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Multidimensional Poverty Alleviation: Policy Optimization and Impact Simulation

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Abstract

This paper characterizes several models of state intervention for tackling multidimensional poverty, encompassing alternative scenarios regarding the policymakers’ capacity to allocate resources and tailor those resources for use by households that need them most. The models are applied to pairs of national demographic surveys in five Arab countries (Algeria 2011–2018, Egypt 2014–2018, Iraq 2011–2018, Mauritania 2011–2015, Tunisia 2011–2018), with the first rounds serving as the baseline and the second rounds serving as the time frame for achieving certain rates of poverty reduction, akin to the challenge presented by the 2030 Agenda. We evaluate the model's policy prescriptions against the observed record of changes in households’ multidimensional deprivations between the two survey rounds, and comment on the prospective policy choices revealed through those achievements. Our optimizations suggest that more cost-effective ways to reduce multidimensional poverty could entail targeting narrower subsets of living conditions. The results suggest that policymakers in Arab middle-income countries should prioritize allocation of more resources to the education sector, while policymakers in low-income countries such as Mauritania should allocate resources to education, housing and access to public services.

Keywords: Multidimensional poverty, Alkire-Foster approach, Poverty-reduction optimization, 2030 Agenda.
JEL Classifications: I32, I38, H5, N35.

ملخص

تتميز هذه الورقة بالعديد من نماذج تدخل الدولة لمعالجة الفقر متعدد الأبعاد، بما في ذلك السيناريوهات البديلة فيما يتعلق بقدرة صانعي السياسات على تخصيص الموارد وتكييف تلك الموارد لاستخدامها من قبل الأسر التي هي في أمس الحاجة إليها. يتم تطبيق النماذج على أزواج من المسوحات الديموغرافية الوطنية في خمس دول عربية (الجزائر 2011-2018، مصر 2014-2018، العراق 2011-2018، موريتانيا 2011-2015، تونس 2011-2018)، حيث تعمل الجولات الأولى كخط أساس والجولات الثانية بمثابة الإطار الزمني لتحقيق معدلات معينة للحد من الفقر، على غرار التحدي الذي يمثله جدول أعمال 2030. نحن نقيم وصفات سياسة النموذج مقابل السجل المرصود للتغيرات في "الحرمان متعدد الأبعاد للأسر بين جولتي الاستطلاع، ونعلق على خيارات السياسة المحتملة التي تم الكشف عنها من خلال تلك الإنجازات. وتشير تحسيناتنا إلى أن السبل الأكثر فعالية من حيث التكلفة للحد من الفقر المتعدد الأبعاد يمكن أن تستلزم استهداف مجموعات فرعية أضيق من الظروف المعيشية. وتشير النتائج إلى أن واضعي السياسات في البلدان العربية المتوسطة الدخل ينبغي أن يعطوا الأولوية لتخصيص المزيد من الموارد لقطاع التعليم، في حين ينبغي لواضعي السياسات في البلدان المنخفضة الدخل مثل موريتانيا أن يخصصوا الموارد للتعليم والإسكان والحصول على الخدمات العامة.

1. Motivation

Arab countries face recurring socioeconomic setbacks due to simmering conflicts and other manmade and natural crises, which have led to negative growth, state budget deficits, increases in inequality along some dimensions of welfare, and shrinking welfare state. Living standards of various socioeconomic classes have been held back along multiple dimensions. The region appears to be off track to meeting the 2030 Agenda's Sustainable Development Goals (SDG) related to deprivations in living conditions (UNDP, 2013, 2020), particularly the SDG target 1.2 calling for the halving of poverty in its various forms by 2030. Judging from the current rates of development, Arab countries would not make sufficient progress in alleviating social deprivations on all fronts (refer to figure 1). As we come nearer to the year 2030, we must therefore redouble our efforts to monitor and project trends in social deprivations and inequalities. Without adequate measurement and impact simulation, policies and efforts commonly adopted to alleviate socioeconomic deprivations may lead the society astray, as they may lead to inclusion and exclusion errors in targeting, and misdirection or over/under-allocation of scarce resources.

Poverty reduction hinges to a large extent on the performance of public programmes and initiatives, most manifestly the allocation of state/government budgets. Given its minor share in the budgets of Arab middle and low-income economies, enhancing efficiency and effectiveness is crucial to maximize the impact on poverty alleviation within the allocated funds. This imperative becomes particularly pronounced during times when economic crises are more frequent and severe, and the pace of recovery is sluggish.

Existing approaches to modeling changes in multidimensional poverty largely involve microsimulations (Tsui, 2002; Klasen, 2012; ESCWA, 2017, 2022, 2023a,b; Makdissi, 2021; UNICEF, 2022). These techniques estimate the changes induced in households' deprivations – and thus in the multidimensional deprivation matrix used to derive multidimensional poverty indices (MPI) – in response to external economic shocks. However, these simulations rely on several critical assumptions including 1) the simulation's targeting ability, 2) the trickle-down effects of economic shocks and policy responses on relevant indicators and households, 3) the capacity of the state to take effective action, and 4) the interlinkages between the affected indicators. Considering the repercussions of these simulations for public policy, it is essential to scrutinize their inputs and assumptions.

This study contributes to existing methodological literature by tackling the challenging questions related to how policymakers should allocate scarce resources with the aim of achieving specific rates of poverty alleviation. Four optimization models are presented, identifying efficient resource allocations given alternative sets of constraints on state intervention. Recognizing the importance of monitoring deprivations and poverty in all their diverse dimensions across the Arab region, with the view of attaining adequate progress on the Sustainable Development Agenda, we apply the models to five heterogeneous Arab countries (Algeria, Egypt, Iraq, Mauritania, Tunisia) and to a period spanning from 2011 to 2030.

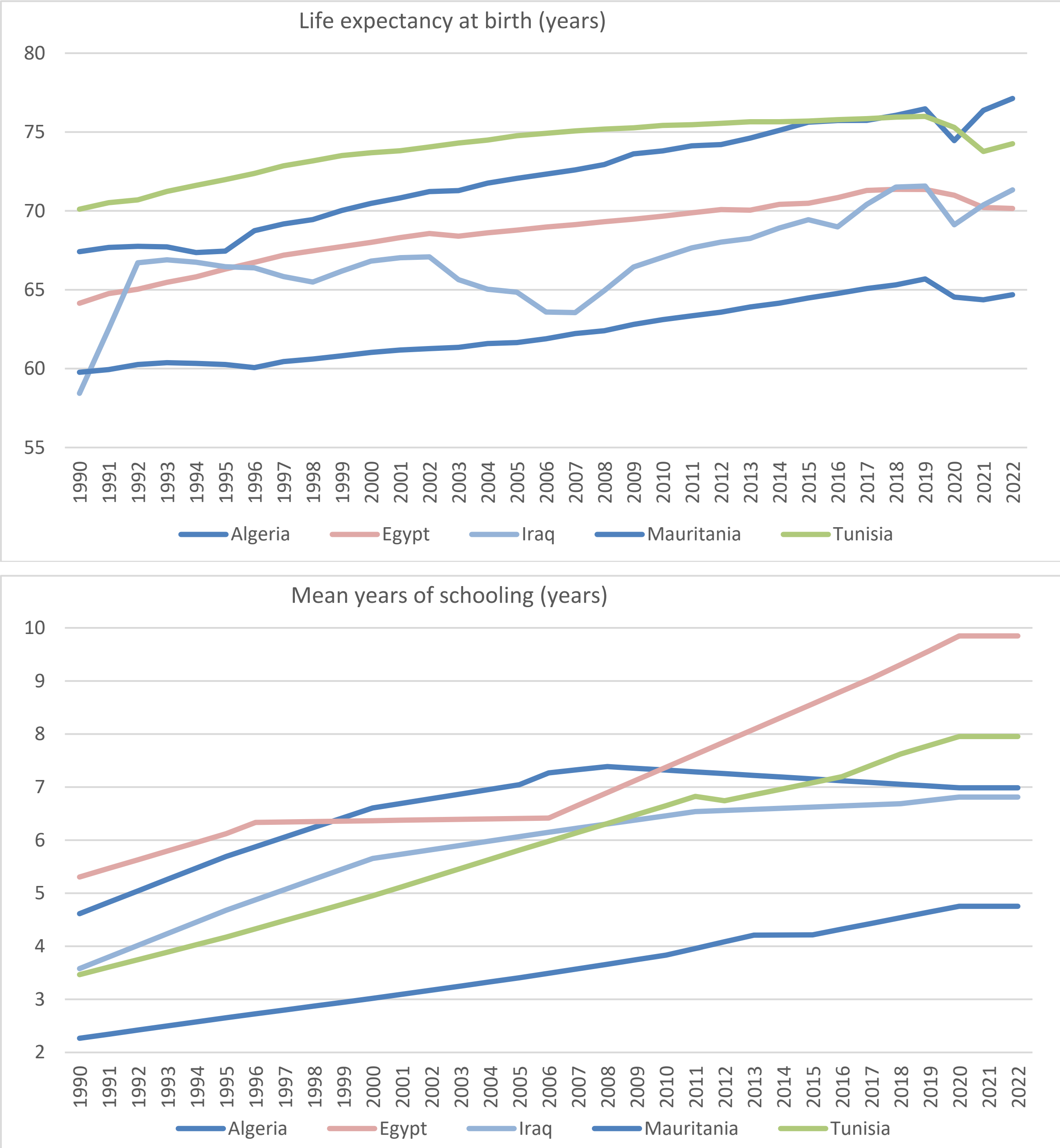
The four models are used to find the optimal poverty-reduction strategies given a set of constraints on the policymakers' ability to allocate resources of various kinds to various policy sectors and various demographic groups. The models are designed in a way to respect the axioms and constraints governing the mathematical formulation of the Alkire–Foster MPI (Sen, 1976; Alkire, 2011, 2014, 2021). Importantly, these models also allow for randomness in the impact of resource allocation on households' deprivations, and introduce an element of waste from imprecise targeting and from households' failure to derive the desired benefits from the resources allocated to them.

The analysis starts by arranging households' experiences – as evidenced through demographic-survey microdata – into a valid deprivation matrix. The logic, assumptions, and complete mathematical formulations of the four alternative MPI-reduction models are developed, and tested against micro-data from demographic surveys. The performance and the results of the four models are highlighted with the aim to support decision-makers in setting priorities, identifying cost-effective poverty-reduction interventions, and putting in place informational and administrative infrastructure conducive to the redistributive performance in the most cost-effective model scenario. That entails the policymakers' ability to identify and target deprived households, identify their needs and tailor the assistance to those needs, and ensure that the assistance leads to the satisfaction of those needs, without waste or spillovers on non-eligible households or non-targeted welfare dimensions.

Our findings suggest that multidimensional poverty reduction models can be successfully characterized and solved, while loosening some of the strong assumptions in micro-simulation regarding the states' ability to target poor households and tailor assistance to them, thus enabling policymakers to mobilize and channel resources effectively. The policy-scenario models can assist practitioners with limiting resource waste on non-critical dimensions of wellbeing and non-deprived population groups, and with identifying appropriate means for delivering assistance. In fact, our results confirm that policy scenarios that prevent the accurate targeting of population and accurate tailoring of assistance to specific needs achieve much lower cost effectiveness. The information environment and policy infrastructure are thus critical components affecting the success of poverty-reduction programmes.

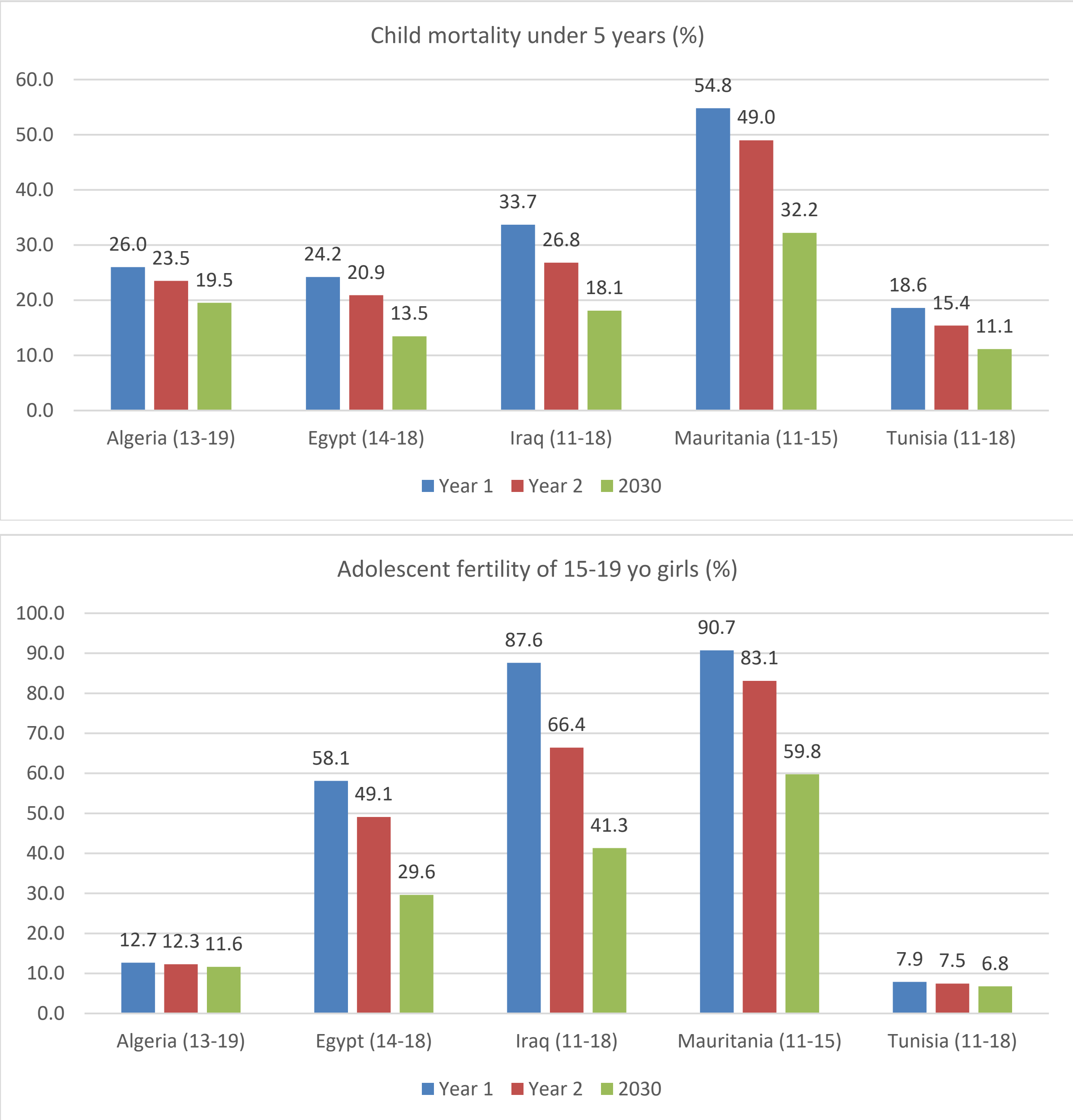
The rest of the paper is organized as follows. Section 2 reviews the rationale for the specific model scenarios considered for the analysis. Section 3 explains the derivation methods, and the application of the models to the data for five Arab countries. Section 4 presents the main results for poverty simulation and poverty reduction optimization under the one of the model scenarios. Finally, section 5 summarizes the key findings and offers concluding remarks and policy recommendations.

Figure 1a. Selected development indicators, 1990-2022



Source: Authors' calculations based on Human Development Reports indicators.

Figure 1b. Selected development indicators, extrapolation of existing trends to 2030



Source: Authors' calculations based on World Bank's World Development Indicators.

Notes: Year 1 refers to the first demographic-survey year under analysis; year 2 to the second survey year. Annualized growth rates between them are used for extrapolation.

2. Modeled policy scenarios

In the absence of full information and effective targeting mechanisms, states may enact misguided or costly policy interventions, potentially derailing the achievement of poverty reduction goals. Our analysis thus considers four distinct scenarios (or, models) of the impact of public policies on households' living conditions, particularly the multidimensional deprivations under analysis and households' resulting status as multidimensionally poor (MP).

Juxtaposing the results of the four models helps to inform the policy debate regarding the importance of the information environment and of the physical and legal capacity of policymakers to implement appropriately targeted and tailored interventions. The modules derive the scale and the form of the needed interventions, the relevant dimensions and indicators to prioritize (e.g., education, health sectors), and the specific geographic or sociodemographic units to target when implementing poverty reduction strategies.

To reach the solutions, integer linear-optimization models are characterized, each with distinct input requirements, assumptions, and targeting approaches. Despite their differences, all models converge on the same objective, addressing the policy questions, identifying priority interventions, and setting targeting priorities.

Mathematically, the search for a solution is consistent with a bottom-up approach, leveraging an existing household-level deprivation matrix with a new target matrix to effectively minimize the MPI while minimizing the state's resource outlay, or 'effort.' For consistency, "effort" encompasses all resources including fiscal disbursements, manpower, time allocation, and the political and logistical will needed to achieve a specific level of MPI reduction.

This section provides a high-level overview of each model's narrative, while the subsequent Section 3 lays out the relevant mathematical formulations.

Assumptions, and caveats of the models

The models presented in this paper rely on the following assumptions:

1. All normative assumptions established during the design and build up phase of the MPI framework (in the baseline year, preceding the implementation of the poverty reduction strategy) remain constant over time.
2. Interventions in one indicator do not to impact the deprivation status of households in other indicators, implying the independence of indicators.
3. Deprivation status is exclusively lifted for targeted households, with all other households unaffected throughout the entire planning horizon of the poverty reduction strategy. That is, there is no inclusion error in targeting.
4. It is not mandatory for all indicators to be targeted, as some may not be considered as sectors requiring consideration (due to various reasons, such as infrastructure may not have been established by policymakers yet, owing to constraints such as budget limitations, among others). The indicators that are not targeted are referred to as non-active indicators. Simulation results may reveal that only a subset of active indicators needs targeting. Achieving MPI reduction targets may be possible by concentrating efforts solely on this subset of indicators.
5. Efforts (resources) required to lift a deprived household out of deprivation in active indicators are assumed to remain constant across additional households (constant marginal cost) or over time (static).

6. MPI reduction targets are predetermined and unaltered over the planning and implementation horizon. The feasibility of these targets is evaluated in each model.
7. Non-poor households are excluded from transitioning into poverty (in the multidimensional context).

Model 1 – Household-level standard no-cost model

The first model is referred to as standard because it relies primarily on the poverty measures defined by the Alkire-Foster method. Poverty can be assessed at the indicator level: *Uncensored headcount* measures the total number of individuals deprived in a specific indicator, while *censored headcount* measures the population deprived in a specific indicator and at the same time multidimensionally poor. While both measures are absolute in nature, a high percentage of deprivation in an indicator may not necessarily translate into a high MPI. Similarly, an indicator with a high concentration of deprived and MP households may not contribute significantly to a high MPI. Hence, a third set of indicator-specific measures introduced by the Alkire-Foster method is crucial: The indicators' contribution to the MPI based on the weight assigned to it in the framework.

Hence, even by simply analyzing the percentage contribution of each indicator to the MPI policymakers can identify which indicators should be prioritized in poverty reduction strategies. The policymaker could allocate efforts to the appropriate sectors and evaluate the resulting alleviation of deprivations and poverty. If the MPI reduction targets are ambitious, efforts could be directed toward multiple of the most contributing indicators. Moreover, the allocation of effort may switch throughout the policy implementation period as the percentage contribution of various indicators evolves endogenously. An indicator deemed most influential at the onset of a social programme is likely to become less contributing over time compared to other indicators. Hence, it is imperative to adopt a dynamic or iterative model.

Model 1 prioritizes indicators that presently have the greatest impact on the MPI, and subsequently targets households deprived in these indicators, in the order of their censored deprivation score. Once the contribution of those indicators is surpassed by others – and if the MPI reduction target is still not met – the focus of interventions shifts to the indicators with the presently highest contribution.

Once the most contributing indicator is targeted, the model proceeds to identify the most deprived households. Here, two versions of Model 1 are introduced, one deterministic and another probabilistic. The first model specification, *Model 1a*, functions within a deterministic framework, under the assumption that the policymaker can precisely identify the households facing the most deprivations across various indicators, that is, the poorest households in the multidimensional sense.

By contrast, a probabilistic *Model 1b* introduces a more realistic approach where the policymaker's targeting policies are less efficient, making it challenging to locate and target the poorest households accurately. This could happen if policymakers observe deprivations only in the indicator in question, but not in other indicators, or policymakers cannot easily rank individuals in terms of their multiple deprivations. In terms of programme implementation, it could entail allocating (adequate) assistance to households randomly chosen from among those deprived, as happens during pilot or limited-financing programmes, or allocating lower assistance to all those deprived, with the result that only some beneficiaries become sufficiently lifted above a deprivation threshold.

The probabilistic approach thus acknowledges the inherent uncertainties or inefficiencies in programme implementation, recognizing that programmes such as cash-transfer schemes encounter challenges related to targeting accuracy, corruption, diversion of funds, and misuse by beneficiaries. The probabilistic model assumes randomness in the lifting of deprivations among households deprived in the currently most contributing indicator. In other words, those lifted out of their deprivation may not be the poorest multidimensionally, corresponding to inclusion and exclusion errors.

Model 2 – Household-level cost-minimizing (first best) model

Much like the deterministic Model 1a above, Model 2 assumes that the state has the capacity to locate and target deprived MP households. Model 2 aims to alleviate the deprivation status of MP households, leading to an efficient reduction in the MPI without allocating efforts to households that are not deprived in the targeted indicators and simultaneously are not the poorest in the multidimensional sense. Compared to Model 1, the indicator-based targeting is not based solely on how much indicators contribute to the MPI, but also on the amount of effort required to lift deprivations in those indicators.

By design, Model 2 focuses on targeting deprived and poor households with the objective of alleviating their deprivation in the indicator in question. In cases where the MPI reduction target is ambitious, the assistance to those households may stop short of lifting them entirely out of multidimensional poverty.

This model is not entirely realistic given its assumptions on the state's capacity to target specific households using detailed insights on their multiple deprivations. For instance, according to these assumptions: 1) The state has the necessary information and capacity to remove a single household from deprivation in a single indicator; 2) The state observes the deprivation status of all households across all indicators; and 3) The state can provide access to any tailored resources, and can limit the access to only those households who are deprived and multidimensionally poor. In other words, the state can prevent all inclusion and exclusion errors.

Through these properties, this model is analogous to a perfectly functioning programme allocating conditional cash transfers (or in-kind transfers, or smart cash-cards targeting specific deprivations), ensuring that the funds are used only for the targeted indicators, only by households deprived in them.

Model 3 – Geographic targeting model

Model 3 retains the assumptions under model 2 regarding the state's capacity to allocate multidimensional resources to various households, but it relaxes the restrictive assumption of the state's perfect knowledge or capacity for perfect targeting. Accordingly, the state can intervene in a uniform or random manner across all those who are deprived in an indicator, without the ability to consider their multidimensional poverty status. The state allocates efforts/ resources at a particular demographic (or geographic) level and observes how many households were (probabilistically) lifted out of deprivation, and lifted out of multidimensional poverty. The incidence of households being lifted out of deprivation by a certain intervention is random – only some households in the pool of all deprived households succeed at exiting deprivation, and only some of the latter households manage to exit multidimensional poverty. In terms of programme implementation, this could happen if the state is forced to select randomly whom to target among the deprived households in a demographic cell – for lack of information or ability to target better – or because the assistance per household is reduced in order to provide uniform aid to all those deprived in the demographic cell.

Aid allocation in Model 3 can produce changes for the following household types: MD poor household becoming MD non-poor; MD poor household staying MD poor, despite a subset of indicators being switched from showing deprivation to non-deprivation; and non-MD poor household staying as non-MD poor, with a subset of indicators being switched from showing deprivation to non-deprivation. Thus, by contrast to Model 2, where only multidimensionally poor households can undergo a reduction in deprivations, Model 3 permits MPI indicators of even non-poor households to transition from deprivation to non-deprivation. In addition to factoring in the cost of eliminating deprivation in each indicator, the model prioritizes households based on the results of two specific indicator ratios. First:

$$Ratio_{1,j} = \sum_{i=1}^{N} \frac{Household\ i\ Deprived\ in\ indicator\ j\ and\ at\ the\ same\ time\ is\ MD\ poor}{Household\ i\ Deprived\ in\ indicator\ j} \quad (1)$$

where $j = 1, \dots, n$ are the sets of indicators. The higher the ratio, the more likely that households deprived in indicator j are also multidimensionally poor. Second:

$$Ratio_{2,j} = \sum_{i=1}^{N} \frac{Deprived\ and\ MD\ poor\ household\ i\ \text{transitions to}\ nonMD\ poor, by\ just\ flipping\ its\ indicator\ j\ from\ 1\ to\ 0}{Household\ i\ Deprived\ in\ indicator\ j\ and\ \text{concurently}\ is\ MD\ poor} \quad (2)$$

The greater the value of Ratio 2, the more probable it is for the household poverty status to change by merely adjusting the household's deprivation score in a single indicator. Thus, the model singles out indicators with the highest scores on these ratios. This ensures the selection of households with the highest likelihood of being in a state of multidimensional poverty, and where a change in their deprivation is associated with a change in their multidimensional poverty status. If costs vary across indicators, the model also places emphasis on lower-cost indicators. It is worth noting that this targeting priority is estimated for each geographic area.

Under limited disaggregation, when population is concentrated in a few geographic areas, the ratio can be interpreted as a probability that a household will be successfully lifted out of poverty from receiving assistance. In the opposite extreme, under highly granular disaggregation, with each household situated in a unique geographic zone, the ratios will be either be zero or one, making the model's targeting approach near deterministic in nature. In that case, the optimization model path is straightforward, targeting households with a ratio of 1, and not targeting those with a value of zero. Model 3 then becomes analogous to Model 2.

Model 4 – Geographic & demographic targeting model

Given the alternative scenarios in models 1–3, which assumptions are best supported, considering the empirical capacity of states to target deprived populations across geographic regions, and the empirical patterns of aid allocation to individual households? Should the welfare programmes be modeled as budget allocations to centralized regional administrations (as in model 3), or should they be modeled as involving personalized aid distribution across narrower population groups?

Similar to the proxy means testing, which employs limited household characteristics information to gauge welfare levels by approximating households' purchasing power and needs, it is reasonable to assume that with such information, the state can be empowered to accurately target and address specific indicator deprivations through the strategic deployment of personalized aid transfers. Such indicators are labelled as private good indicators. In our context, the state can likely estimate this proxy using data on income and wealth, typically acquired through a survey.

By contrast, the state may possess significantly less information and capability to address public indicator deprivations among households, especially in the realm of access to utilities and services. To address these deprivations, the state may find it necessary to rely on more detailed information that is normally found in centralized regional administrations (at the level of population groups regions, or the entire country). This could involve addressing these issues through initiatives like public infrastructure projects. Furthermore, indicators are classified as either public or private goods based on whether households can obtain or manage them independently (private goods) or if public provision or coordination is necessary (public or coordination goods).

The stochastic approach of Model 3 is utilized for public-good indicators, concentrating on targeting households at the geographic population-cell level. As for the private-good indicators, the household targeting mechanism is reinforced by household cluster identifiers, particularly income-proxy subgroups. This approach achieves a commendable level of targeting efficiency, especially when the clustering method accurately identifies the households experiencing the most significant deprivation. Clustering entails grouping data using an unsupervised machine learning technique and partitioning the sample around a given number of median values. The data is the deprivation matrix of the private-good indicators, in addition to the income or expenditure vector proxy. This approach is used to identify how high incomes (or different consumption patterns) and deprivation levels at distinct groups of households.

Comparison of models

One can compare the results of the models and calculate the efficiency for each. Efficiency is determined by the post-optimized effort allocation of each model, resulting in an equivalent level of poverty reduction across all models. It is evident that models 1 and 2 are likely to yield the most efficient outcomes, given that a smaller number of deprived households needs targeting to achieve the same level of poverty reduction compared to other models. However, it's crucial to interpret the results with an awareness of the model assumptions and their alignment with reality. For more on the theoretical feature comparison between models, kindly refer to Table 1.

Table 1. Comparison of features of the proposed models

	Model 1a: HH-level, no-cost, deterministic	**Model 1b: HH-level, no-cost, probabilistic**	**Model 2: HH-level, variable cost, deterministic**	**Model 3: Geographic targeting**	**Model 4: Geographic & demographic targeting**
Any deprived household can be targeted	*N* *only those that are poor*	*N* *only those that are poor*	*N* *only those that are poor*	*Y* *but subject to exclusion error*	*Y* *but subject to exclusion error*
Resource waste from aid going to non-deprived households	*N*	*N*	*N*	*N*	*N*
Multidimensionally poor households targeted precisely	*Y*	*Y*	*Y*	*N*	*N*
Resource waste from aid going to poor households without lifting them from poverty (no effect on H)	*Y*	*Y*	*N* *except in rare cases, where MPI reduction targets are high*	*Y*	*Y*
Resource waste from aid going to deprived but non-poor households (no effect on I or H)	*N*	*N*	*N*	*Y*	*Y*
Private and public good deprivations distinguished	*N*	*N*	*N*	*N*	*Y*
State able to target/tailor cash transfers according to households' consumption patterns	*N*	*N*	*N*	*N*	*Y*
Resource waste in cash transfers from moral hazard (households using aid on non-deprivations)	*Y*	*Y*	*Y*	*Y*	*Y*

Source: Authors' compilation.

3. Empirical methods

Model 1 – Standard no-cost models

Input variables are categorized into two groups: original and computed variables. Original input variables are those provided directly by the modeler, while computed input variables are additional variables calculated before the optimization routine. Table A.1 provides detailed variable definitions. Decision variables are classified into two categories: external and internal decision variables. External decision variables are the variables that users can directly observe and result from the optimization process. Internal decision variables are introduced to facilitate the running of the optimization process or to transform logical constraints into linear ones. (Further details regarding this transformation can be found in the appendix 1) Households' status P_i is defined as follows:

$$'\forall i \in I, \qquad P_i = \begin{cases} 1, & if \sum_J M_{ij} \cdot w_j \ \geq \mathrm{k} \\ 0, & if \sum_J M_{ij} \cdot w_j \ < \mathrm{k} \end{cases} \tag{3}$$

That is, households are considered poor when $P_i = 1$. The contribution of households to the MPI, C_i, is:

$$\forall i \in I, \qquad C_i = \begin{cases} \sum_J M_{ij} \cdot w_j \ \cdot HS_i \cdot HW_i, & if \ P_i = 1 \\ 0, & if \ P_i = 0 \end{cases} \tag{4}$$

MPI and poverty headcount H are defined as:

$$MPI = \frac{\sum_I C_i}{\sum_I HS_i \cdot HW_i} \qquad H = \frac{\sum_I HS_i \cdot HW_i \cdot P_i}{\sum_I HS_i \cdot HW_i} \tag{5}$$

The intensity of poverty, I, is obtained by the ratio of MPI to the poverty headcount H. Uncensored Headcount UH_j considers the concentration of deprived households in an indicator. The higher the number of deprived households in an indicator, the higher the uncensored rate. MPI contribution considers the concentration of deprived and poor households in an indicator as well as the weight of the indicator.

$$UH_j = \frac{\sum_I M_i * \mathrm{HW_i} * HS_i}{\mathrm{HW_i} * HS_i} \qquad MPI\_Cont_j = \frac{W_j * \sum_{i=1}^{n} M_i \ * \mathrm{HW_i} * HS_i * P_i}{\sum_{i=1}^{n} \mathrm{HW_i} * HS_i} \tag{6}$$

The MPI contribution could also be normalized, so that the sum of the MPI_Cont_j is equal to 1. This is done to easily locate the most contributing indicator and compute its contribution as the percentage relative to other indicators.

Model 1 prioritizes addressing the indicator that has the greatest impact on the MPI initially and subsequently targets – within the most contributing indicator – deprived households, without consideration of cost and budget constraints. This process is carried out iteratively until the poverty reduction target is achieved, as follows:

$$\frac{\sum_I C_i}{\sum_I HS_i \cdot HW_i} \leq MPI_s \cdot (1 - MPI_r) \tag{7}$$

At each iteration, priority is assigned to targeting the indicator with the greatest contribution to the MPI. As noted in the preceding section, two configurations of that model have been set up.

In the deterministic model, the policymaker is assumed to have the capability to identify the most contributing indicator and subsequently directs attention to households experiencing severe deprivation, not only in the prioritized indicator but also across all other indicators. In this scenario, households with the highest C_i score are consistently being targeted. By contrast, the probabilistic model identifies the most contributing indicator at the outset but then employs a random targeting approach instead of focusing exclusively on the most deprived households. Consequently, the households selected for targeting may not necessarily have the highest C_i.

The deterministic version of model I can be resolved in a single simulation run. Conversely, the second version lends itself to a probabilistic interpretation, accommodating a more realistic scenario, in which the state is assumed to have limited information, on the status of deprivation for all households across all indicators. To validate the probabilistic model results and policy recommendations, calculations should be iteratively solved. This approach, known in the literature as Monte Carlo simulation, generates diverse outcomes by accounting for random variables, specifically within the context of household targeting within selected indicators.

Mathematically, this entails conducting additional tests to assess the robustness of outcomes. Specifically, there is a need to examine the sufficiency of the number of iterations for "random sampling." This involves testing whether the sample size is adequate to accurately represent the mean of the population, which is inherently unknown. We refer to the Central Limit Theorem, writing $E(X) = \mu$ and $Var(X) = \sigma$, to obtain

$$P\left(\left|\frac{\overline{X_n} - \mu}{\sigma/\sqrt{n}}\right| > z_{score}\right) = \text{Threshold} \tag{8}$$

There is approximately a 95% probability that the sample mean $\underline{X_n}$ is within the distance of $1.96 \times \frac{\sigma}{\sqrt{n}}$ of the true mean μ. As the degree of precision increases, the threshold decreases, and the needed sample size increases. Depending on the required level of precision, the minimum number of simulations, denoted as n, can be calculated. An in-depth interpretation of the n results can then be performed to further assess the uniqueness and robustness of the outcomes and policy recommendations. This involves observing the convergence of simulation-run results toward a consistent policy narrative. Key considerations include determining whether the poverty reduction target is consistently achieved, examining other MPI disaggregation such as headcount poverty and intensity, and assessing the stability of the ranking of indicators that need to be targeted across all simulation runs. Additionally, it is crucial to evaluate the consistency in the ranking of geographic regions in the simulation results.

Model 2 – Household-level targeting model

The three remaining models are classified as integer linear programming, given that both the objective function and constraints follow linear patterns, and certain decision variables take integer values. Specifically, Model 2 aims to minimize the total resources (or effort) allocated for poverty reduction purposes:

$$min \sum_{J} E_j \tag{OBJ 2}$$

The objective function in those models is bound by the following constraints. First, deprivations can only be eliminated, and cannot increase in number.

$$\forall i \in I, \forall j \in J, N_{ij} \leq M_{ij} \tag{Con 1}$$

Household contribution to the new MPI can be estimated. In logical form, this means:

$$\forall i \in I, \sum_{J} N_{ij} \cdot w_j \ \geq k \Rightarrow C_i = \sum_{J} N_{ij} \cdot w_j \ \cdot HS_i \cdot HW_i \tag{Con 2}$$

$$\forall i \in I, \sum_{J} N_{ij} \cdot w_j \ < k \Rightarrow C_i = 0 \tag{Con 3}$$

The value of optimized allocated resources (effort) by indicator are then estimated:

$$\forall j \in J, E_j = EpF_j \cdot \sum_{I} HW_i \cdot (M_{ij} - N_{ij}) \tag{Con 4}$$

The resources allocated to each indicator are constrained by minimum and maximum thresholds:

$$\forall j \in J, E_j \geq l_j \qquad \forall j \in J, E_j \leq u_j \qquad \text{Con 5 \& 6)}$$

The post-optimization MPI is the sum of the contributions to the MPI by all households divided by population (sample-weighted).

$$\frac{\sum_I C_i}{\sum_I HS_i \cdot HW_i} \leq MPI_s \cdot (1 - MPI_r) \tag{Con 6}$$

Model 3 – Geographic targeting model

Model 3 assumes that the effort is exercised at the level of population cells (geographic regions) d. Additional variables are introduced. Those variables are listed in table A.2.

Efforts are now computed at the level of population cells and indicators.

$$min \sum_{J} \sum_{D} E_{jd} \qquad \text{(OBJ 3)}$$

That function is subject to all constraints listed in Model 2 with some adjustments. Most notably, constraint 4 is replaced by:

$$\forall j \in J, \forall d \in D, E_{jd} = EpF_j \cdot \sum_{I[d]} HW_i \cdot (M_{ij} - N_{ij}) \qquad \text{(Con 4*)}$$

Constraints 5 and 6 are replaced as follows:

$$\forall j \in J, \sum_{D} E_{jd} \geq l_j \qquad \forall j \in J, \sum_{D} E_{jd} \leq u_j \qquad \text{(Con 5* \& 6*)}$$

Additional constraints are introduced to address the stochastic impact of efforts E_j on indicator j and its effect on household deprivation scores. The total number of deprivation switches that E_{jd} induces is E_{jd}/EpF_j switches in column j of the deprivation matrix. The probability that household i has its indicator j switched because of effort E_j is:

$$min\left(\frac{E_{jd}/EpF_j}{\sum_{i' \in I[d_i]} M_{i'j}}, 1\right) \qquad (9)$$

Accordingly, given the random matrix R (whose cells are random numbers generated from the uniform distribution [0,1]), household i has its indicator j switched to non-deprivation because of effort E_j when the following condition holds:

$$R_{ij} \leq \frac{E_{jd}/EpF_j}{\sum_{i' \in I[d_i]} M_{i'j}} \qquad (10)$$

In logical form, those conditions translate to:

$$\forall i \in I, \forall j \in J, R_{ij} \leq \frac{\frac{E_{jd}}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \Rightarrow N_{ij} = 0 \qquad \text{(Con 8)}$$

$$\forall i \in I, \forall j \in J, R_{ij} > \frac{\frac{E_{jd}}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \Rightarrow N_{ij} = M_{ij} \qquad \text{(Con 9)}$$

These conditions guarantee that every household facing a deprivation in indicator j, and located in a certain geographic zone, has an equal likelihood of being alleviated from deprivation through an intervention.

Model 4 – Geographic & demographic targeting model

Model 4 assumes that effort is applied at the geographic cell level for public indicators and at the type of household level for individual indicators, utilizing the same probabilistic approach as employed in Model 3. Additional variables are listed in table A.3.

Let $J = U \cup V$ where U represents index of individual indicators and V index for public indicators; I set of HH index; D set of region index. In addition, we consider T index of different types of Households.

$$min\left[\sum_{j\in U}\sum_{t\in T} E_{jt} + \sum_{j\in V}\sum_{d\in D} E_{jd}\right] \tag{OBJ 4}$$

That function is subject to all the constraints found in Model Two, with some additions. Most notably, the following equation is added to constraint 4*

$$\forall j \in U, \forall t \in T, E_{jt} = EpF_{jt} \cdot \sum_{i\in I[t]} HW_i \cdot (M_{ij} - N_{ij}) \tag{Con 4**}$$

Constraints 10 and 11 are added to the model

$$\forall \mathrm{t} \in \mathrm{T}, \forall i \in I[t], \forall j \in \mathrm{U}, \mathrm{if}\ R_{ij} \leq \frac{\frac{E_{jt}}{EpF_{jt}}}{\sum_{I[t]} M_{ij}} \Rightarrow N_{ij} = 0 \tag{Con 10}$$

$$\mathrm{t} \in \mathrm{T}, \forall i \in I[t], \forall j \in \mathrm{U}, R_{ij} + bigM \cdot \left(1 - b3_{ij}\right) > \frac{\frac{E_{jt}}{EpF_{jt}}}{\sum_{I[t]} M_{ij}} \tag{Con 11}$$

Empirical application to Arab countries

The revised Arab MPI is comprised of 5 dimensions and 14 indicators, all with predefined thresholds designed to consistently capture moderate levels of multidimensional deprivation. The health and education dimensions reflect the social and non-material well-being of individuals, each carrying a 25% weight and consisting of three equally weighted indicators. Both health and education have enduring impacts on various aspects of well-being, influencing individuals' cognitive abilities, knowledge, school-to-work transition, and employment opportunities. The remaining three dimensions focus on the living standards of individuals, specifically housing, access to services, and assets. These material well-being dimensions are equally weighted (1 / 6) and contribute to the overall multidimensional assessment. Aligning with the 2030 agenda, all dimensions and indicators collectively form an integral part of the poverty assessment framework. The classification of multidimensional poverty applies to households with a weighted deprivation score (C_i) exceeding 20%, chosen to better capture moderate forms of poverty. Additional details of the framework are available in Table A.4. All 14 indicators are measured across five countries, except for Egypt's early pregnancy indicator, for which there is no available data from the demographic and health survey conducted in 2014 and the household income and expenditure survey conducted in 2018.

The revised Arab MPI framework, unlike the global MPI, focuses on capturing deprivations more specific to Arab middle-income countries rather than acute or extreme poverty. The SDG target 1.2 mandates that by 2030, governments must strive to reduce, at least by half, the proportion of men, women, and children of all ages living in poverty across all its dimensions, as per national definitions. The global MPI framework, not constituting a national definition and inconsistent with the standards of living in middle-income countries, is not aligned with this objective. This misalignment is a significant factor prompting the authors to opt for a revised framework that closely adheres to the SDG definition.

Aligning development policies and programmes with these poverty indices can enhance the design of targeted initiatives, addressing the severity and multidimensional definition of poverty. Any poverty reduction strategy in the region should prioritize stability and security, recognizing that recurrent episodes of conflict and violence hinder poverty alleviation efforts. In addition to the four middle-income Arab countries—Algeria, Egypt, Iraq, and Tunisia—this study also includes the lower-middle-income Mauritania, all utilizing the revised Arab MPI. For all five countries and all the available surveys, MPI measurements were conducted using the same benchmark framework. Acknowledging the evolving nature of poverty definitions amid economic development, the authors opt for an absolute poverty definition, allowing for consistent measurement against the same benchmark over a relatively short period (decade) and across countries.

Data

To calculate the revised Arab MPI and provide simulated and optimized results to non-survey years, we use pairs of surveys for five middle-income Arab countries: Algeria (2013-19), Egypt (2014-18), Iraq (2011-18), Mauritania (2011-15) and Tunisia (2011-18). These surveys (detailed in Table A5) span the relatively stable period between the wave of Arab spring uprisings of 2011, and the outbreak of COVID-19 in 2019, facilitating the comparison of households' deprivations between survey rounds. Except for Mauritania, no country conducted a survey in 2015, making it challenging to measure progress in the MPI from 2015 to 2030. To address this issue, we advocate for a more pragmatic approach that recognizes the observed changes made in certain countries (e.g., Algeria) beyond 2015. The proposed targets required to meet the SDG in 2030, based on the most recent observed survey year, for each country, are outlined in Table A.6. For instance, in Algeria, achieving a 50% reduction in MPI between 2015 and 2030 (considering the newly computed and interpolated MPI in 2015) requires a 20% reduction in the MPI index from 2019 (the latest observed survey in that country) to 2030. This reduction reflects the observed and achieved improvements between 2015 and 2019.

Beginning with the application of Model 1, its utilization serves two primary objectives. First, it is applied for out-of-sample-testing to evaluate the model's performance against observed changes. The model is applied individually to each country, spanning the period between the two observed survey years. The first observed survey serves as the baseline year, with the MPI-reduction target set to be achieved in the second observed year. Taking Algeria as an example, the Algerian MPI diminished by 47% between the observed years of 2013 and 2019. This reduction renders Algeria's MPI in the year 2019, of 0.054, the MPI value that shall be achieved post-optimization.

Out-of-sample testing is typically conducted in forecasting analyses to compare model results with observed data that were not used for parameterizing the model. In this analysis, the observed poverty rates in the countries' second observed years are used to assess how reasonable and feasible the simulated and optimized results are, even though the observed values may not reflect sound welfare programmes rolled out during the inter-survey period.

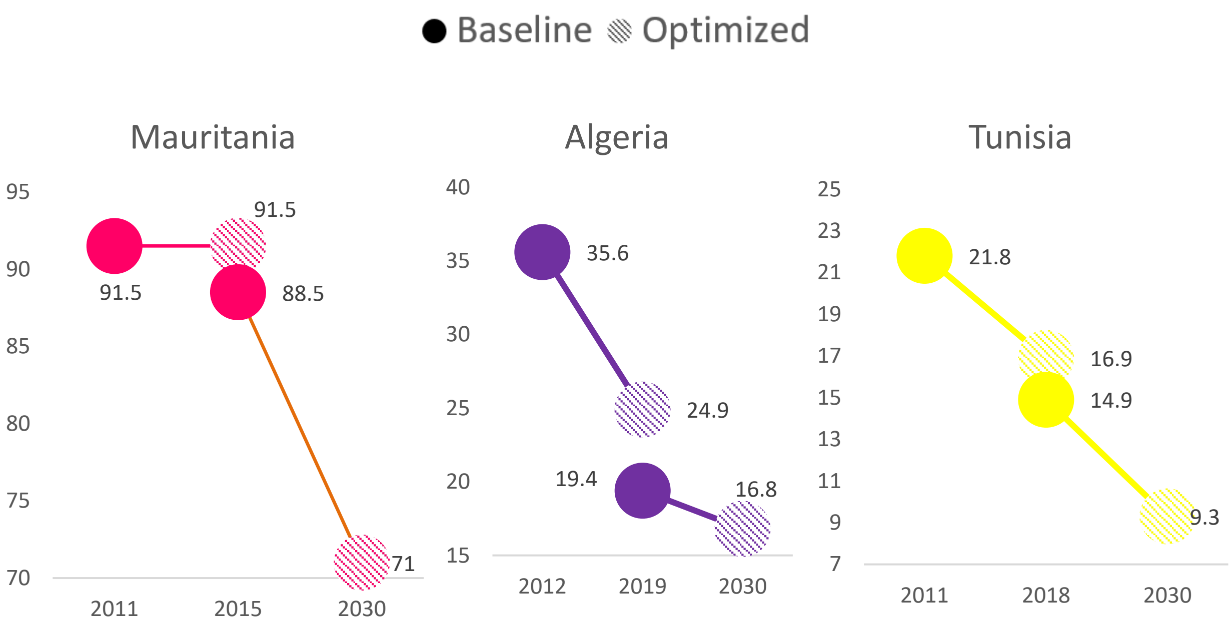
This evaluation aids in comparing the evolution of the MPI as measured by programmes with the results of the optimization model. While the reader lacks clear information on policies enacted or setbacks encountered during the inter-survey period, this comparison remains valuable. In an ideal scenario, disregarding external factors and focusing on the most contributing MPI indicators, the Alkire-Foster method is designed to guide policymakers toward the most optimized approach for reducing MPI. External factors are linked to state capability, resources, and efforts at hand (as defined in previous sections in models 2, 3 and 4). Any external factor, such as war or political instability, enforced on the business-as-usual conditions in that country over time, can also impact the results. With this in mind, the comparison becomes useful and interesting.

Secondly, the optimization routine is also applied to investigate the feasibility of reaching the SDG target 1.2 by 2030. This exploration aims to identify the most appropriate targeting paths that policymakers should adopt from the latest observed survey onward.

4. Main results

Observing the declining trend in MPI values between the paired surveys (Table A.5 and Figure 2a), it becomes apparent that all these countries have made progress in reducing poverty. While the degree of improvement varies among nations, the percentage change indicates a noticeable reduction in MPI, especially in the four middle-income countries: Algeria, Egypt, Iraq and Tunisia. The poverty threshold remains constant throughout the inter-survey period. As previously emphasized, this consistency is vital for cross-survey comparability and ensures a uniform measurement across space and time. When comparing the levels recorded in the initial year of observation with those in subsequent years (spanning from 2011 to 2019), most countries exhibit a decrease in the poverty headcount ratio (Figure 2b). In terms of absolute difference, Algeria stands out with the most substantial decline in the headcount ratio, dropping from 35.6% to 19.4%. Algeria has also made the most progress in reducing its MPI and headcount values (Figures 2a and b). Algeria ranks lowest among the five countries in terms of the relative improvement in intensity over the period (Figure 2c). This suggests that the majority of the MPI reduction can be attributed to individuals transitioning out of poverty. However, those remaining classified as poor have not experienced substantial improvement, and the poverty gap has remained near constant, decreasing only from 28.8% to 28%. The reduction in poverty headcount is more significant in relative terms for all countries across time, when compared with the reduction in poverty intensity. Nevertheless, the recent reduction in both poverty intensity and the headcount ratio throughout this period, for all countries, remains significant. Operating within the framework of the AF method, where the MPI is the product of both poverty headcount and deprivation intensity, any alteration in the deprivation status of one or multiple households consistently results in a more substantial MPI reduction if it concurrently leads to a change in the households' poverty status.

Figure 2a. MPI time trends: Observed vs. simulated



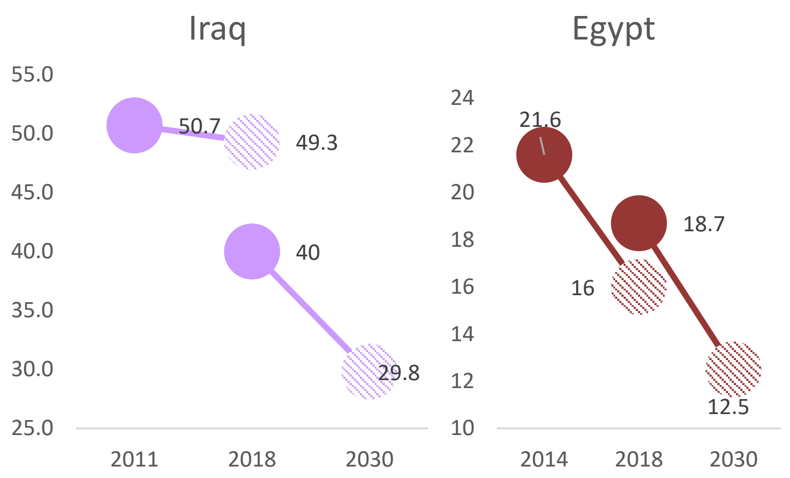
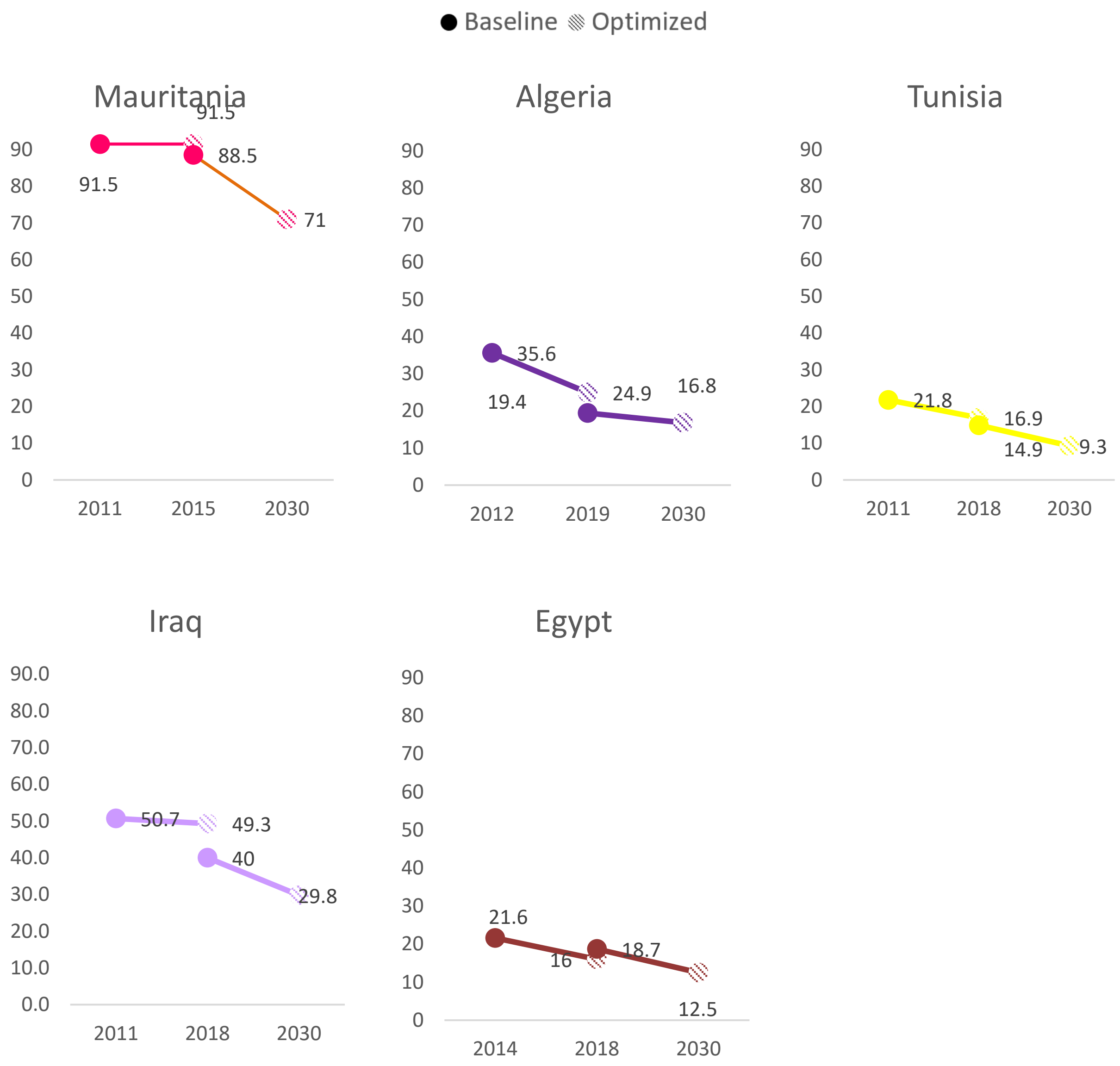
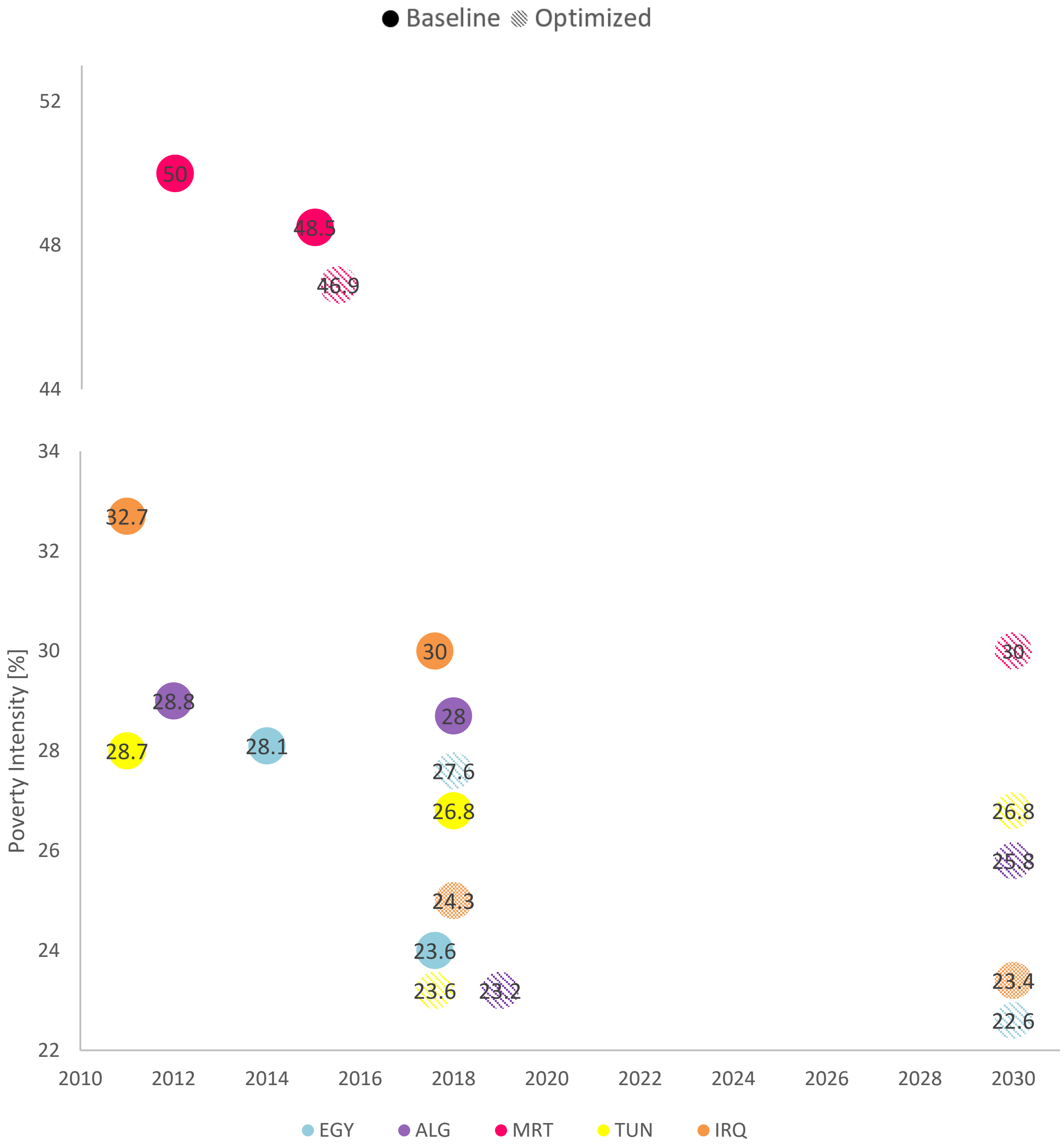

Iraq
55.0
50.0
45.0
40.0
35.0
30.0
25.0
50.7
49.3
40
29.8
2011
2018
2030
Egypt
24
22
20
18
16
14
12
10
21.6
18.7
16
12.5
2014
2018
2030

Figure 2b. Poverty headcount time trends: Observed vs. simulated



Source: Authors' calculations.

Figure 2c. Intensity of poverty time trends: Observed vs. simulated



Source: Authors' calculations.

Comparing results between out-of-sample results and first observed survey

The out-of-sample (optimized) findings reveal that nearly all countries, with the exception of Egypt, exhibit higher poverty headcount ratios when compared to the year during which the second survey for each country is conducted (Figure 2b and Table 2). When analyzing the comparison between the results of both observed years as scenario one, and the optimized results of year 2 against the baseline results of year 1 as scenario two, it becomes evident that Egypt has experienced a more substantial poverty reduction (Headcount H) in the latter scenario, with a 5.6% reduction in absolute difference terms, by contrast to the 2.9%

reduction observed in scenario 1. However, the reverse holds true for the remaining four countries (Algeria, Iraq, Mauritania, and Tunisia – check Figure 2c and Table 2).

Table 2. Poverty headcount and intensity results for various scenarios across the 5 countries

Scenario	Country	MRT	EGY	ALG	TUN	IRQ
1	Delta H - Observed Y2 vs. Observed Y1	-3	-2.9	-16.2	-6.9	-11
2	Delta H - Optimized Y2 vs. Observed Y1	0	-5.6	-10.7	-4.9	-1
1	Delta I - Observed Y2 vs. Observed Y1	-1.5	-4.5	-0.8	-1.9	-3
2	Delta I - Optimized Y2 vs. Observed Y1	-3.1	-0.5	-5.6	-5.1	-8

Source: Authors' calculations.

This implies that, among the targeted deprived households in Egypt, more often than not (in probabilistic terms), these households are finding success in graduating from poverty. In the remaining countries, while certain deprivations are alleviated, leading to a reduced level of multidimensional deprivations among the poor, the probability of successfully transitioning out of poverty is comparatively lower than that recorded in Egypt. One plausible explanation for this phenomenon is that a significant proportion of Egyptian individuals living in poverty are situated near the poverty line threshold. Upon scrutinizing the poverty intensity for all countries at their first survey year baseline, it is noteworthy that Egypt has the lowest intensity. Consequently, even minor changes in the welfare status of these individuals, whether an improvement or regression, directly impact their poverty status—resulting in either graduation from poverty or a descent into poverty.

Taking a closer look at the uncensored headcount time trend, which measures the share of the total population deprived in an indicator across indicators and comparing the results of the baseline year (first observed survey year) with the optimized results, we find that for all countries, the age schooling gap is consistently being targeted, indicating a persistent focus on addressing this indicator. In addition to addressing the age schooling gap, the model consistently targets the indicators of mobility assets, overcrowding, and school attendance in middle-income countries.

When comparing the uncensored headcount ratios across indicators results in the second observed year and contrasting them with the optimized results:

The model typically does not target households experiencing deprivations in the dimensions of access to services, and health & nutrition. This suggests that the model does not consider household deprivations in indicators such as drinking water, sanitation, electricity, child nutrition, child mortality, and early pregnancy. Consequently, there is no change in deprivation levels in those indicators as per the model's targeting approach.

The primary focus of targeting is concentrated in the education dimension (specifically schooling gap indicator), followed by dimensions related to assets and housing. It is noteworthy that if the available survey data had allowed for the inclusion of indicators on education quality, deprivations might have increased further. Persistent deficits in the quality of education and knowledge over the years have played a role in widening the skills and knowledge gaps between education and labor market outcomes. The primary reason lies in the design of the model, which directs its indicator targeting approach toward the dimensions/ indicators that contribute the most to MPI. Figure 8 illustrates that the education dimension is the foremost contributor to MPI in the first survey year across the five countries.

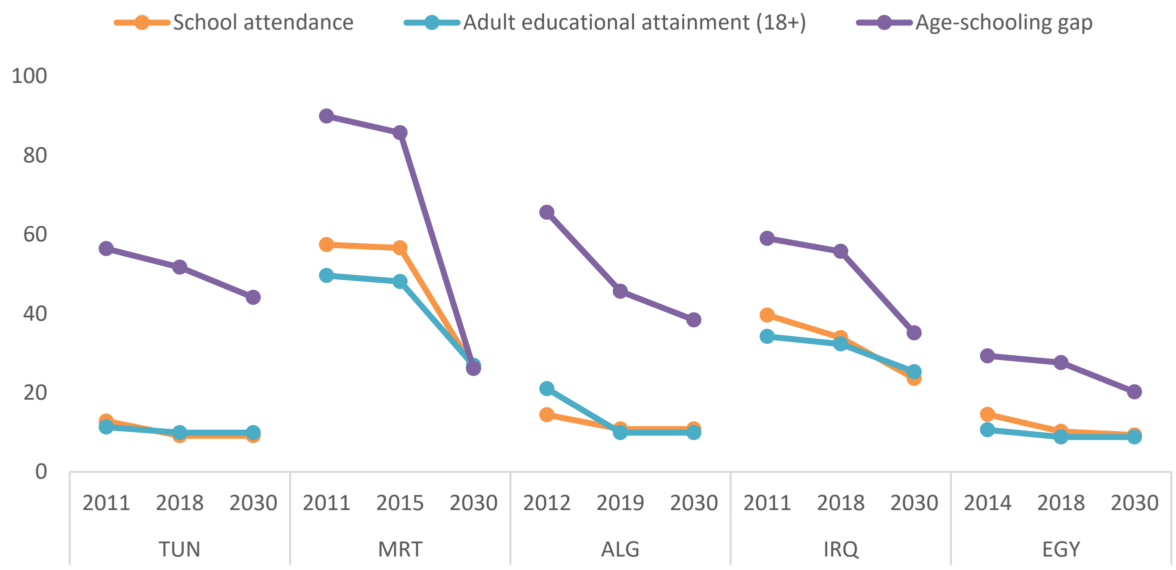
Trends in multidimensional poverty, 2011-2030

Previous results offer valuable insights into crucial metrics such as MPI, poverty headcount ratio, intensity of poverty, uncensored headcount by indicator, and MPI contribution by dimension. The analysis spans the time frame from 2011 to 2030 and focus on five chosen Arab countries. The country-specific trend line begins with data points reflecting results from the two observed surveyed years, while the 2030 values correspond to the optimized results.

While MPI, poverty headcount, and poverty intensity show a decreasing trend across the observed years for all countries, this is not uniformly reflected. More specifically, not all indicator-specific uncensored headcount ratios exhibit a decline over the specified period (Figure 3, 4, 5, 6 and 7). In particular, the provision of drinking water poses a persistent nationwide challenge (Figure 4) for Tunis, Algeria, and Egypt, with its uncensored poverty headcount experiencing an increase during the initial two periods of the time trend.

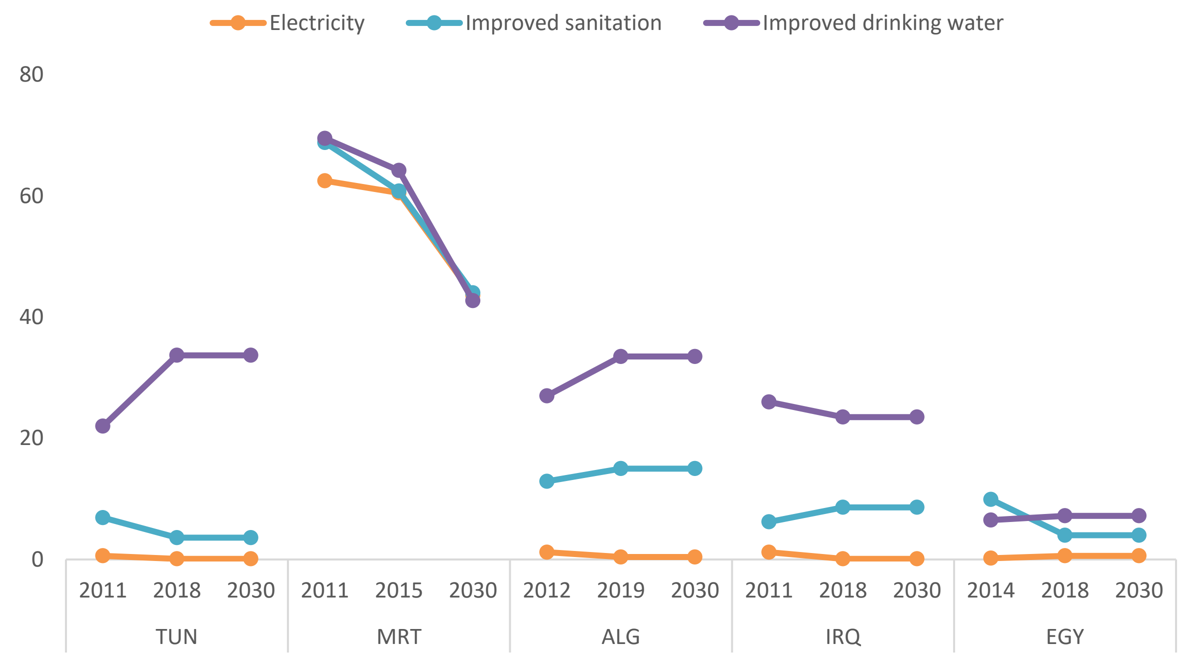
This implies that during the inter-survey period, the sector may have encountered challenges due to either insufficient policy and investment emphasis from the respective governments or a scenario where the sector was not considered a policy priority. In either case, some households have witnessed a deterioration in their welfare conditions over this time. However, according to the optimization findings, a decrease in indicator-specific welfare conditions for households is not tolerable. Consequently, welfare levels can be improved by directing efforts toward deprived households, effectively eliminating their deprivation, or they may be considered ineligible for targeting, allowing their deprivation to persist.

Figure 3. Uncensored headcount time trend by indicator [Education dimension] country - 2011 to 2030



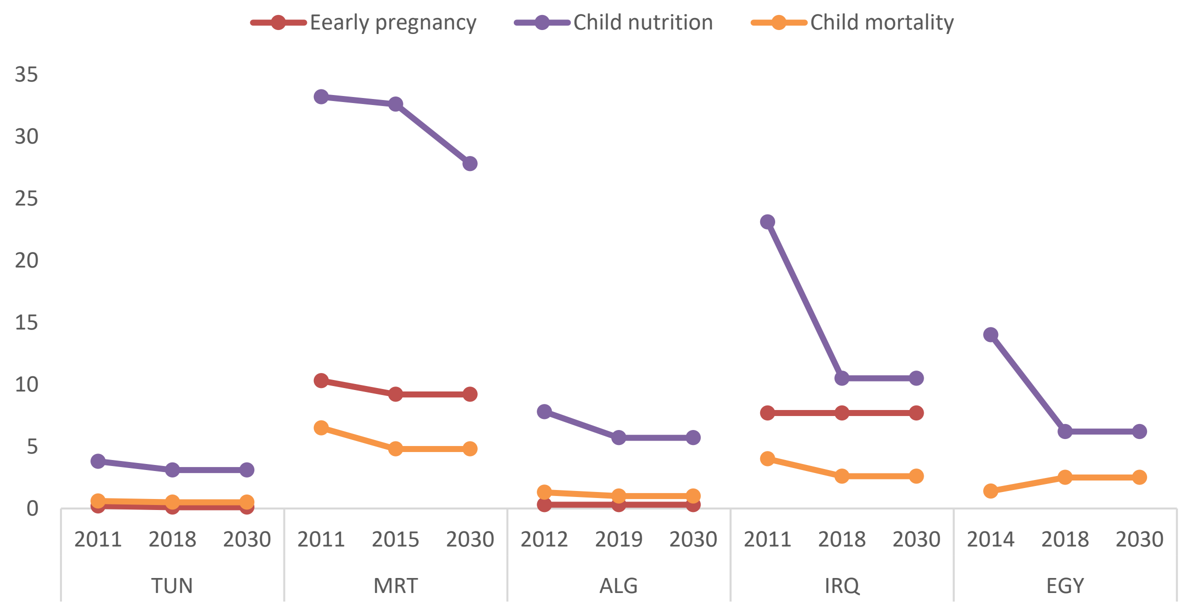
Source: Authors' calculations.

Figure 4. Uncensored headcount time trend by indicator and country, 2011 to 2030: Access to services dimension



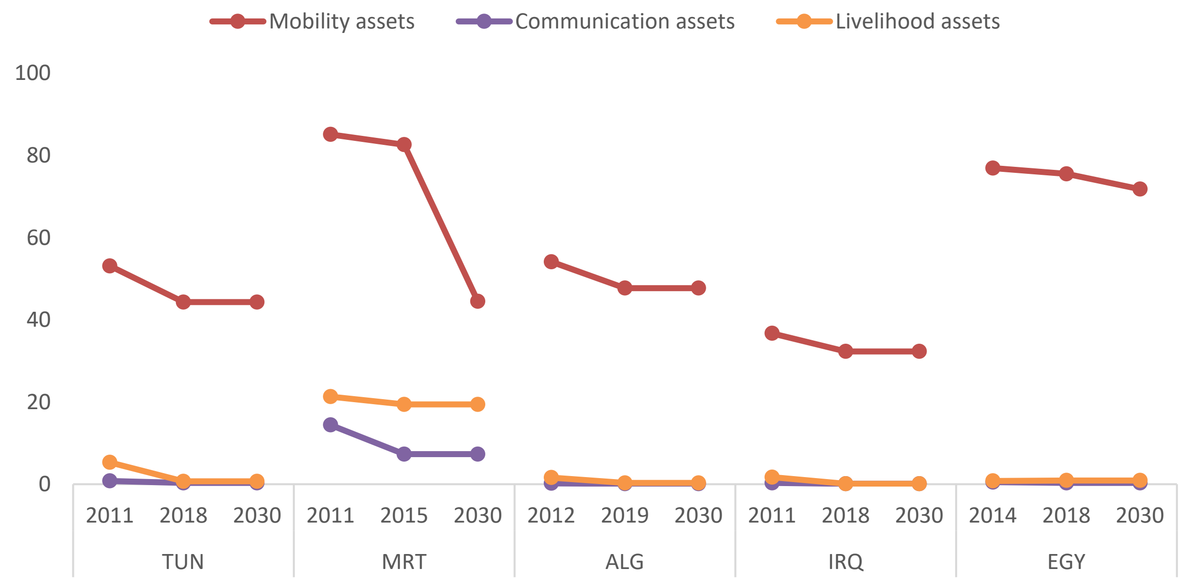
Source: Authors' calculations.

Figure 5. Uncensored headcount time trend by indicator and country, 2011 to 2030: Health & nutrition dimension



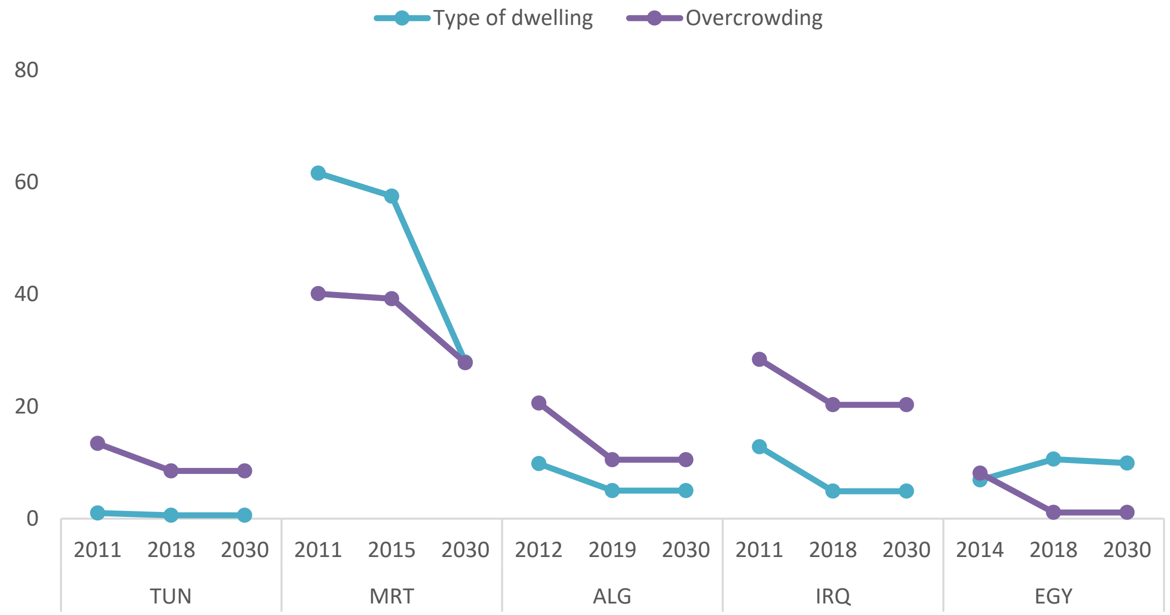
Source: Authors' calculations.

Figure 6. Uncensored headcount time trend by indicator and country, 2011 to 2030: Asset dimension



Source: Authors' calculations.

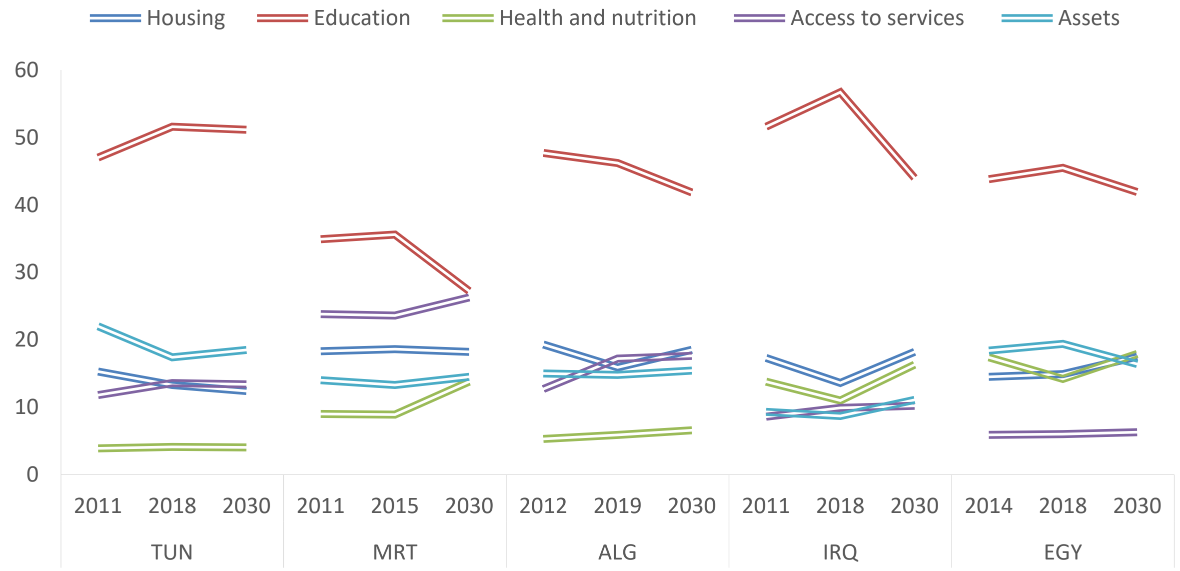
Figure 7. Uncensored headcount time trend by indicator and country, 2011 to 2030: Housing dimension



Source: Authors' calculations.

The 2030 results appear promising, revealing a consistent decreasing trend across all countries and various poverty measures. Furthermore, across all five countries, households experiencing deprivations in all three indicators within the education dimension consistently observe a reduction over the period extending until 2030. This underscores the imperative for policymakers to prioritize the education sector if they aim to achieve SDG target 1.2. The outcomes for the year 2030, as illustrated in Figure 8, indicate a decline in the MPI percentage contribution for the education dimension across all countries. This trend is attributed to the optimization model's focused targeting of households deprived of education-related indicators. Notably, this dimension holds the highest contribution to MPI in both observed survey years for all countries. However, for the low-income country of Mauritania, enhancement in the education sector alone is insufficient. To achieve their SDG target by 2030, Mauritanian policymakers must address all indicators within the education, housing, and access to services sectors/ dimensions. Additionally, they should focus on enhancing the health and well-being of children, particularly by improving their nutrition. The model also indicates that policymakers in both Egypt and Mauritania should address the mobility assets indicator to ensure the attainment of their SDG targets.

Figure 8. MPI percentage contribution time trend by dimension and country, 2011 to 2030



Source: Authors' calculations.

Additional country-specific time trend results for the following variables can be found in appendix 2: MPI indicator percentage contribution and censored headcount ratio. Additionally, the annex presents disaggregated poverty results based on geographic areas.

5. Discussion

This study has contributed a formal analysis assisting national planners in identifying tailored interventions for prioritizing household-level support to tackle multidimensional poverty. First and foremost, our findings indicate that successful characterization and resolution of new multidimensional poverty reduction models can be achieved, challenging some of the rigid assumptions in micro-simulation regarding states' capacity to target impoverished households and customize assistance. Also critically, the comparison of outcomes from alternative policy scenarios reveals that the information environment and policy infrastructure are critical components affecting the success of poverty-reduction programmes, and must be modeled carefully.

Within the Arab region, the standard no-cost model is applied across five countries with middle and low incomes. For each country, the analysis delves into two observed surveys covering the relatively stable period from 2011 – in the wake of the wave of Arab spring uprisings – to the onset of the COVID-19 outbreak in 2019. The MPI measurements are conducted using the revised Arab MPI framework. While acknowledging the evolving nature of poverty definitions, the authors choose an absolute constant poverty definition over time for consistency purposes.

The application of the model serves two primary objectives: Conducting out-of-sample testing to evaluate its performance against observed changes. The model spans the period between the two observed survey years, with the MPI value from the first year serving as the baseline. The level of the MPI value in the second observed year is set as the target for attainment. Additionally, a second optimization routine is employed to track poverty measurements against SDG target 1.2 by the year 2030, suggesting optimal targeting paths for policymakers to adopt. To the best of the authors' knowledge, this manuscript represents the first attempt in the literature to track multidimensional poverty over the two-decade span from 2011 to 2030.

Comparing results between observed surveys over the first decade reveals a significant reduction in both poverty intensity and the headcount ratio across all countries, albeit at different paces. This consistent observation offers valuable insights, underscoring that effective reduction in MPI is achieved as changes in the deprivation status of households align with shifts in their poverty status. While MPI, poverty headcount, and poverty intensity exhibit a decreasing trend across the observed years for all countries, it's noteworthy that not all uncensored headcount ratios by indicator demonstrate a decline. Particularly, access to drinking water remains a persistent challenge, with its uncensored poverty headcount increasing during the initial two periods of the time trend for most middle-income countries.

Analyzing out-of-sample results, the primary emphasis in targeting is on the education dimension, particularly the schooling gap indicator, followed by dimensions related to assets and housing. The model tends to overlook households facing deprivations in access to services, health, and nutrition dimensions, leading to no change in deprivation. This is ascribed to the model's design, which steers its indicator targeting toward dimensions with the greatest contribution to MPI.

Putting their SDG 2030 target 1.2 to the test and quantifying the necessary measures to achieve it, results indicate that all four middle-income countries can efficiently reduce half of the proportion of all their citizens living in poverty across all dimensions by concentrating solely on the single dimension of education. However, Egypt must also prioritize the mobility asset indicator to ensure the attainment of its target. By contrast, for Mauritania to achieve its target optimally, almost 10 out of the 14 indicators must be targeted. In the forthcoming paper, models 2, 3 and 4 will be applied to the same subset of countries using the revised Arab MPI framework. In these models, state intervention, encompassing its capacity to allocate specific resources and, crucially, policymakers’ proficiency in transferring these resources to the households most in need, will be put to the test.

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Appendix 1

The linear equivalent for some of the constraints shall be derived. We note the following equivalence:

$$A \Rightarrow B \equiv B \vee \neg A$$

Therefore enforcing $A \Rightarrow B$ is equivalent to enforcing $B \vee \neg A$. The latter is enforced if at least one of the two sides of the "or" relation is imposed.

Starting with Model One, constraints 2 and 3 are displayed in logical form. Constraint 2 is equivalent to:

$$\forall i \in I, \left(C_i = \sum_J N_{ij} \cdot w_j \cdot HS_i \cdot HW_i \right) \vee \left(\sum_J N_{ij} \cdot w_j < k \right)$$

which is equivalent to the following three linear constraints where $b1_i$ are binary decision variables and $bigM$ is a sufficiently large number:

$$\forall i \in I, C_i + bigM \cdot b1_i \geq \sum_J N_{ij} \cdot w_j \cdot HS_i \cdot HW_i \qquad \textit{(Lin 1)}$$

$$\forall i \in I, C_i - bigM \cdot b1_i \leq \sum_J N_{ij} \cdot w_j \cdot HS_i \cdot HW_i \qquad \textit{(Lin 2)}$$

$$\forall i \in I, \sum_J N_{ij} \cdot w_j - (1 - b1_i) \cdot bigM < k \qquad \textit{(Lin 3)}$$

and where $b1_i$, are binary decision variables required to transform logical constraints into linear constraints.

The logic behind this equivalence is the following: When $b1_i = 0$, *(Lin 1)* and *(Lin 2)* are imposed with a neutralized effect of $bigM$ and *(Lin 3)* is always true. This equivalently imposes the first element of the "or" relation in constraint 2 while relaxing the second element. When $b1_i = 1$, *(Lin 1)* and *(Lin 2)* are always true and *(Lin 3)* is imposed with a neutralized effect of $bigM$. This equivalently relaxes the first element of the "or" relation in constraint 2 and imposes the second element.

Constraint 3 is equivalent to:

$$\forall i \in I, (C_i = 0) \vee \left(\sum_J N_{ij} \cdot w_j \geq k \right)$$

The above constraint is equivalent to the following two linear constraints where $b2_i$ are binary decision variables and $bigM$ is a sufficiently large number:

$$\forall i \in I, C_i - bigM \cdot b2_i \leq 0 \qquad \textit{(Lin 4)}$$

$$\forall i \in I, \sum_J N_{ij} \cdot w_j + bigM \cdot (1 - b2_i) \geq k \qquad \textit{(Lin 5)}$$

and where $b2_i$ are binary decision variables required to transform logical constraints into linear constraints.

The logic behind this equivalence is the following:

When $b2_i = 0$, *(Lin 4)* is imposed with a neutralized effect of $bigM$ while *(Lin 5)* is always true. This equivalently enforces the first element in the "or" relation in constraint 3 and relaxes the second element. In fact, this imposes $C_i \leq 0$, but given that C_i is defined as a continuous decision variable with a minimum of 0, then this imposes that $C_i = 0$. When $b2_i = 1$, *(Lin 5)* is imposed with a neutralized effect of $bigM$ while *(Lin 4)* is always true. This equivalently enforces the second element in the "or" relation in constraint 3 relaxes the first element.

Looking at the linear representations of constraints 2 and 3, identified above as *(lin 1 to 5),* one can notice that $b2_i$ can be replaced by $(1 - b1_i)$ to reduce the number of decision variables.

For Model Two, in addition to constraints 2 and 3, which are linear equivalents, constraints 8 and 9 must be linearized as follows. Constraint 9 can be written as:

$$\forall i \in I, \forall j \in J, (N_{ij} = 0) \vee \left(R_{ij} > \frac{\frac{E_j}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \right)$$

This is equivalent to the following two linear constraints where $b2_{ij}$ are binary decision variables:

$$\forall i \in I, \forall j \in J, N_{ij} - bigM \cdot b2_{ij} \leq 0 \qquad \textit{(Lin 6)}$$

$$\forall i \in I, \forall j \in J, \frac{E_j}{EpF_j \sum_{i' \in I[d_i]} M_{i'j}} - bigM \cdot \left(1 - b2_{ij}\right) < R_{ij} \qquad \textit{(Lin 7)}$$

Constraint 8 can be written as:

$$\forall i \in I, \forall j \in J, (N_{ij} = M_{ij}) \vee \left(R_{ij} \leq \frac{\frac{E_j}{EpF_j}}{\sum_{i' \in I[d_i]} M_{i'j}} \right)$$

This is equivalent to the following three linear constraints where $b3_{ij}$ are binary decision variables and $bigM$ is a sufficiently large number:

$$\forall i \in I, \forall j \in J, N_{ij} + bigM \cdot b3_{ij} \geq M_{ij} \tag{Lin 8}$$

$$\forall i \in I, \forall j \in J, N_{ij} - bigM \cdot b3_{ij} \leq M_{ij} \tag{Lin 9}$$

$$\forall i \in I, \forall j \in J, \frac{E_j}{EpF_j \sum_{i' \in I[d_i]} M_{i'j}} + bigM \cdot \left(1 - b3_{ij}\right) \geq R_{ij} \tag{Lin 10}$$

Looking at the linear representations of constraints 10 and 11, identified above as *(lin 6 to 10)*, one can notice that $b3_{ij}$ can be replaced by $\left(1 - b2_{ij}\right)$ to reduce the number of decision variables.

For Model Three, constraints 11 and 12 must be linearized as well, in the same manner that constraints 8 and 9 are, noting however that the that probabilistic narrative is now attributed to type of the type of household type cell $I[t]$ instead of the geographic cell $I[d_i]$

Table A1. Basic nomenclature for models 1–4

Input variables	
I	Set of households
J	Set of individual indicators
k	Poverty threshold
$\forall j \in J, w_j$	Weights of the various indicators. The sum of all weights is 1
$\forall j \in J, l_j$	Lower bound on the effort spent per indicator
$\forall j \in J, u_j$	Upper bound on the effort spent per indicator
$\forall j \in J, EpF_j$	Effort required to induce a flip per indicator
$\forall i \in I, \forall j \in J, M_{ij}$	Binary deprivation per household and indicator
$\forall i \in I, HS_i$	Household size per household
$\forall i \in I, HW_i$	Statistical weight of household
MPI_s	Starting MPI (pre-optimization)
MPI_r	Reduction required in MPI, continuous variable between 0 and 1
Computed input variables	
$\forall i \in I, \forall j \in J, Mw_{ij}$	Weighted deprivation per household and indicator
$\forall i \in I, P_i$	Binary input variable indicating if a household is originally poor (1) or not (0)
External decision variables	
$\forall i \in I, \forall j \in J, N_{ij}$	Binary decision variable member of the post-optimization deprivation matrix N
$\forall j \in J, E_j$	Effort in the corresponding indicator j
Internal decision variables	
$\forall i \in I, C_i$	Contribution of a household to the post optimization MPI. C_i is a continuous variable with a minimum of zero and is also referred to as weighted deprivation score

Source: Authors' derivation.

Table A2. Additional nomenclature for model 3

Input variables	Description
$\forall i \in I, \forall j \in J, R_{ij}$	A random number between 0 and 1 to determine whether the corresponding entry in the deprivation matrix will be flipped as a result of the effort exerted.
D	Set of population cells
$\forall i \in I, d_i$	Population cell
$I[d]$	Set of households belonging to a population cell d (computed input)
Decision variables	**Description**
$\forall j \in J, \forall d \in D, E_{jd}$	Effort in corresponding indicator j and geographic cell d

Source: Authors' derivation.

Table A3. Additional nomenclature for model 4

Input variables	Description
T	Set of type of households
$\forall i \in I, t_i$	Type of household
$I[t]$	Set of households belonging to the type of household t (Computed input from the clustering technique)
Decision variables	**Description**
$\forall j \in U, \forall t \in T, E_{jt}$	Effort in corresponding indicator j and household type t

Source: Authors' derivation.

Table A4. Revised Arab Multidimensional Poverty Index framework

Dimension	Indicator	Description
Education	School attendance	Any child in the household aged 6–18 years is not currently attending school and has not completed secondary education.
	Educational attainment	All household members aged 19 years and above have not attained secondary education completion.
	Schooling gap	Any child aged 8–18 years is enrolled at two or more grade levels below the appropriate grade for their age.
Access to services	Water	The household lacks any of the following: piped water into a dwelling, piped water into a yard, or bottled water.
	Sanitation	The household lacks access to improved sanitation, either entirely or shares improved facilities with other households.
	Electricity	The household does not have access to electricity
Health and nutrition	Child mortality	A child in the household has passed away before reaching the age of 5 within the last five years.
	Child nutrition	Any child (0–59 months) is stunted (height for age < -2) or any child is underweight (weight for age < -2).
	Early pregnancy	Any women aged 15–24 years in the household experienced childbirth before reaching the age of 18. (Unavailable in Egypt 2014, 2018)
Housing	Overcrowding	There are three or more individuals aged 10 years or older per sleeping room in the household.
	Dwelling	The housing situation satisfies at least one of the following conditions: (i) the residence is a place other than a stand-alone house or apartment, (ii) it features a non-permanent floor, or (iii) it has a non-permanent roof.
Assets	Communication assets	The household lacks a phone (mobile or landline), television, or computer.
	Livelihood assets	Despite having access to electricity, the household does not possess a refrigerator, washing machine, any form of heaters, or any type of air conditioning or cooler.
	Mobility assets	The household does not own a car/truck, motorbike, or bicycle.

Source: Authors' compilation.

Table A5. Available household surveys per country over the period of 2011 and 2019

Country	Survey year one	Survey year two	MPI year 1	MPI year 2
TUN	Multiple Indicator Cluster 2011	Multiple Indicator Cluster 2018	0.063	0.040
IRQ	Multiple Indicator Cluster 2011	Multiple Indicator Cluster 2018	0.166	0.120
ALG	Multiple Indicator Cluster 2013	Multiple Indicator Cluster 2019	0.103	0.054
EGY	Demographic and Health 2014	Household Income, Expenditure & Consumption 2018	0.061	0.044
MRT	Multiple Indicator Cluster 2011	Multiple Indicator Cluster Survey 2015	0.458	0.429

Source: Authors' calculations.

Table A6. SDG 2030 targets by country

Country	MPI in year 2015 (Under the assumption of Linear interpolation)	MPI reduction by half in 2030 (from baseline year 2015)	Adjusted target (relative change needed from latest observed survey)
TUN	0.050	0.025	37.85%
IRQ	0.139	0.070	41.75%
ALG	0.086	0.043	20.42%
EGY	0.057	0.028	35.96%
MRT	0.429	0.215	50.00%

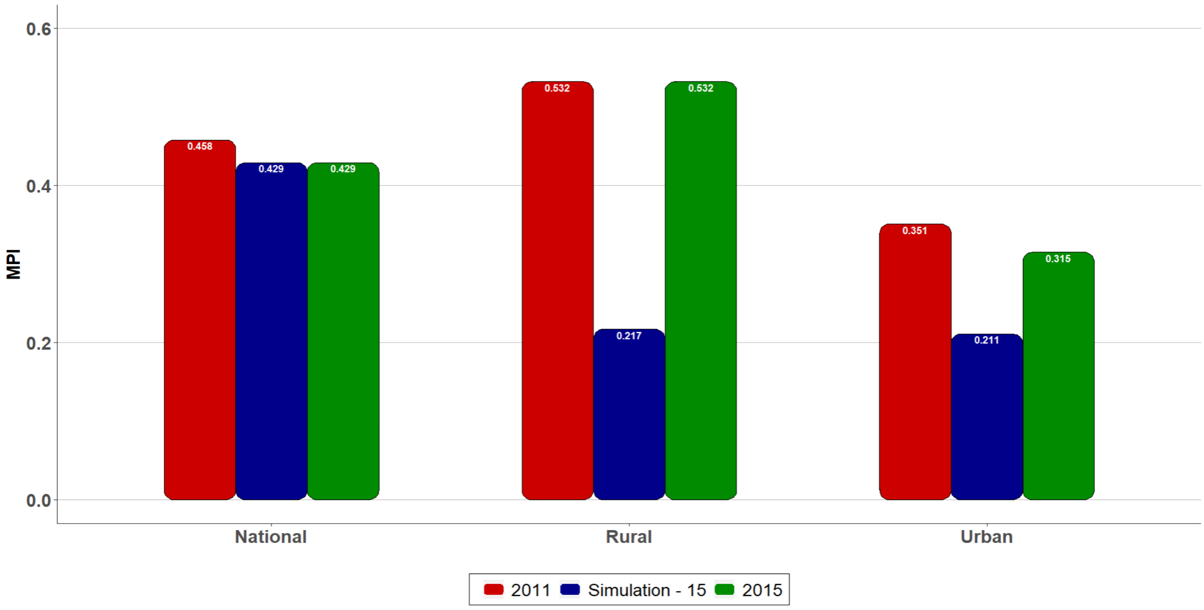
Source: Authors' calculations.

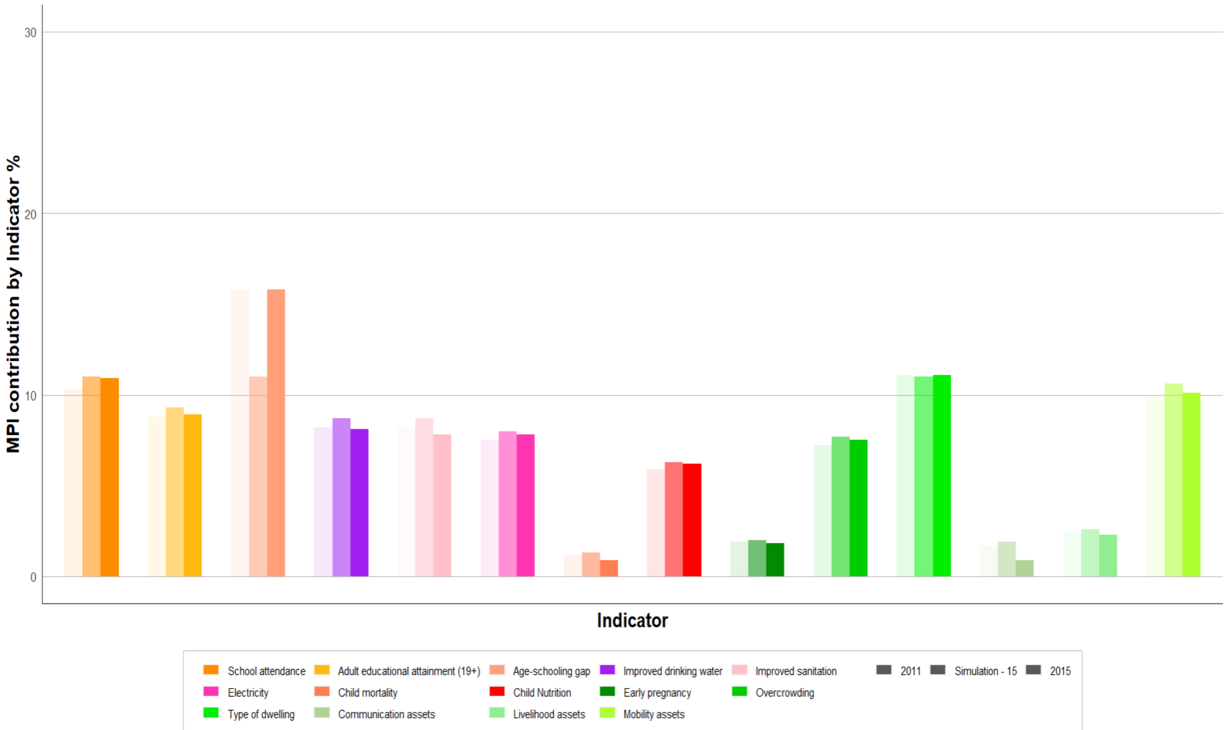
Appendix 2: Additional results

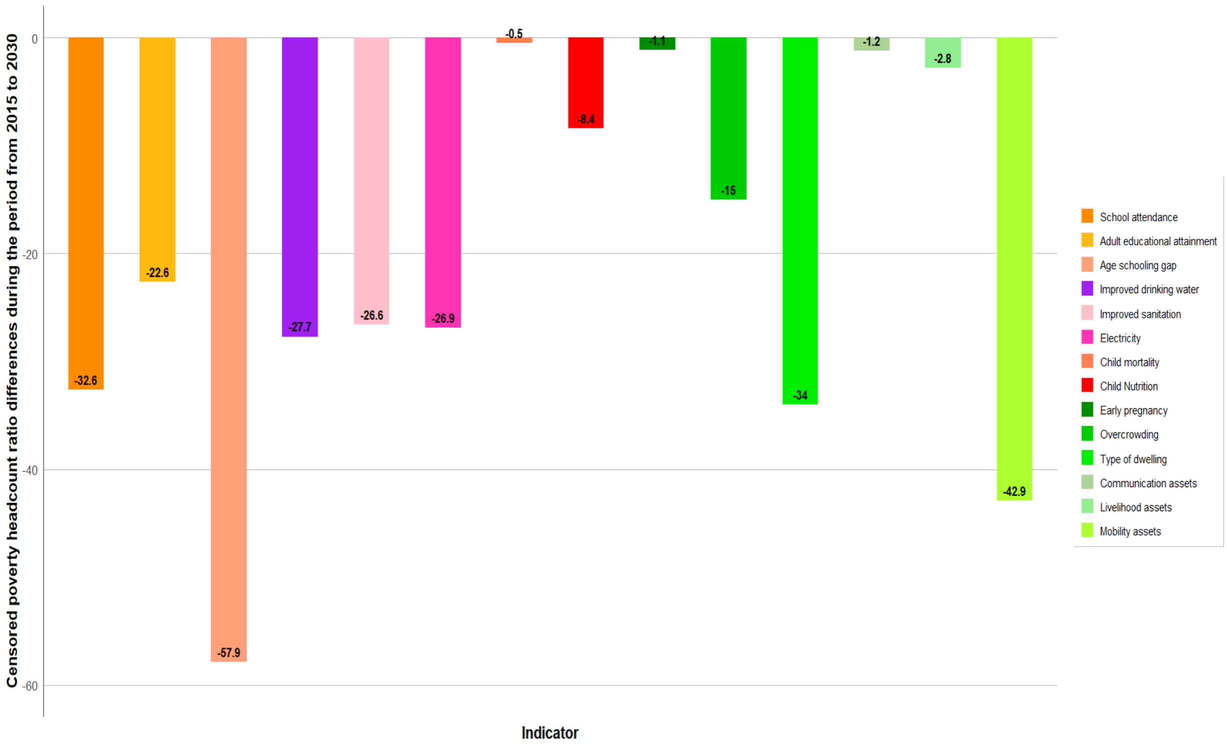
For each country, figure A1 plots the following: 1) MPI across the selected years, national and disaggregated by rural and urban areas; 2) Indicators' percentage contribution to the MPI across the years; and 3) Percentage difference in the censored headcount ratio between the latest observation and the year 2030 simulation.

Figure A1. MPI extended results and simulations by country, 2011-2030

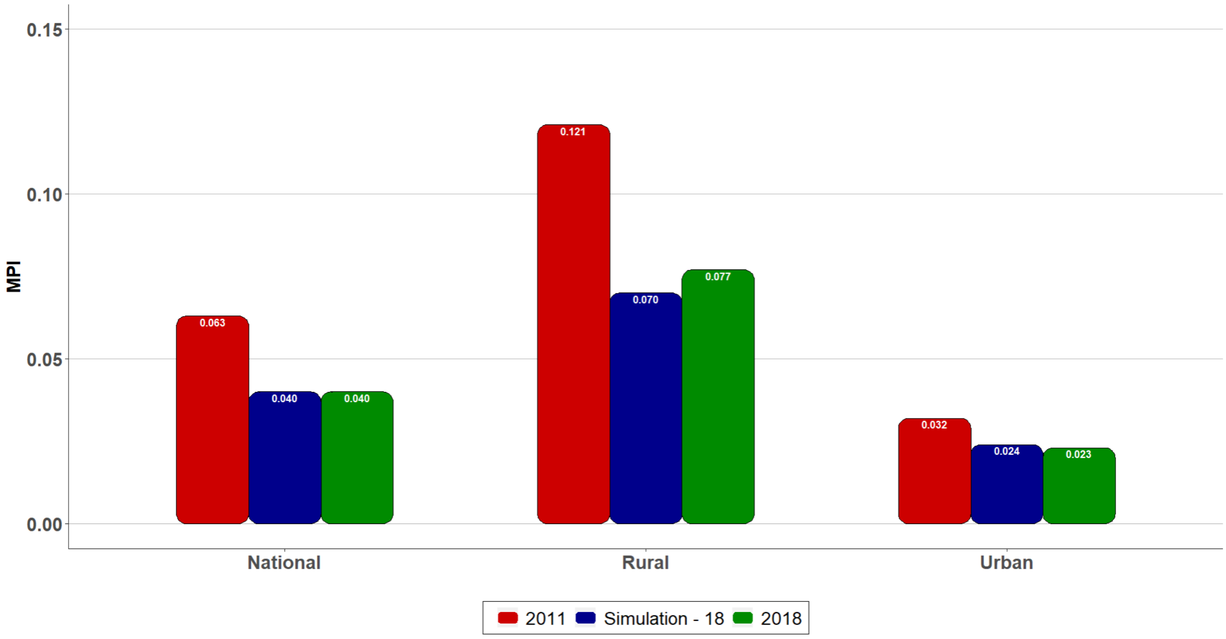
Mauritania



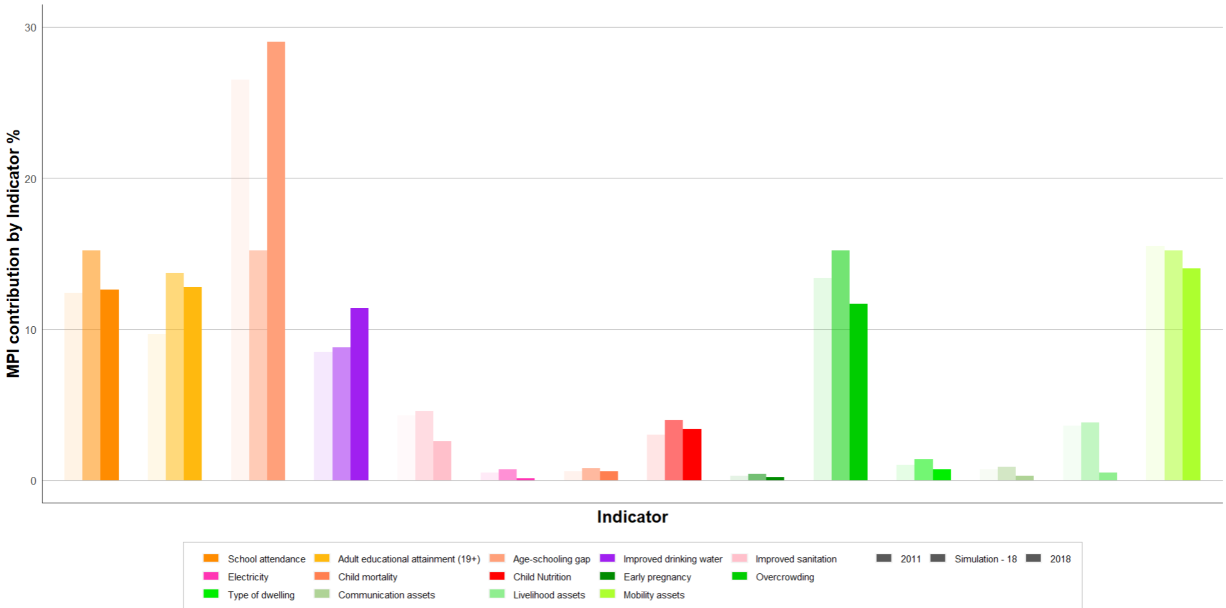



Censored poverty headcount ratio differences during the period from 2015 to 2030
0
-20
-40
-60
-32.6
-22.6
-57.9
-27.7
-26.6
-26.9
-0.5
-8.4
-1.1
-15
-34
-1.2
-2.8
-42.9
Indicator
School attendance
Adult educational attainment
Age schooling gap
Improved drinking water
Improved sanitation
Electricity
Child mortality
Child Nutrition
Early pregnancy
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets

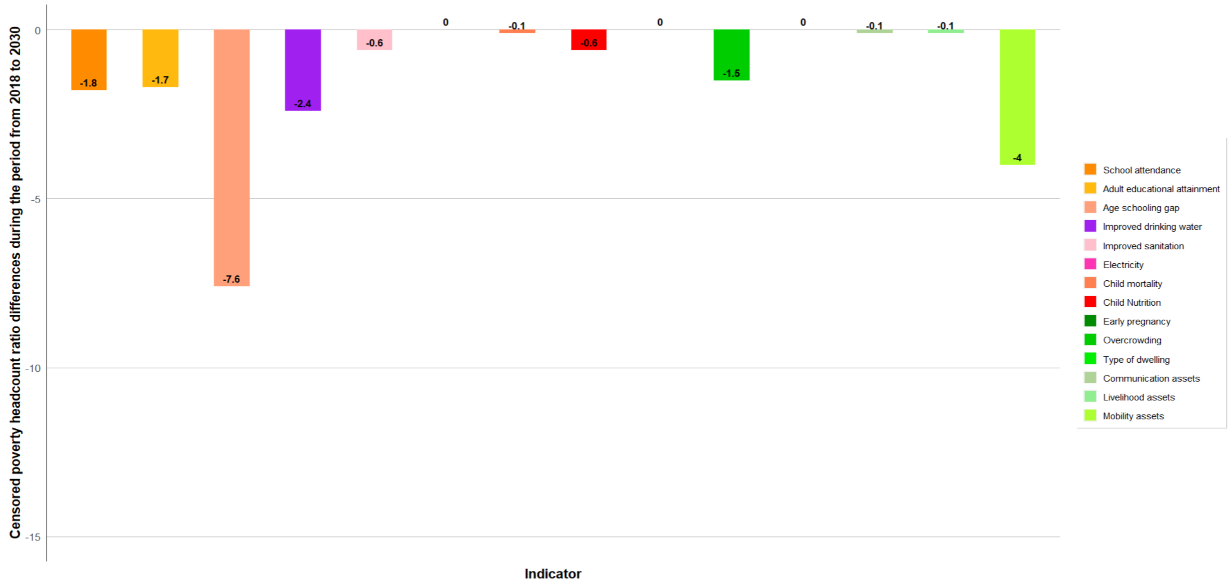
Tunisia



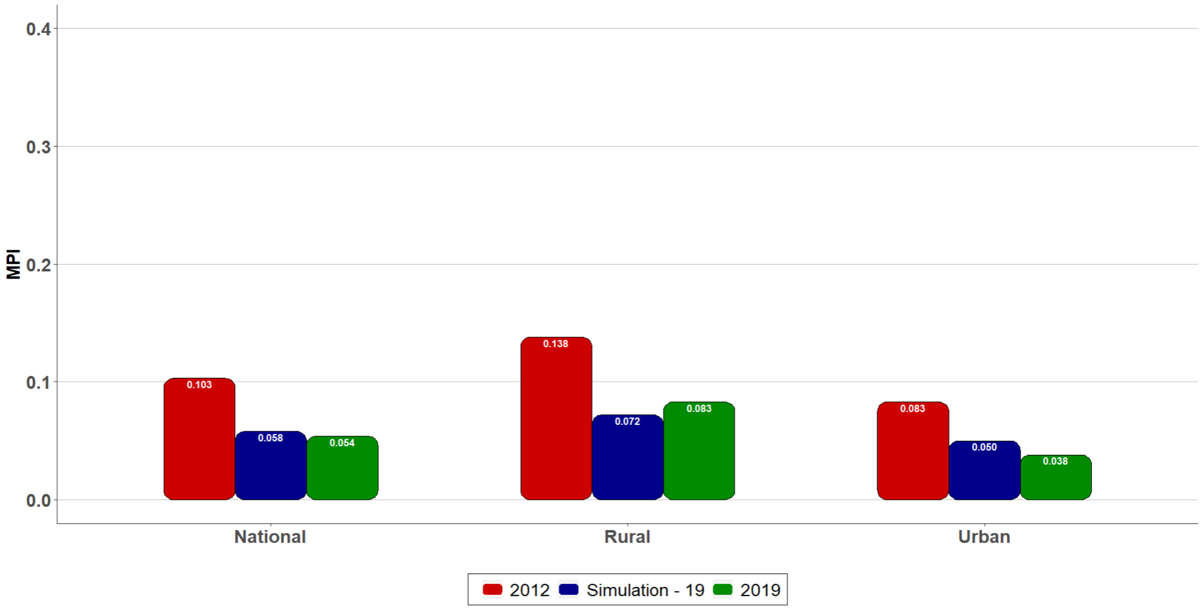
0.15
0.10
0.05
0.00
MPI
0.063
0.040
0.040
0.121
0.070
0.077
0.032
0.024
0.023
National
Rural
Urban
2011
Simulation - 18
2018



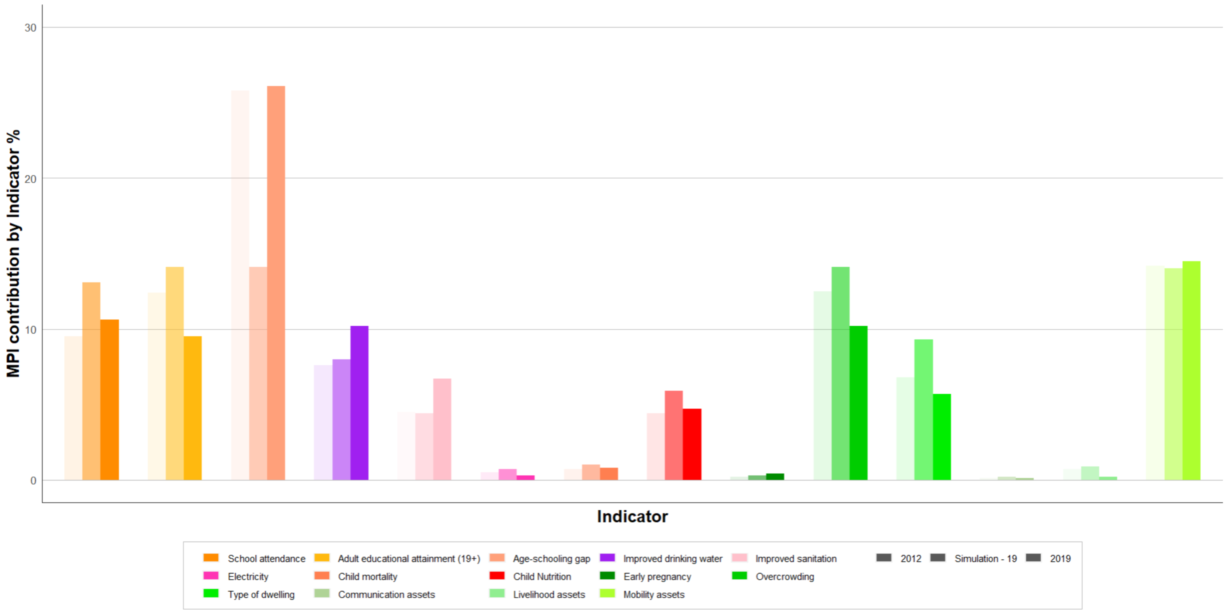
30
20
10
0
MPI contribution by Indicator %
Indicator
School attendance
Adult educational attainment (19+)
Age-schooling gap
Improved drinking water
Improved sanitation
Electricity
Child mortality
Child Nutrition
Early pregnancy
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets
2011
Simulation - 18
2018


Censored poverty headcount ratio differences during the period from 2018 to 2030
0
-5
-10
-15
-1.8
-1.7
-7.6
-2.4
-0.6
0
-0.1
-0.6
0
-1.5
0
-0.1
-0.1
-4
Indicator
School attendance
Adult educational attainment
Age schooling gap
Improved drinking water
Improved sanitation
Electricity
Child mortality
Child Nutrition
Early pregnancy
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets

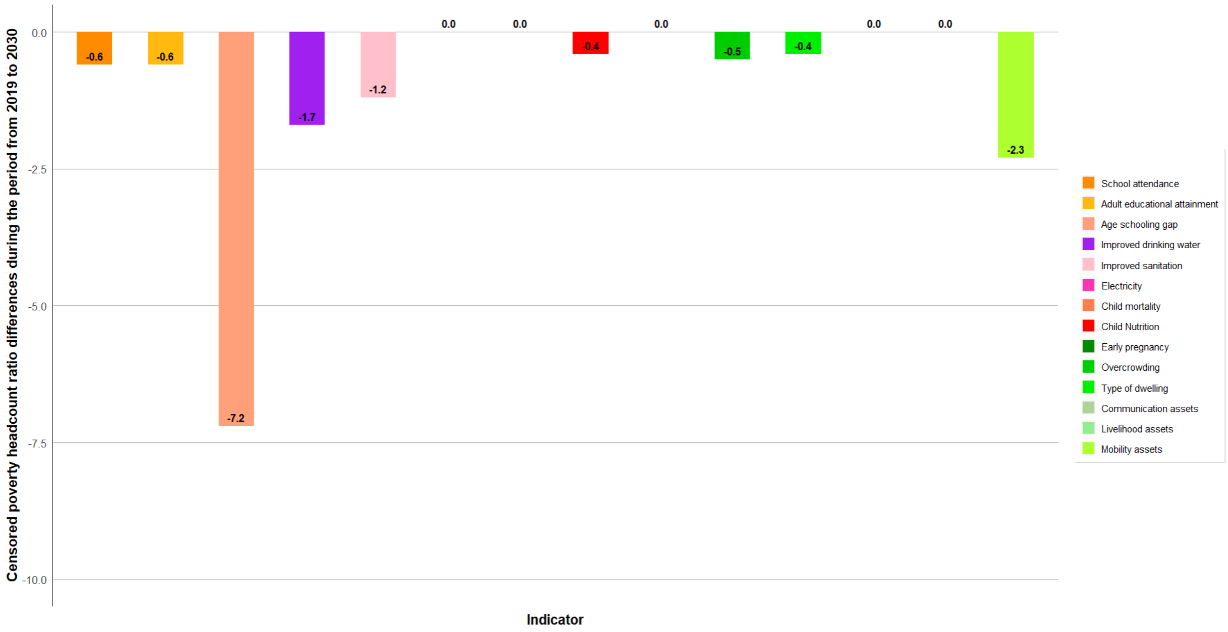
Algeria



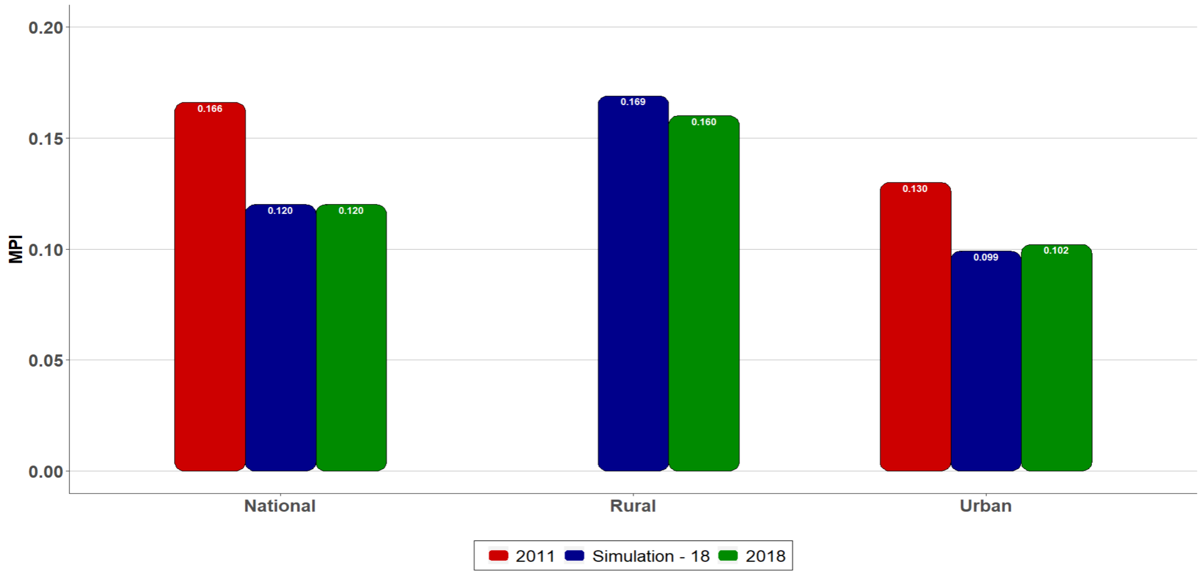
0.4
0.3
0.2
0.1
0.0
MPI
0.103
0.058
0.054
0.138
0.072
0.083
0.083
0.050
0.038
National
Rural
Urban
2012
Simulation - 19
2019



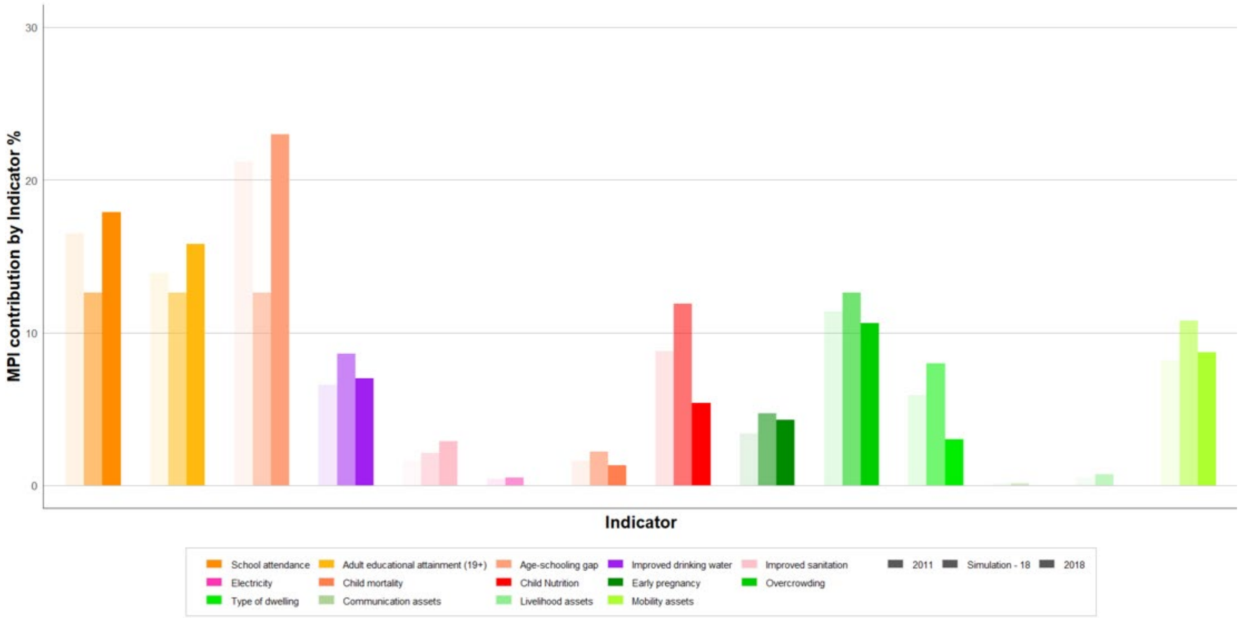
30
20
10
0
MPI contribution by Indicator %
Indicator
School attendance
Adult educational attainment (19+)
Age-schooling gap
Improved drinking water
Improved sanitation
2012
Simulation - 19
2019
Electricity
Child mortality
Child Nutrition
Early pregnancy
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets


Censored poverty headcount ratio differences during the period from 2019 to 2030
0.0
-2.5
-5.0
-7.5
-10.0
-0.6
-0.6
-7.2
-1.7
-1.2
0.0
0.0
-0.4
0.0
-0.5
-0.4
0.0
0.0
-2.3
Indicator
School attendance
Adult educational attainment
Age schooling gap
Improved drinking water
Improved sanitation
Electricity
Child mortality
Child Nutrition
Early pregnancy
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets

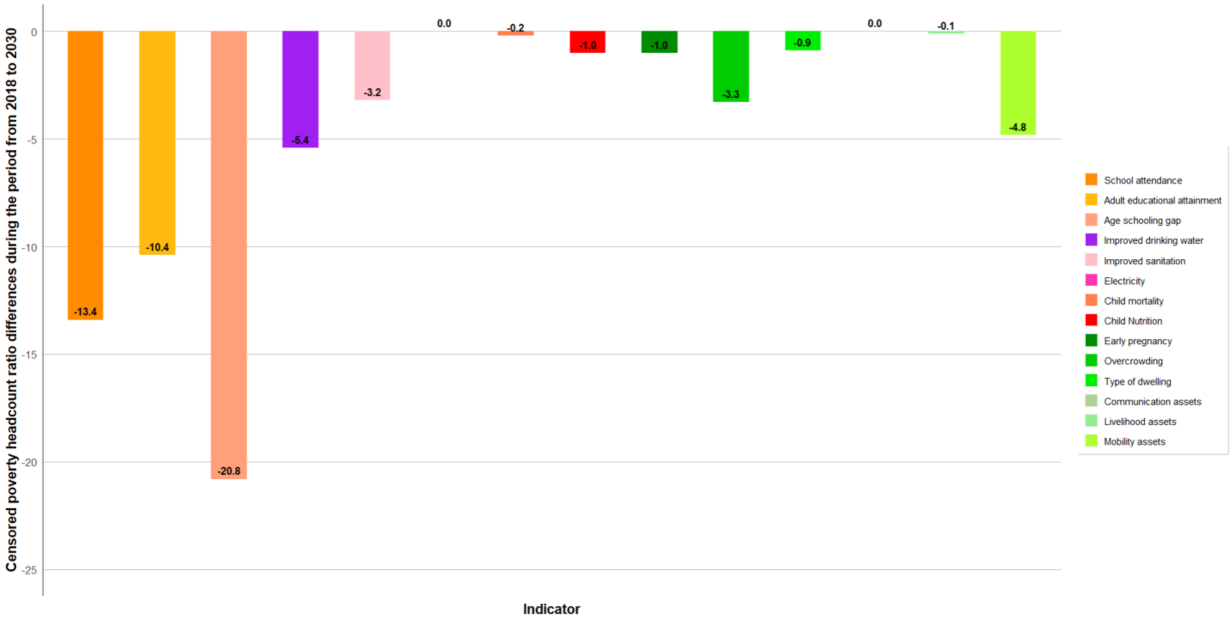
Iraq



0.20
0.15
0.10
0.05
0.00
MPI
0.166
0.120
0.120
0.169
0.160
0.130
0.099
0.102
National
Rural
Urban
2011
Simulation - 18
2018

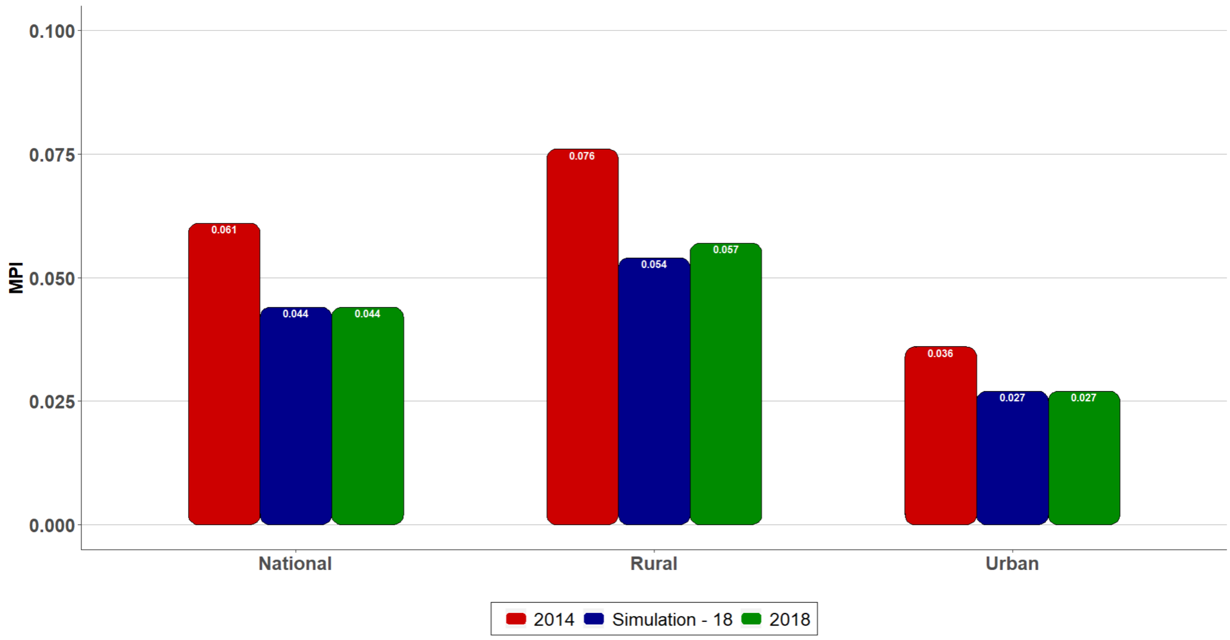


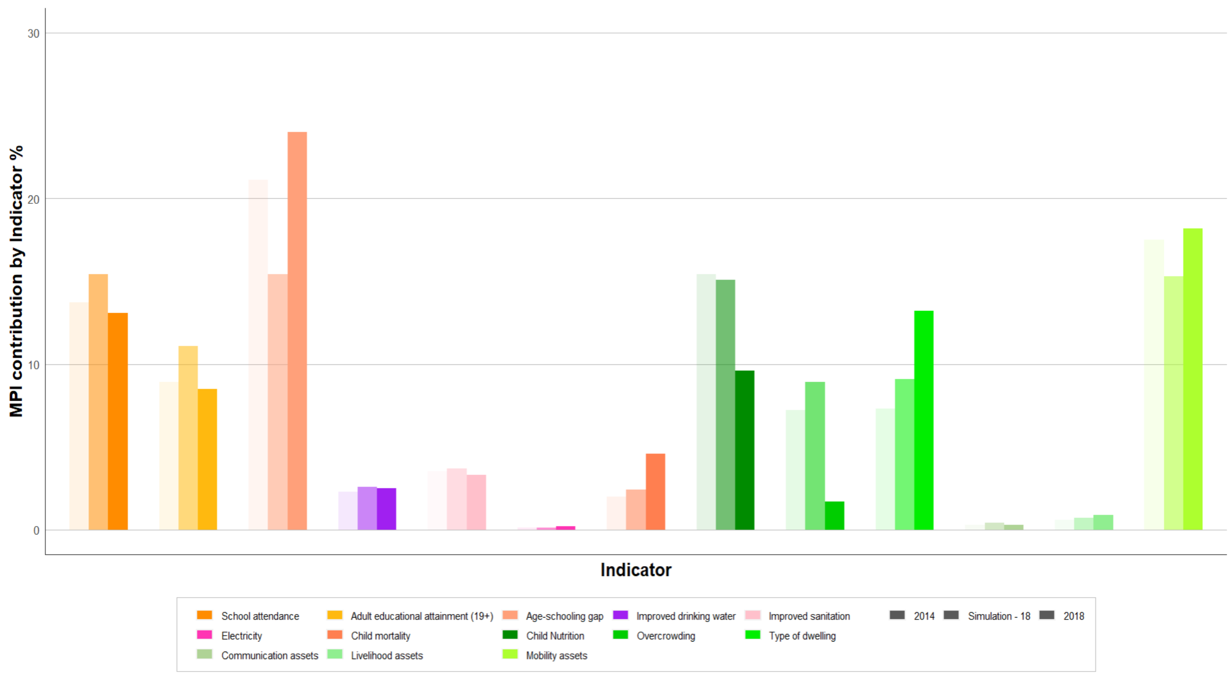
30
20
10
0
MPI contribution by Indicator %
Indicator
School attendance
Adult educational attainment (19+)
Age-schooling gap
Improved drinking water
Improved sanitation
Electricity
Child mortality
Child Nutrition
Early pregnancy
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets
2011
Simulation - 18
2018

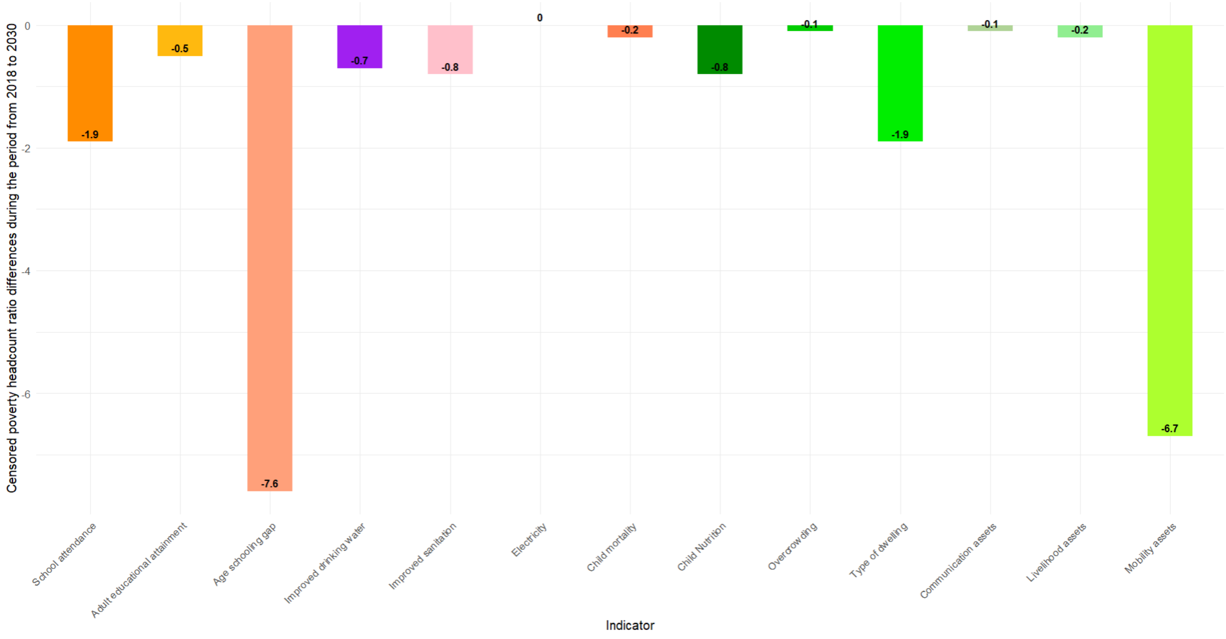


Censored poverty headcount ratio differences during the period from 2018 to 2030
0
-5
-10
-15
-20
-25
-13.4
-10.4
-20.8
-5.4
-3.2
0.0
-0.2
-1.0
-1.0
-3.3
-0.9
0.0
-0.1
-4.8
Indicator
School attendance
Adult educational attainment
Age schooling gap
Improved drinking water
Improved sanitation
Electricity
Child mortality
Child Nutrition
Early pregnancy
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets

Egypt


0.100
0.075
0.050
0.025
0.000
MPI
0.061
0.044
0.044
0.076
0.054
0.057
0.036
0.027
0.027
National
Rural
Urban
2014
Simulation - 18
2018


30
20
10
0
MPI contribution by Indicator %
Indicator
School attendance
Adult educational attainment (19+)
Age-schooling gap
Improved drinking water
Improved sanitation
Electricity
Child mortality
Child Nutrition
Overcrowding
Type of dwelling
Communication assets
Livelihood assets
Mobility assets
2014
Simulation - 18
2018



Source: Authors' calculations.