indicators stipulated in the Alkire-Foster framework and aimed to determine whether they fit the respective country construct and data sets used. These are indicators of child mortality, nutrition, school attendance, years of education, improved water, improved housing, improved sanitation, clean cooking fuel, electricity and asset ownership.

We utilized the 2014 and 2022 DHS surveys for analysis to compare multidimensional poverty before and after Kenya's adoption of the SDGs. The choice of the MPI is due to the method encompassing the most indicators compared to other non-monetary measures of poverty such as the asset indices. The MPI indicators also encompass several other SDG goals thus allowing for an assessment of the progress that Kenya is making towards achievement of other SDG goals. We assess the reliability of individual indicators in the MPI specification and find all but the child mortality indicator, are reliable measures of multidimensional poverty in Kenya. A descriptive investigation of the child mortality indicator across the surveys shows that a small proportion of individuals are deprived in this indicator; i.e., 3.8% in 2014 and 2.78% in 2022. This explains why child mortality is not a reliable indicator of multidimensional poverty. We therefore adopt other indicators that have been used in the measurement of multidimensional poverty. The inclusion of these indicators results in a reliable model for the measurement of poverty. Our analysis therefore used 12 indicators compared to the 10 indicators used in the global MPI calculation. We also find that the specification of multidimensional poverty with the same dimensions as used in the global MPI but with equal non-normalized weights across the indicators is the most valid model. We used the negative binomial framework to determine the poverty line and found that an individual is considered poor if they are deprived in 7 or more of the 12 indicators. This contrasts the global MPI framework which sets the poverty line third of the weighted indicators, which in our context would translate to 4 or more indicators.

Poverty has generally reduced as shown by the lower poverty headcounts and MPI in 2022 compared to 2014. This is evident nationally and also across subgroups. However, the intensity of poverty experienced by the poor has not improved in the same time period. Looking at the spatial aspect of poverty, most counties have had a drop in the poverty headcount and the MPI. The highest reductions in the poverty headcount and the MPI were experienced in counties with relatively lower levels of poverty.

It has been argued that to reduce the MPI, the government can initiate programs that reduce the poverty headcount or intensity. [48] The most arithmetically simple way to reduce H would be to focus on the least poor people with the least deprivations

48 *(Apablaza and Yalonetzky, 2013; Alkire* et al.*, 2015)*

such that it is easier to reduce their deprivations and reduce the headcount and intensity of poverty and consequently the MPI. However, such an approach implies that the government would in effect be focusing on the less poor and leaving the extremely poor in abject poverty to fend for themselves. A more ethical way to reduce poverty is to focus on the poorest poor and work on reducing the intensity of poverty. While the poverty headcount might not change in this scenario, the MPI would reduce.

Given that access to clean energy sources is the largest contributor to the MPI, the government can work on making electricity and clean fuels such as LPG more accessible to the public. This is especially so given that high tariffs on these two make them expensive and inaccessible. Kenya has made progress in expanding its electricity sources and access to clean cooking fuel through projects such as the Last Mile Connectivity Program, Lake Turkana Wind Power, Mwananchi Gas, etc. [49] However, this has not translated into more access by households since individuals are still highly deprived of these indicators. A plausible reason is the cost of being connected to the electricity grid is quite high and the payments for electricity usage are still substantial due to the high tariffs imposed. In terms of improved housing, which is one of the largest contributors to the MPI, this requires interventions from three facets, namely, improved roofs, improved walls and improved floors. While this is primarily on the household level rather than the government level, the Kenyan government has also endeavoured to build low-cost housing, especially in informal settlements.[50]

While the nutrition variable contributes a relatively low proportion to the MPI, on a spatial level the prevalence of malnutrition is concentrated in Tana River, Mandera, Turkana, Samburu and West Pokot counties where 30-50% of the individuals are deprived in the nutrition indicator. These counties are classified as Arid and Semi-Arid Lands (ASAL) which contributes to low food security resulting in malnutrition. The main economic activity in these areas is pastoralism and therefore the communities living in these areas have to purchase all non-meat food products thus

49 (Ministry of Devolution and Planning, 2017)
50 (National Treasury and Planning, 2020)

limiting their dietary range. It is also pertinent to note that while approximately half the individuals are deprived of access to a bank account, recent technological advances have resulted in more financial inclusion. The proliferation of mobile phones and the advances in the mobile money sector have ensured that individuals, even in previously financially excluded areas, are now financially included.

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Appendix

Figure A1: Sensitivity analysis of the poverty headcount, poverty intensity and multidimensional poverty index to different poverty cut-offs

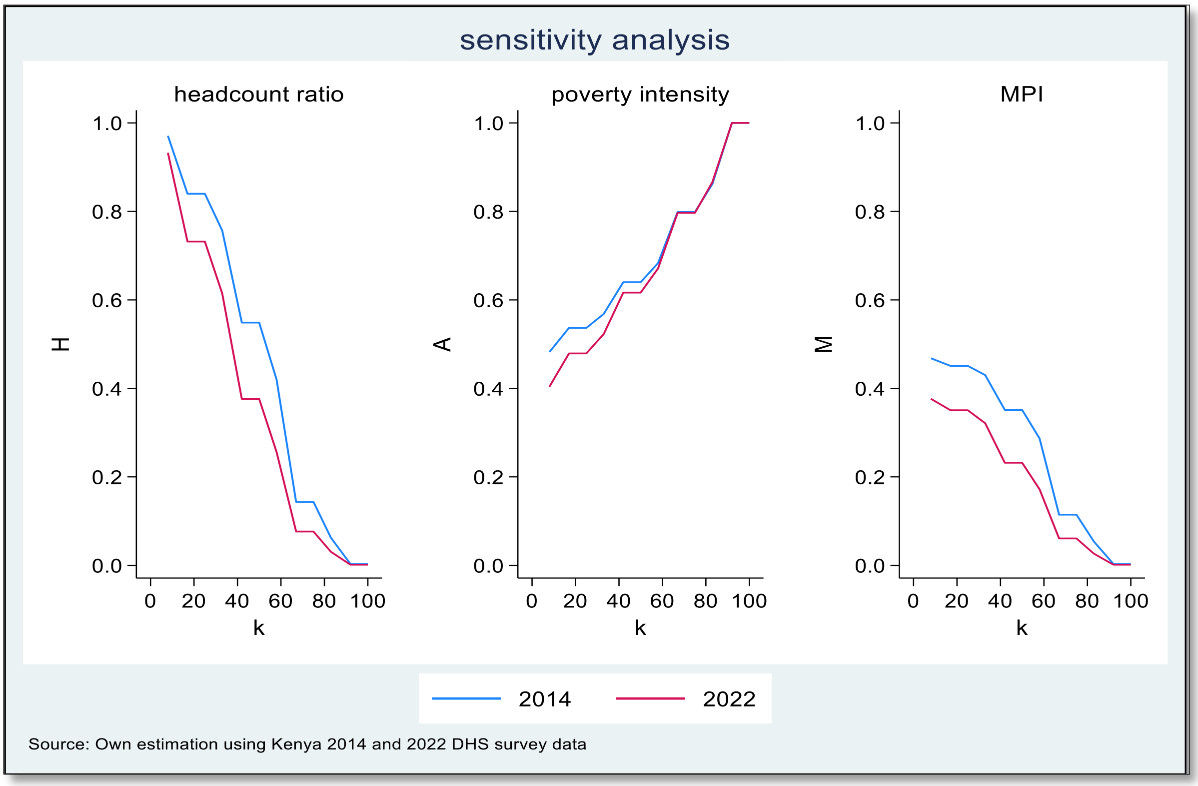


Figure A2: Indicator deprivations by the area of residence over time

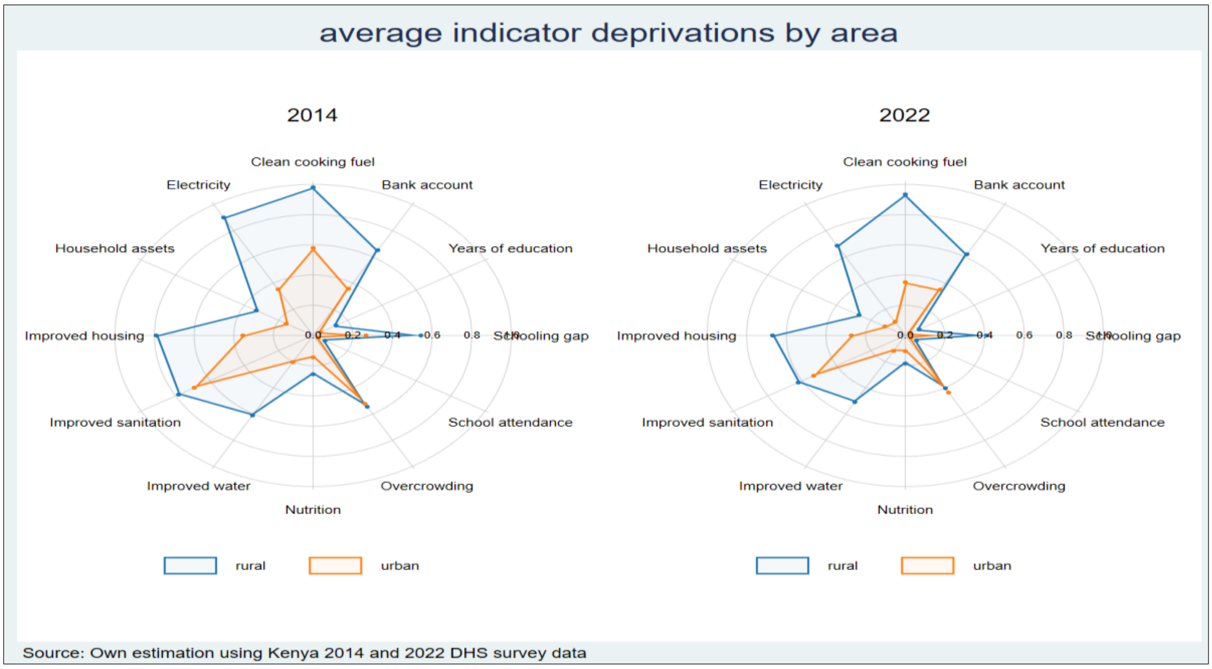


Table A1: Kenya counties and their shortcodes

County	***Shortcode***	***County***	***Short***	***County***	***Short***
Baringo	BAR	Kisumu	KIS	Narok	NRK
Bomet	BMT	Kitui	KTU	Nyamira	NYI
Bungoma	BGM	Kwale	KLE	Nyandarua	NDR
Busia	BSA	Laikipia	LKP	Nyeri	NER
Elgeyo Marakwet	EGM	Lamu	LAU	Samburu	SMB
Embu	EBU	Machakos	MCS	Siaya	SYA
Garissa	GSA	Makueni	MUE	Taita Taveta	TVT
Homa Bay	HMA	Mandera	MDA	Tana River	TAN
Isiolo	ISL	Marsabit	MAR	Tharaka Nithi	TNT
Kajiado	KAJ	Meru	MRU	Trans Nzoia	TRN
Kakamega	KAK	Migori	MIG	Turkana	TUR
Kericho	KCO	Mombasa	MBA	Uasin Gishu	USG
Kiambu	KBU	Murang'a	MRA	Vihiga	VHG
Kilifi	KLF	Nairobi	NBO	Wajir	WJR
Kirinyaga	KIR	Nakuru	NKU	West Pokot	PKT
Kisii	KSI	Nandi	NDI		

Source: http://www.statoids.com/uke.html

Figure A3: Average deprivations in the nutrition indicator across counties

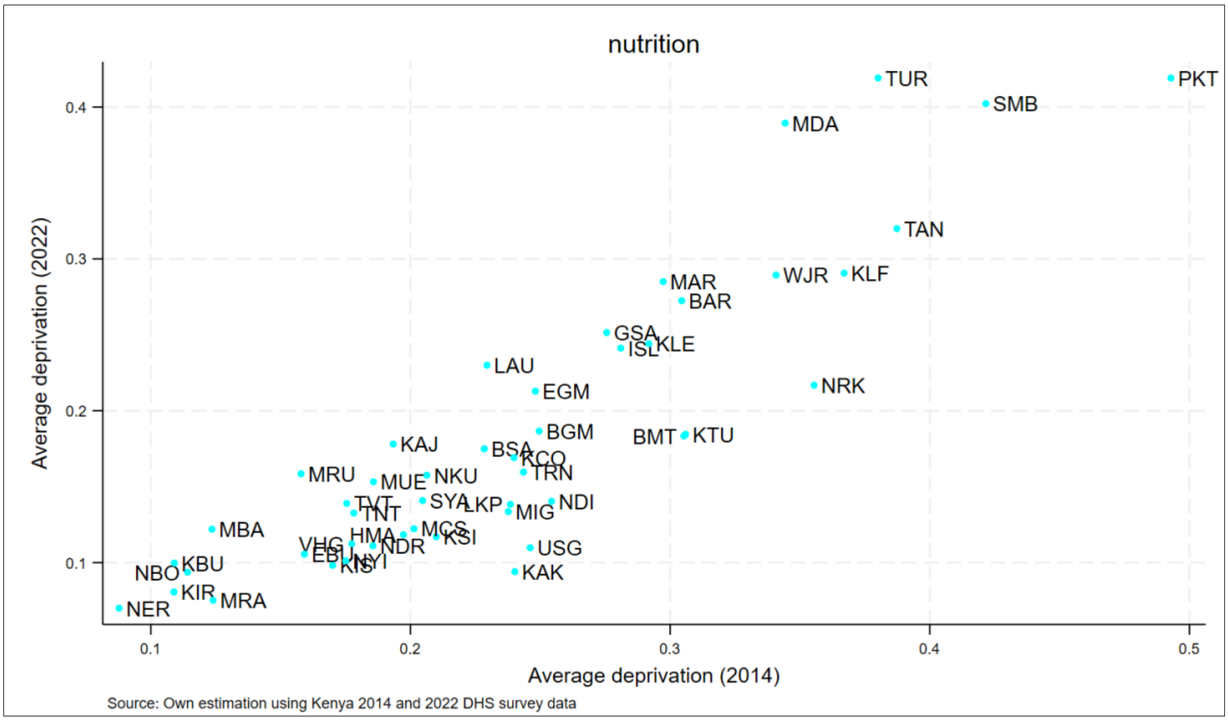


Figure A4: Average deprivations in the school attendance indicator across counties

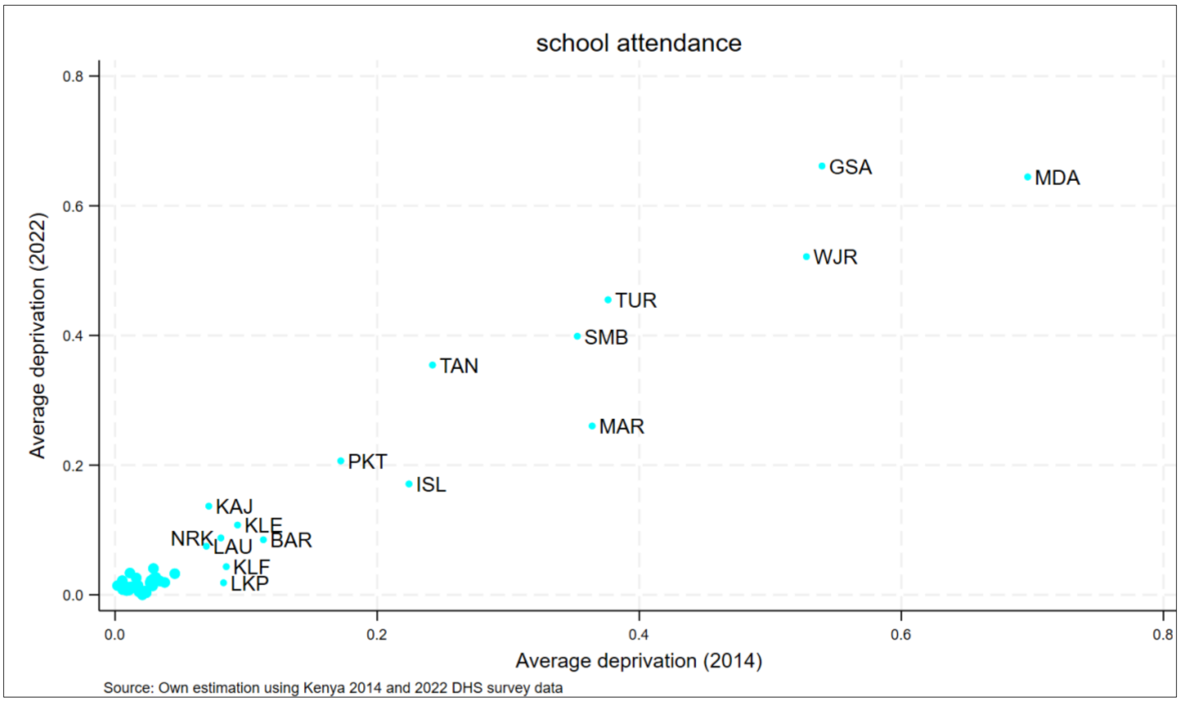


Figure A5: Average deprivations in the years of education indicator across counties

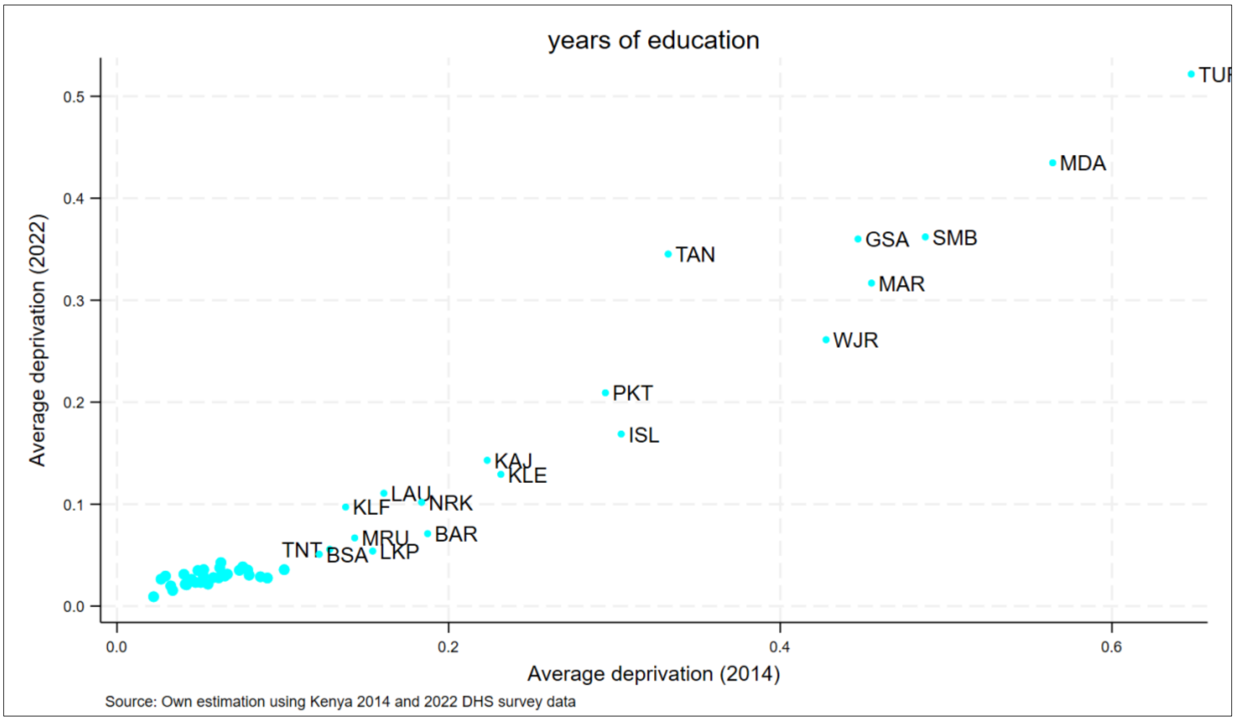


Figure A6: Average deprivations in the schooling gap indicator across counties

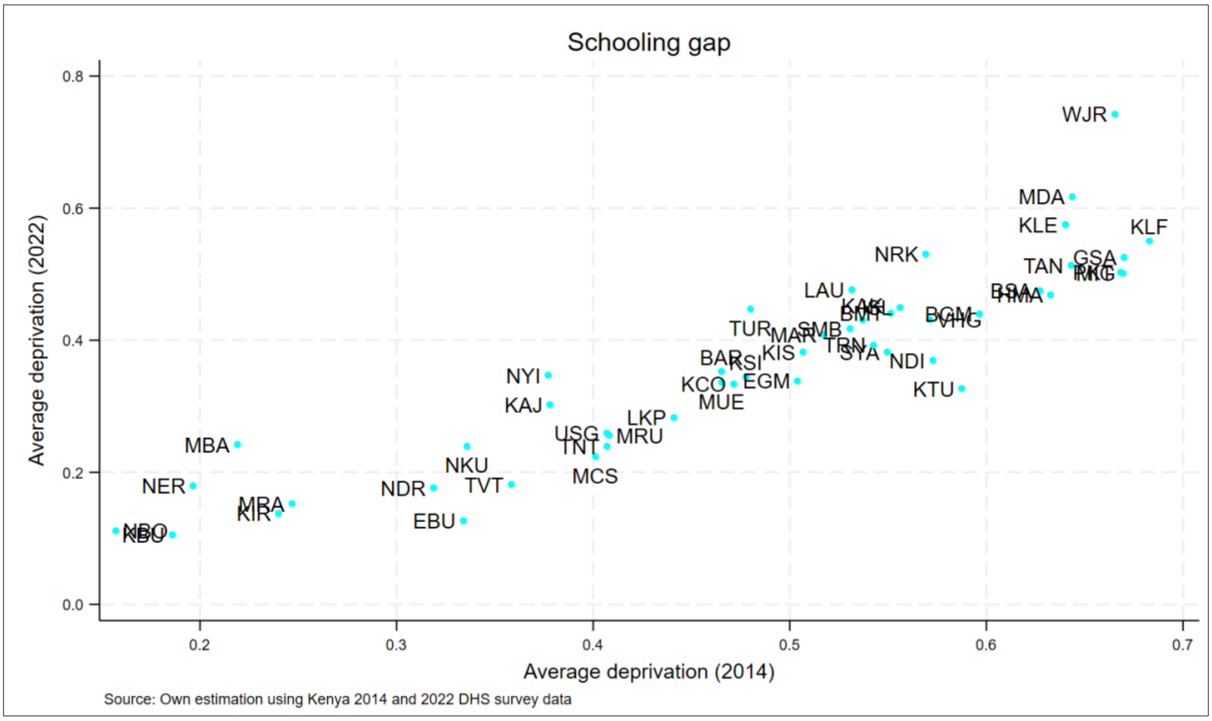


Figure A7: Average deprivations in the electricity indicator across counties

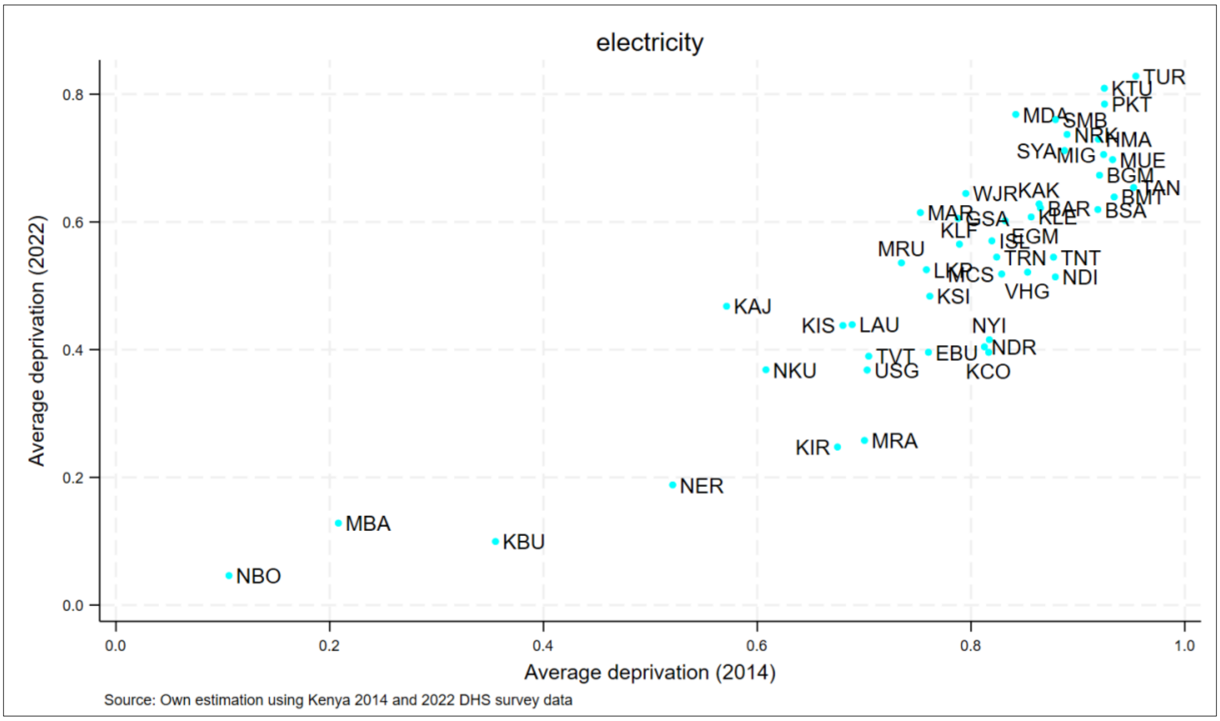


Figure A8: Average deprivations in the improved water indicator across counties

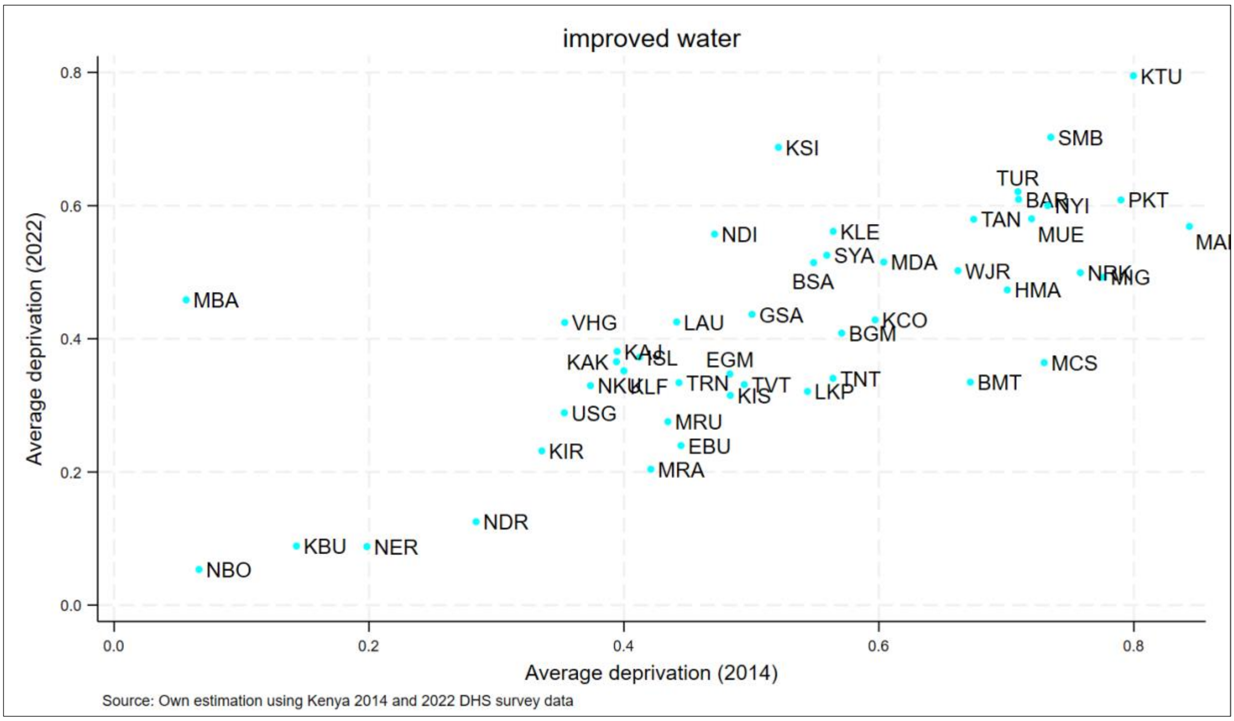
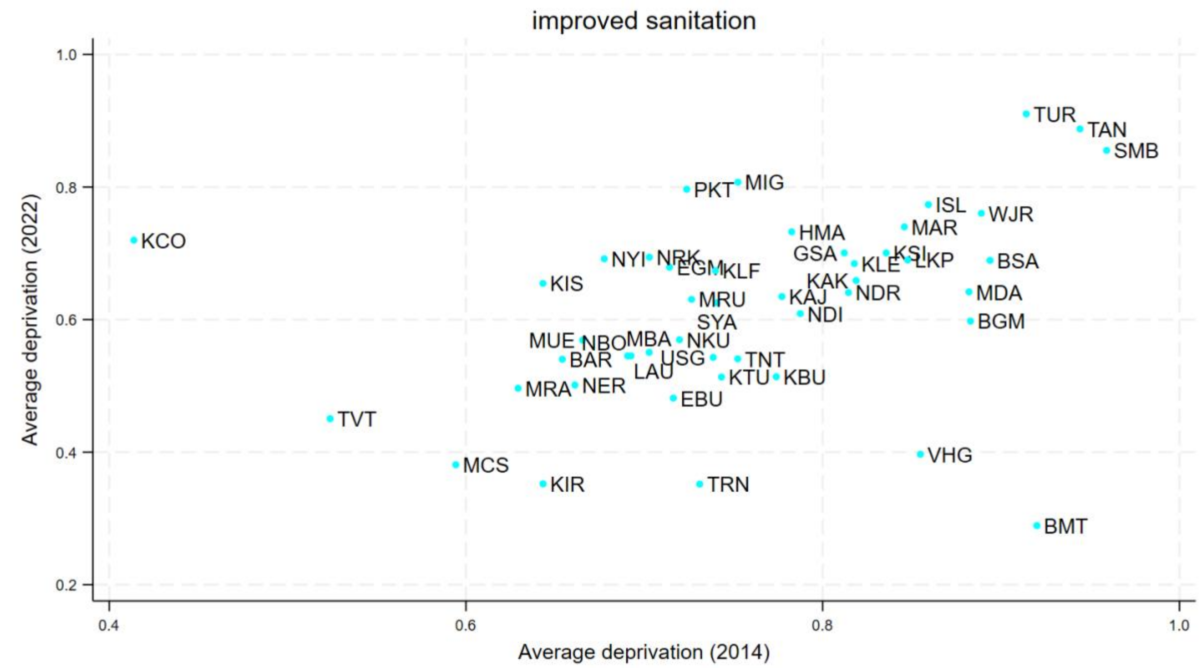
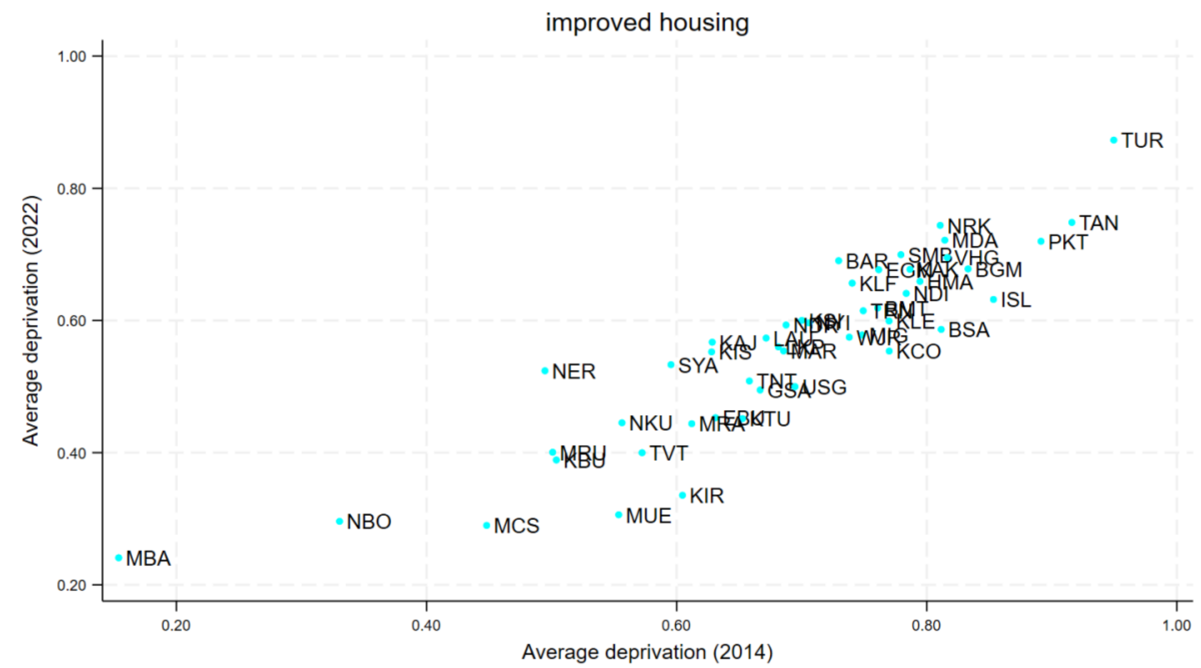


Figure A9: Average deprivations in the improved sanitation indicator across counties



Source: Own estimation using Kenya 2014 and 2022 DHS survey data

Figure A10: Average deprivations in the improved housing indicator across counties



Source: Own estimation using Kenya 2014 and 2022 DHS survey data

Figure A11: Average deprivations in the overcrowding indicator across counties

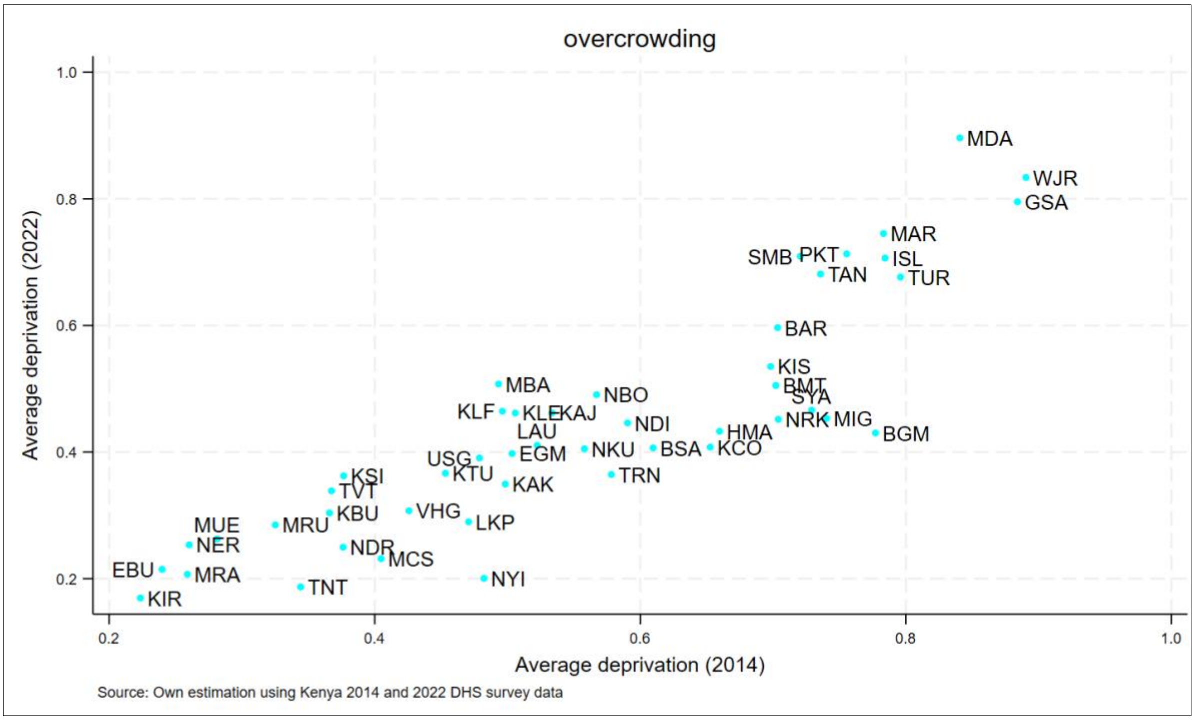


Figure A12: Average deprivations in the clean cooking fuel indicator across counties

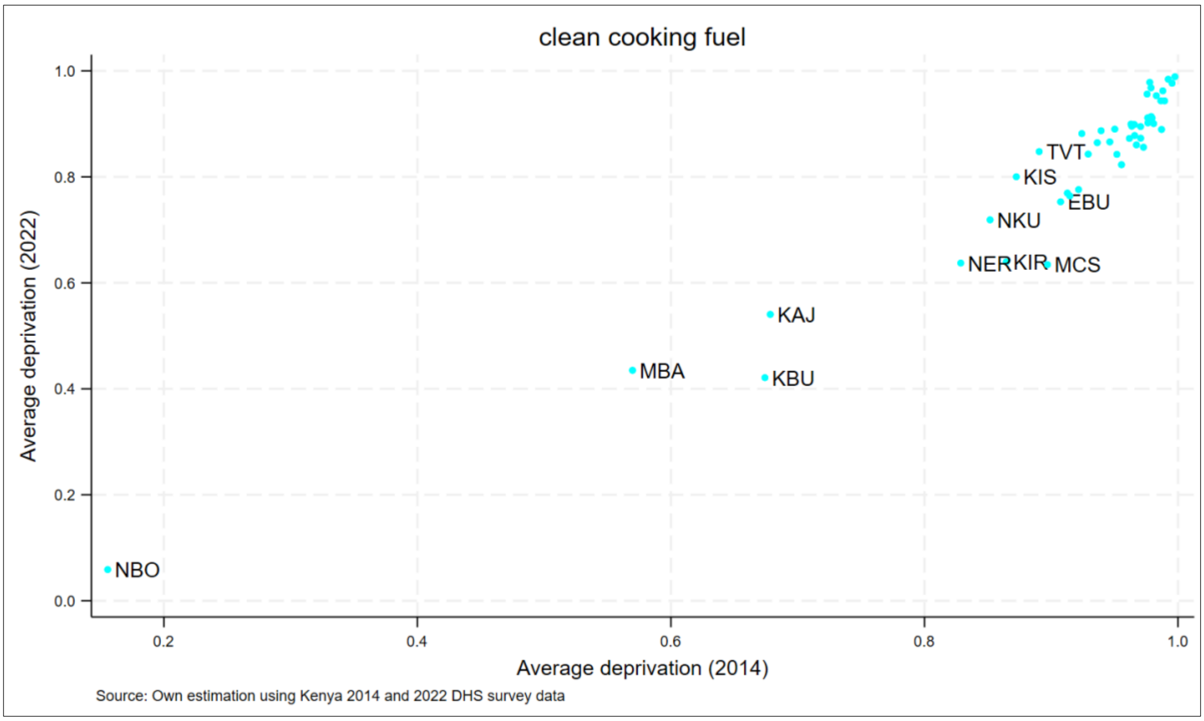


Figure A13: Average deprivations in the household assets indicator across counties

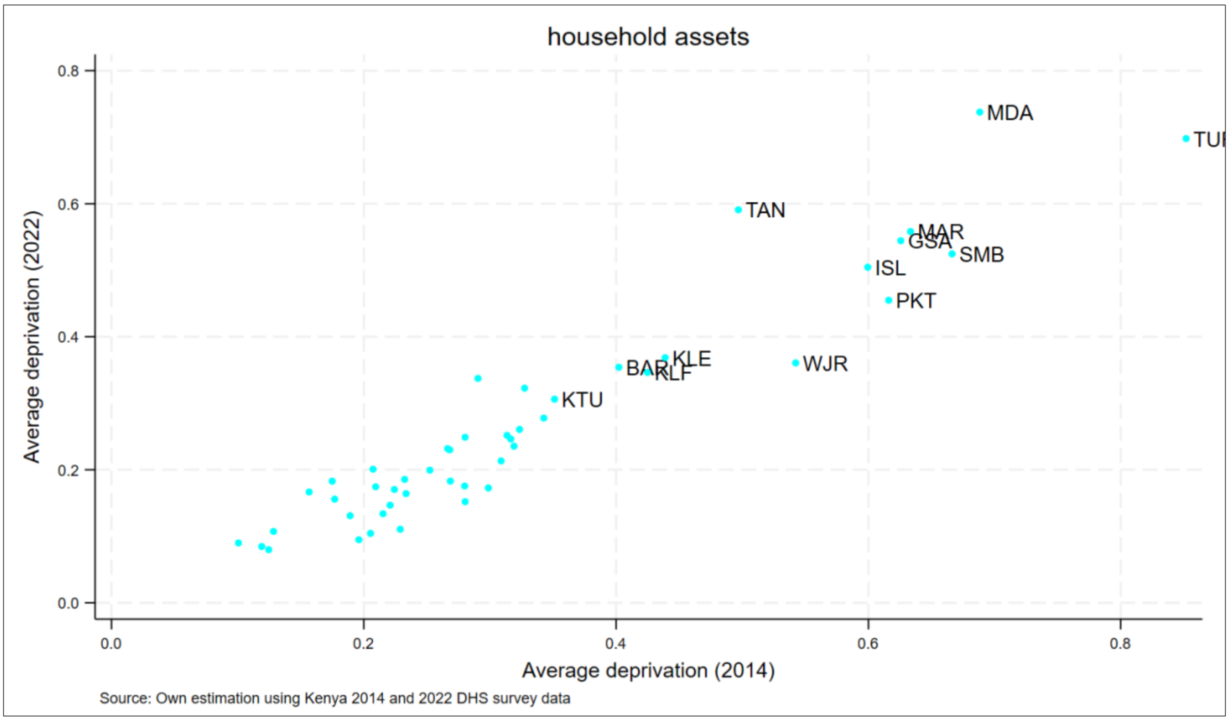
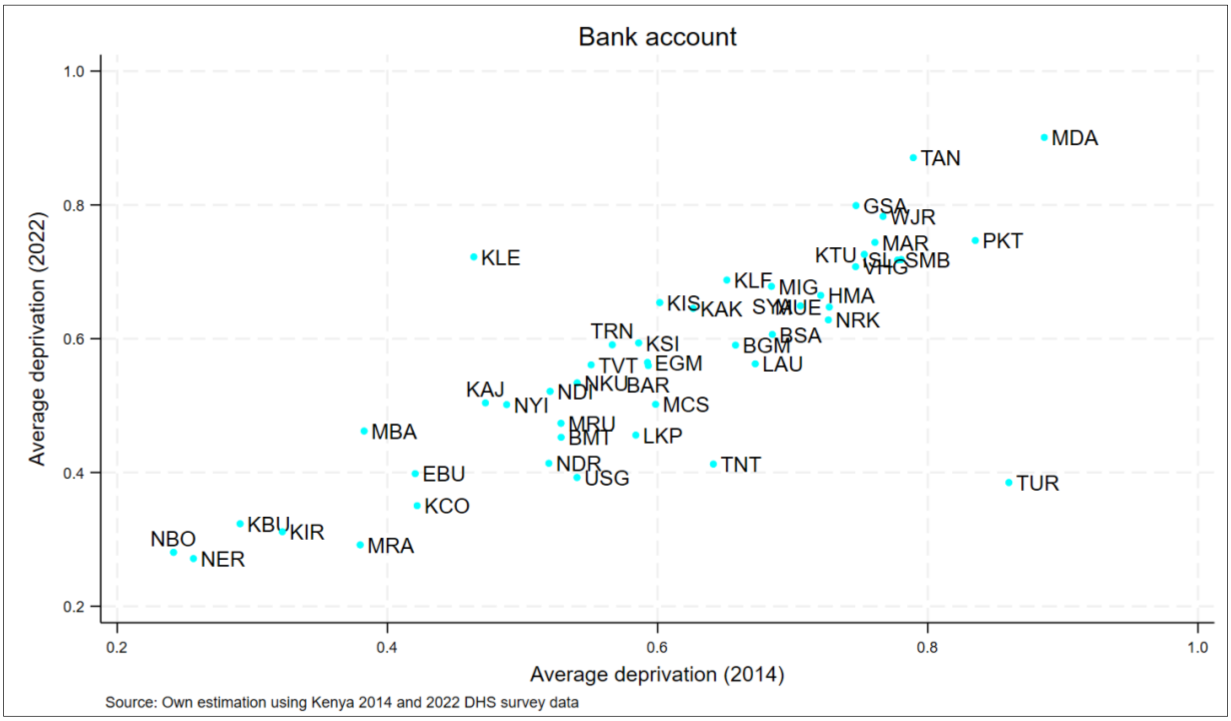


Figure A14: Average deprivations in the bank account indicator across counties



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