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Alternative targeting methods for social assistance programs: Evidence from Tunisia

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Abstract

Social assistance programmes are crucial in alleviating poverty, reducing inequality, and addressing social exclusion. The efficacy of these programmes hinges on the precision and efficiency of their targeting methods. Governments, especially in developing countries, can enhance the impact of social assistance programmes and ensure equitable resource distribution by accurately identifying the right individuals or households. This paper proposes two approaches to targeting beneficiaries of social benefits in Tunisia, including cash transfers and healthcare programmes. The first approach, a Mixed Means Test, extends the Proxy Means Test model by integrating individual/household assessments with explicit geographical targeting methods. The second is a multidimensional targeting strategy that explicitly considers the various deprivations faced by the households. Utilising data from the 2015 National Survey on Household Budget, Consumption, and Standard of Living, our results indicate that the targeting performance of the Mixed Means Test surpasses existing programmes both nationally and regionally, notably minimising inclusion and exclusion errors in the poorest regions of Tunisia. However, the multidimensional targeting approach identifies a higher number of potential beneficiaries compared to the current selection process in Tunisia. Including these households in social programmes may be hindered by limited monetary resources and the country's financial constraints. To address this, the multidimensional targeting approach enables the categorisation of potential beneficiaries into three mutually exclusive and collectively exhaustive groups based on their degree of deprivation.

KEYWORDS
mixed means test, multi-dimensional targeting model, targeting social programs, Tunisia

1 | INTRODUCTION

Effectively identifying the beneficiaries of a targeted social programme is a challenge compared to a universal programme that covers everyone without specific eligibility criteria (Gentilini et al., 2020; Hana & Olken, 2018; Leseman & Slot, 2020). While the universality of a social programme is an excellent means to reach the poorest, it may include individuals who do not require this form of public assistance, resulting in the inefficient use of resources (Brown et al., 2018; Karlan & Thuysbaert, 2019). To concentrate programme benefits on those in need and maximise social impact with limited resources, governments, particularly in developing countries, have experimented with various methods to accurately select recipients for programme aid.

In practice, three common targeting methods have been employed (Coady et al., 2004; Grosh et al., 2022).[1] The first method is categorical targeting, where all individuals within a specified category, such as a particular age group or region, are eligible for benefits. This approach establishes eligibility based on individual or household characteristics that are relatively easy to observe, difficult to falsely, and correlated with poverty (e.g., Duflo, 2000; Ravallion & Wodon, 1997).

The second method focuses on establishing eligibility criteria to select households and individuals. These criteria may involve a direct measurement of income or consumption. Known as the means test, this method relies on mechanisms to verify the accuracy of potential beneficiaries' claims, requiring a well-developed administrative system (see, e.g., Seleka & Lekobane, 2020). However, implementing such verification processes is often impractical in developing countries (Alatas et al., 2012; Basurto et al., 2019; Lavallee et al., 2010). Alternatively, eligibility criteria can be derived from a score generated using a set of variables reflecting a household's living conditions. This approach is referred to as the proxy means test (PMT), where field workers collect demographic, asset, or housing information to roughly assess a household's poverty status (e.g., Premand & Schnitzer, 2021).

The third method involves selecting programme beneficiaries through local and regional commissions, while the central authority maintains control over fund allocation and regional quotas (e.g., Bardhan & Mookherjee, 2005; Conning & Kevane, 2002). Advocates of this targeting method argue that local levels often process more comprehensive insights into poverty. Local authorities are typically more accountable to the community, incentivising them to use locally available information to enhance targeting effectiveness (Galasso & Ravallion, 2001).

The performance of targeting methods is frequently a subject of active policy debates and research. In the literature, achieving a consensus on this issue requires improvement. For instance, Ravallion (2007) argues that improved targeting should be viewed not as an end but as a means to reduce poverty. Conversely, some contend that targeting should be solely evaluated against the programme's eligibility criteria (Devereux et al., 2017).

A common analytical approach to assessing the targeting effectiveness of alternative transfer mechanisms involves comparing under-coverage and leakage rates (e.g., Coady et al., 2004, Quentin et al., 2016; Bah et al., 2018). This Analysis is often presented through a two-by-two matrix. Under-coverage signifies exclusion errors and denotes the proportion of poor households omitted from the programme. On the other hand, leakage represents the portion of the program recipients who are designed as nonpoor (inclusion errors).

Comparative studies that directly juxtapose alternative targeting methods in real-world settings are relatively scarce in the literature (Premand & Schnitzer, 2021). For example, Alatas et al. (2012) employed randomised evaluation techniques to contrast the targeting performance of the PMT method with methodologies that involve varying degrees of community involvement in decision-making and are based on diverse conceptions of poverty in Indonesia. Some comparative studies are rooted in practically implementing one targeting method while simulating another. For instance, Basurto et al. (2019) conducted a study comparing PMT and selection by community leaders in Malawi. Similarly, Schleicher et al. (2016) evaluated community-based targeting using five PMT procedures in north-western Burkina Faso. Another study by Azevedo and Robles (2013) examined geographic targeting followed by a household proxy-means test and a multidimensional targeting based on the deprivations of poor households in Mexico.

In Tunisia, key social programmes, such as the direct cash transfer schemes PNAFN (Assistance Program for Needy Families, Elderly, and Disabled), and health access program like AMGI (providing free access to public medical institutions) and AMGII (offering reduced-rate access) play a significant social role in the country (Machado et al., 2018; Nasri, 2022). Researchers and policymakers are increasingly focusing on the effectiveness of targeting these programmes. While PMT simulation results for Tunisia are promising (Muller & Bibi, 2010; World Bank and CRES, 2022), the PMT model is based only on the household's characteristics. Contextual or regional variables (characteristics of the area in which the household lives) are completely ignored. This article addresses the spatial dimension of poverty in Tunisia and the inclusion of regional variables in the selection process. The contribution of this research is to provide estimates of targeting performance indicators in a comparative framework. In this paper, we compare the targeting accuracy of Tunisia's current social safety net with two alternative targeting methods. The first method, the Mixed Means Test (MMT), extends the Proxy Means Test (PMT) by incorporating hierarchical/multilevel models that combine individual and geographic targeting approaches. The second method involves a multi-dimensional targeting based on household deprivation. The comparison will rely on under-coverage and leakage rates, commonly analysing the performance of various targeting methods (e.g., Quentin et al., 2016; Bah et al., 2018).

The structure of the paper is as follows: Section 2 provides the background on the social safety nets in Tunisia. Section 3 describes the sample characteristics details the data sources. In section 4, we outline the specific methods employed for data analysis, including statistical models or algorithms. Section 5 presents the findings of our study, highlighting the main trends and patterns observed in the data. Finally, in Section 6, we offer concluding remarks on our results.

2 | BACKGROUND ON SOCIAL SAFETY NETS IN TUNISIA

The management of social programmes in Tunisia falls under the purview of the Ministry of Social Affairs (MSA), operating through a vast regional network comprising 24 regional divisions and 264 social promotion units distributed across spread the country's 264 delegations (administrative units). In 1986, the MSA instituted the PNAFN program to accompany the Structural Adjustment Program, aiming to provide regular, permanent, and unconditional assistance to needy and poor families. In 2016, the PNAFN program constituted approximately 53% of the total expenditures of the MSA, accounting for 1.9% of government spending and around 0.5% of the gross domestic product (GDP).

The PNAFN not only offers financial assistance but also grants beneficiaries free access to public healthcare through the AMGI program. Recognising the rights of children from needy families to education and protection against academic failure and dropout, Tunisia strengthened the PNAFN program by introducing a quarterly increase of 30 dinars per child for eligible families with school-age children. The program benefits are awarded on family requests made involve multiple stakeholders.

The selection process typically unfolds as follows: (i) Families initiate the cash transfer claim, asserting that their household income falls below the poverty threshold; (ii) Social workers conduct an investigation into the household income, taking into account additional socio-economic criteria (refer to Table A1 in the appendix); (iii) A list of eligible families is compiled and forwarded to local and regional commissions, where a final beneficiary list is prepared, considering the regional budget allocated by the MSA and outlined in the circular setting (some of which are discretionary, allowing flexibility for social workers). Families qualify for the AMGII program if their annual income does not exceed the Interprofessional Guaranteed Minimum Wage (SMIG): SMIG for families with fewer than two persons, 1.5SMIG for families with 3 to 5 persons, and 2SMIG for families with more than five persons (Nasri, 2020).

In 2020, the total number of PNAFN beneficiaries surged to 260,000, marking a substantial increase from 124,000 in 2010 – an impressive average annual growth rate of 7.7%. concurrently, the average monthly transfer rose from TND 56.7 in 2010 to TND 180 in 2020 (approximately 67 dollars per month). The cash transfer program covers about 8.4% of the population, and approximately 24% enjoy health coverage through either the AMGI program or, at a reduced rate, the AMGII program.

Despite enhancements in monthly allowances following the 2011 revolution and improvement in regional coverage and household standard of living, various studies have identified clear signs of leakages and under-coverage in Tunisia's social programmes. Notably, 48.9% of low-income families are excluded from the key social programmes, with unclear eligibility criteria for the AMG program (Silva et al., 2013), rendering the system susceptible to inefficiencies and leakages. Moreover, the absence of an official appeal system contributes to inefficiencies in addressing exclusion errors.

According to 2013, around half of the poor population and 39.4% of those living in extreme poverty in Tunisia do not benefit from any component of the PNAFN program, indicating notable exclusions issues. The CRES and BAD (2017) study on the cash transfer program revealed that of the 8.4% of households intended to be covered by the PNA FN, 4.6% were not, resulting in a concerning exclusion rate of 53.1%. Nasri et al. (2022) further notes that the official eligibility criteria for both social programmes are not consistently adhered to during beneficiary selection.

To enhance the effectiveness of social programmes, a new initiative called 'Amen Social' was established under organic law No. 10-2019 in January 2019. This program aims to support individuals in poor and limited-income categories whose lack of resources affects their income, health, education, access to public services, and overall living conditions. Representing a comprehensive social safety net, 'Amen Social' consolidates various existing social assistance programmes in Tunisia, including the cash transfer program (PNAFN/AMGI) and the AMGII program, under the auspices of the Ministry of Social Affairs (MSA). The primary objectives of 'Amen Social' include expanding coverage and fostering greater transparency, equity, and efficiency within social protection programmes (Nasri et al., 2022).

For the identification and validation of beneficiaries in direct cash transfers or reduced/free medical assistance within the 'Amen Social' program, the PMT model has been officially chosen as the fundamental targeting model.

3 | DATA AND DESCRIPTIVE STATISTICS

The dataset used in this study is derived from the National Survey on the Household Budget, Consumption, and Standard of Living (EBCNV) conducted in 2015.[2] The National Institute of Statistics (INS) collected the data over one-year period, from May 2015 to May 2016. Initial data for the 2015 EBCNV survey were obtained from a random sample of 27,108 households, representing 1% of all households in the country. Among the 27,108 households, 25,140 responded to the survey questionnaire, involving 105,081 individuals, resulting in a response rate of 92.7%. The sample is representative at the national level, encompassing both rural and urban areas as well as the seven economic regions of the country.

The selection of the 27,108 households in each governorate was conducted through a two-stage process of stratified random sampling. In the initial stage, a sample of primary stage units (districts) was chosen with a probability proportional to their size (PPS) in the number of households. The General Census of Population 2014 defined the district as a geographic area containing over 70 households.

The EBCNV aims to provide a comprehensive overview of the structure and level of household expenditures, assess living conditions, measure poverty, and identify the profiles of poor households. It also sheds light on various aspects of household living conditions and access to public services, including education, health coverage, and medical care. According to the 2015 survey, per capita spending in Tunisia increased from 2601 dinars in 2010 to an average of 3871 Tunisian dinars yearly, reflecting a significant 48.8% increase. Despite the improvement in per capita expenditure in rural areas compared to 2010, there continues to be a substantial urban–rural gap in terms of spending, as indicated in Table 1.

The poverty rate, defined as the share of households with expenditures below the poverty line, increased to 15.2% in 2015 compared to 15.5% in 2010. At the regional level, the highest poverty rates in 2015 were estimated at 30.8% and 28.4%, respectively, in the Central West and the Northwest. In contrast, the Great Tunis region had the lowest poverty rate at 5.3%. The rates in the North-East and Center-East regions were 11.5% and 11.6%, respectively (Figure 1).

4 | EMPIRICAL STRATEGY

Targeting, in the context of social policy, refers to the mechanisms employed by policymakers to identify individuals or households eligible for resource transfers (Sabates-Wheeler et al., 2015). It involves a process of establishing eligibility criteria, identifying, verifying, and registering beneficiaries, and periodically validating and adjusting the list as eligibility statuses may change over time. The most common targeting methods fall into three categories (Coady et al., 2004): individual/household assessment (such as means test – MT, proxy means test – PMT, hybrid means test – HMT), categorical targeting, and self-targeting (refer to Table A2 for a comparison between these methods). There

TABLE 1 Household and per capita expenditure, poverty and welfare ratio by area.

	2010	2015
Per capita Expenditure (in DT)		
Urban	3102	4464
Rural	1644	2585
Total	2601	3871
Ratio (urban/rural)	1.89	1.73
Poverty		
Urban	11.8	10.1
Rural	22.7	26.0
Total	15.5	15.2
Ratio (urban/rural)	0.52	0.39
Welfare ratio		
Urban	0.73	0.64
Rural	0.49	0.32
Total	0.65	0.54
Ratio (urban/rural)	1.47	2.03

Note: Authors' calculation using EBCNV surveys.

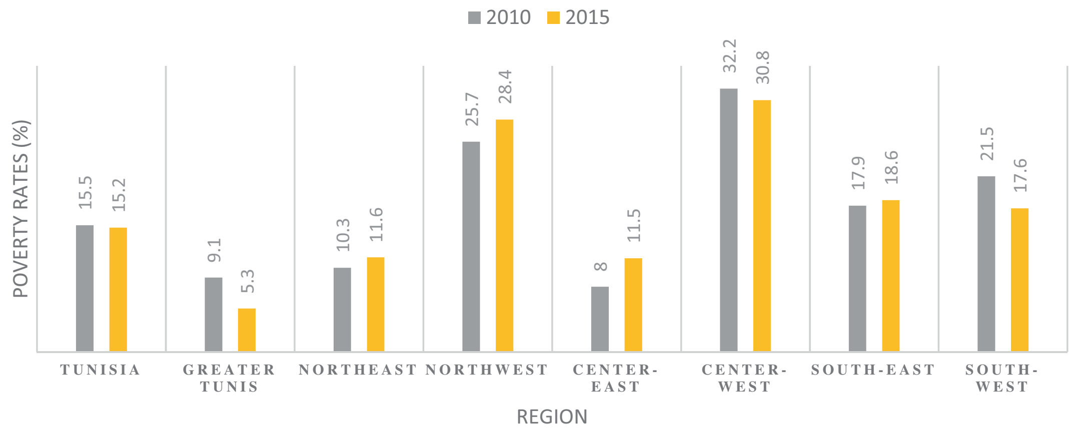

FIGURE 1 Poverty rates at national and regional levels. *Source*: Nasri et al. (2022). [Colour figure can be viewed at wileyonlinelibrary.com]

is no one-size-fits-all solution, and each country chooses a model that aligns with its specific needs and characteristics. Besley and Kanbur (1993) assert that transitioning from universal coverage towards narrowly targeted programmes involves an inevitable trade-off between targeting costs and targeting accuracy.

The primary objective of this paper is to provide estimates of targeting performance indicators within a comparative framework. In this paper, we compare the targeting accuracy of Tunisia's current social safety net with two alternative targeting methods. To achieve this purpose, the first part of this section focuses on the Mixed Means Test approach, extending the Proxy Means Test model to explicitly combine individual/household assessment and geographical targeting methods. The second part introduces the Multidimensional Targeting Model.

4.1 | Mixed means test (MMT) methodology

Case studies on performance in targeting incidence suggest that the PMT model works well for developing countries, where a large proportion of households are self-employed or informally employed (Grosh, 1994). The PMT was notably used in Latin America and the Caribbean (Chile – Ficha CAS system, Columbia – SISBEN, Mexico – Oportunidades Program), in Asia (India, Indonesia, China, Thailand, and the Philippines), and in Africa (Burkina Faso, Ethiopia, Ghana, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda (Brown et al., 2018), Egypt (Ahmed & Bouis, 2002), Tunisia (Muller & Bibi, 2010; World Bank and CRES, 2022)). The results found are very encouraging. For example, in Chile and Mexico, approximately 90% of social assistance reached the bottom 40% of the population when a PMT model was adopted (Sebastian et al., 2018).

In the case of Tunisia, due to the absence of reliable and available data on household incomes and the presence of a relatively high rate of informality, the PMT can be used as an appropriate targeting model for assistance programmes (PNAFN and AMGII). However, identifying poor households using the PMT model relies solely on the household's characteristics with contextual or regional variables (characteristics of the area in which the household lives) being completely disregarded.

Given the spatial dimension of poverty in Tunisia, where poverty is concentrated in the two regions of North West and Central West, we introduce a new targeting model in this paper. This model explicitly combines individual targeting with geographic targeting and is referred to as a Mixed Means Test (MMT), involving a two hierarchical/multilevel structure where households (level 1) are nested within governorates (level 2).

The MMT model was initially developed by Bigman et al. (2000) for targeting anti-poverty programmes and public projects aimed at assisting impoverished communities in Burkina Faso. This approach integrates a comprehensive dataset sourced from various outlets to identify the pivotal determinants of the standard of living in both rural and urban areas. Moreover, the mixed model adeptly incorporates considerations for the household survey design, encompassing analytic weights and the design structure (strata and primary sampling unit – PSUs).

Considering the hierarchical structure of the data, we can explicitly account for the various sources of variability inherent in the data collected at the household level. In developing countries, where reliable surveys or information on household income are often lacking, the most frequently employed welfare measure is the per capita expenditure. This metric is widely regarded as a robust predictor of neediness (Deaton, 1997; Gazeaud, 2020).

To account for regional difference in living costs among households, this paper employs the welfare ratio. The welfare ratio is calculated as the annual per capital expenditure of household i at governorate $j\,(y_{ij})$ divided by the cost of living (the poverty line z_j) at governorate j. A household can cover its basic needs if its welfare ratio is greater than 1; conversely, if the ratio falls below 1, the household is unable to meet its basic needs.

Formally, for household i at governorate j with a per capita expenditure y_{ij} and a vector of K covariates $(x_{1i,j},\ldots x_{Ki,j})$, the empirical regression function of the MMT model is expressed as follows:

$$wr_{ij} = \gamma_{00} + x_{ij}\gamma_{10} + Q_j\gamma_{01} + [\mu_{0j} + e_{ij}] \tag{1}$$

In the equation, wr_{ij} represents the welfare ratio (in logarithm) for household i in governorate j, x_{ij} is the row vector of household characteristics, and Q_j is the row vector of regional characteristics specific to governorate j. All these variables (refer to Table A3 in the appendix) cannot be manipulated or changed following an occasional intervention. The household characteristics include, among others, the sex of the household head, their labour status and education level, the household size and composition, and dwelling characteristics. As for regional variables, we considered, among others, the unemployment rate, the share of agricultural activity, the share of manufacturing activity, the poverty rate, the proportion of the population with a higher level of education, and so forth.

The deterministic part of the model $(\gamma_{00} + x_{ij}\gamma_{10} + Q_j\gamma_{01})$ comprises all the fixed coefficients, with γ_{00} representing the overall mean of the welfare ratio across governorates. The stochastic component is enclosed within the brackets of equation (1). The household-level residuals e_{ij} are assumed to follow a normal distribution with a mean zero and variance σ_e^2; while μ_{0j} is the random error at the governorate level with an expected value of zero and variance $\sigma_{u_0}^2$. Importantly, it is assumed to be independent of the household-level residuals e_{ij}.

The coefficients representing the weights in equation (1) are estimated using the restricted maximum likelihood estimation (REML). The fitted values, denoted as the MMT score in equation (1) $(\widehat{wr}_{ij})$, are utilised to rank households from most eligible to least eligible for social assistance programmes.

$$\widehat{wr}_{ij} = \widehat{\gamma}_{00} + x_{ij}\widehat{\gamma}_{10} + Q_j\widehat{\gamma}_{01} \tag{2}$$

More specifically, a household becomes eligible for the program if its wr_{ij} score, represented by $\widehat{wr}_{ij}$ in (equation (2)), falls below a predetermined cut-off score. The targeting model may result in excluding some eligible households from the program, leading to exclusion errors, while including other ineligible households, resulting in inclusion errors. These errors also known as type I and type II errors, as detailed in Table 2 (Sebastian et al., 2018). The performance of the targeting model is assessed using the following indicators:

4.2 | The inclusion error rate, also known as the leakage rate

$$IER = \frac{\sum_{i=1}^{n} w_i 1\left(wr_{ij} > 0 \mid \widehat{wr}_{ij} \leq 0\right)}{\sum_{i=1}^{n} w_i 1\left(\widehat{wr}_{ij} \leq 0\right)} = \frac{e_2}{m_1} \tag{3}$$

TABLE 2 Illustration of type I and type II errors.

	Target group	Non-target group	
Eligible: predicted by MMT formula	Targeting success (s_1)	Type II error (e_2)	m_1
Ineligible: predicted by MMT formula	Type I error (e_1)	Targeting success (s_2)	m_2
Total	n_1	n_2	n

Note: Adopted from Sebastian et al., 2018.

The Exclusion Error rate, also known as the under-coverage rate:

$$EER = \frac{\sum_{i=1}^{n} w_i 1\left(\widehat{wr}_{ij} > 0 | wr_{ij} \leq 0\right)}{\sum_{i=1}^{n} w_i 1\left(wr_{ij} \leq 0\right)} = \frac{e_1}{n_1} \tag{4}$$

In the equation, w_i represents the appropriate sample weights ($\sum_{i=1}^{n} w_i = 1$), and n is the total number of households in the sample. The Inclusion Error Rate (*IER*) gives the proportion of the non-poor households identified as poor, while the Exclusion Error Rate (*EER*) defines the proportion of the poor who are not identified as poor by the MMT model. If predictions are perfect ($wr_{ij} = \widehat{wr}_{ij}$ for all households), both error rates must be zero ($IER = EER = 0$).

While both error measures help evaluate the targeting model, their interpretation differs depending on the policy objectives set by the government. If the budget allocated to the social assistance program is limited, the government may prioritise minimising the Inclusion Error to prevent non-poor household from benefiting from the program allocated only for the poor.

4.3 | Multi-dimensional targeting model

The proposed multi-dimensional targeting model draws from the identification step of the family of multidimensional poverty measures developed by Alkire and Foster (2007, 2011). In this paper, identification implies, first, selecting dimensions from which potential beneficiaries will be identified and, second, defining a deprivation threshold for each dimension. In this regard, Anand and Sen (1997) observe that issues of poverty in developing countries involve crucial matters, such as hunger, illiteracy, and the lack of health services and safe water. However, these deprivations may not be common in more developed countries, where hunger is rare, literacy is close to universal, and health services are typically widespread. Robeyns (2006) strongly advocates that however, the dimensions are selected; the reports of researchers, analysts, and government officials should include explicit descriptions of the process used to select those dimensions as a means of fostering public debate and feedback. She suggests that authors should justify the methodology by which the dimensions were selected and articulate the dimensions considered important.

In this paper, the proposed targeting strategy allows for a full consideration of the social safety nets' objectives, as we define the dimensions in line with the interventions of the programmes (PNAFN and AMG). Furthermore, the eligibility criteria officially fixed for social safety nets are also used as deprivation thresholds for each considered dimension (Nasri & Belhadj, 2022). For this purpose, it is worth recalling that the PNAFN and AMGII programmes, as indicated above, have intended to improve achievements in three dimensions (food, health, and education) that have the same importance in society and contribute to the welfare of households nationwide (Nasri & Belhadj, 2017). Hence, we propose giving the same weight to each selected dimension.

Explicitly, we consider (y_{ij}) as the achievement of the i^{th} household in the j^{th} dimension, for all $j = 1,2,3$ and all $i = 1,\ldots,n$. Each of these achievements is compared with the corresponding deprivation cut-off (z_j) (Table A4 in the appendix). Thus, each household is deprived of food if its achievement in this dimension is below the food threshold estimated by INS for each stratum. This threshold is estimated at 1085 TND in the metropolitan area, 1050 TND in the municipal area, and 952 TND in the non-municipal area. A household is deprived of education if a child between

6 and 16 does not pursue an education or training cycle. Households are deprived in the health dimension if their annual income does not exceed the Interprofessional Guaranteed Minimum Wage (SMIG), estimated by 314 TND if the family contains fewer than two persons, (1.5*SMIG) if the family is composed of 3 to 5 persons, and (2*SMIG) if the family is composed of more than five persons.

Based on this comparison, we construct an n-dimensional column vector $= |c_i|$, where each element c_i indicates the number of deprivations suffered by the i^{th} household. This deprivation intensity column vector allows us the identification of three groups (Group_1, Group_2, and Group_3) of potential beneficiaries according to their deprivation degree. Group_1, Group_2, and Group_3 represent, respectively, the total number of potential beneficiaries experiencing three deprivations, two deprivations, and one deprivation.

With the proposed multi-dimensional targeting, if a household experiences deprivation in a dimension or an additional dimension, it will automatically be considered a potential beneficiary included in one of the three groups highlighted above. In addition, public decision-makers can limit or expand the scope of their interventions depending on the country's economic and financial situation.

5 | RESULTS AND DISCUSSION

5.1 | Results of the two-level empty MMT

In the initial phase of our analysis, we commence by fitting a two-level empty model, often referred to as the 'Random intercept model', 'null model', or 'intercept-only' model. This model predicts the level 1 (household) intercept of the dependent variable (log of the welfare ratio) as a random effect of the level 2 (governorate), without including independent variables at levels 1 or 2. The purpose of this step is to assess the significant of intercept variance, essentially testing the necessity for mixed modelling. If the intercept variance is found to be insignificant (indicating no substantial geographical differences in the welfare ratio of the households), it can be fixed for subsequent steps. The following equation represents the estimation for the empty MMT model:

$$wr_{ij} = \gamma_{00} + [\mu_{0j} + e_{ij}] \tag{5}$$

Table 3 presents the results of the empty model for the two dependent variables: the log of the welfare ratio using the extreme poverty line (column 1) and the log of the welfare ratio using the poverty line (column 2). The LR

TABLE 3 Empty model results.

	Welfare ratio using extreme poverty line	Welfare ratio using poverty line
Intercept	1.05***	0.559***
Standard error	(0.045)	(0.039)
Variance of the error term at level 2 ($\sigma^2_{u_0}$)	0.048***	0.036***
Variance of the error term at level 1 (σ^2_e)	0.263***	0.259***
ICC $= \sigma^2_{u_0} / \left(\sigma^2_{u_0} + \sigma^2_e\right)$	15.33%	12.03%
Likelihood Ratio test (chi2(1))	3796***	3046***
Log restricted likelihood	−18,950	−18,793

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. The ICC is the ratio between the variance of level 2 and the total variance (variance of level 1 + variance of level 2). Authors' calculations.

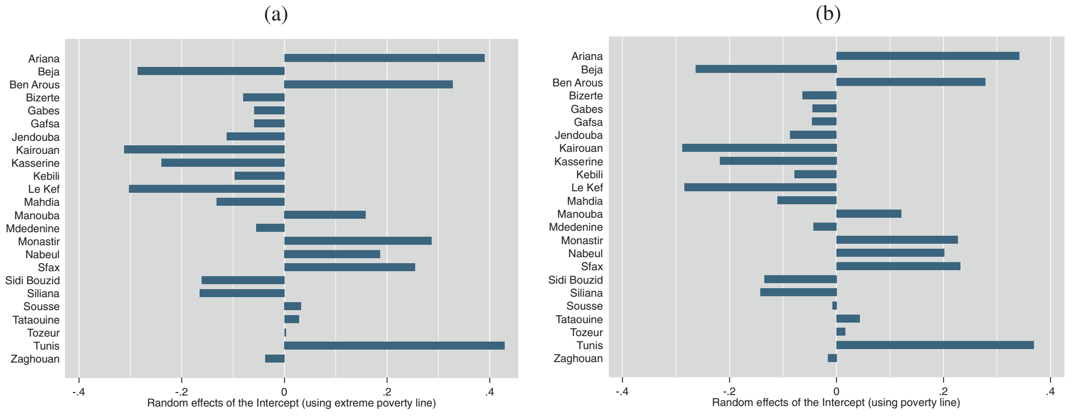

FIGURE 2 Variation in random intercept of empty model across governorates. *Source*: Authors' calculations using 2015 EBCNV survey. [Colour figure can be viewed at wileyonlinelibrary.com]

tests indicate that a mixed or multilevel model is more appropriate than a simple model, as the LR tests are significant at the 1% level. This justifies the use of a mixed modelling approach. The between-governorate variance ($\sigma^2_{u_0}$) is found to be non-zero for both dependent variables, signifying the necessity of incorporating a geographical dimension in the targeting process in Tunisia. This conclusion is further supported by the intraclass correlation coefficients (ICCs), revealing substantial clustering of households categorised as 'extremely poor' or 'poor' within governorates.

Figure 2a,b depict the variations across governorates in random intercept for both dependent variables. Notably, coastal governorates, including Tunis, Ariana, Manouba, Ben Arous, Monastir, Nabeul, and Sfax, exhibit comparatively higher welfare ratios. In contract, non-coastal governorates such as Beja, Kairouan, Kasserine, Le Kef, Siliana, and Sidi Bouzid display relatively lower welfare ratio. This visual representation underscores the geographical disparities in welfare ratios across different regions in Tunisia.

5.2 | Results of the full MMT model

The subsequent step consists of introducing, firstly, the set of variables related to the household (x_{ij}), and subsequently, the set of regional variables (Q_j). Given our primary interest in identifying the appropriate specification for estimating the score to classify households according to their standard of living, we focus on presenting the goodness of fit for two models: the MMT model with only household characteristics (MMT at the household level or PMT model)[3] and full MMT that incorporates both sets of variables – at both household and governorate levels.

Figure 3 illustrates that, in comparison to the MMT at the household level, the gap between the two distributions decreases for the full MMT that includes regional variables. This is evidenced by the Spearman correlation, which increases from 0.71 to 0.73.

Table 4 provides the distribution of beneficiaries by deciles of the true welfare ratio (rows) for six cut-off scores (columns) under the full MMT model, which includes both household and regional explanatory variables. The MMT cut-off is set at the 10th, 15th, 20th, 25th, 30th, and 40th percentiles of the welfare ratio distribution. This implies that approximately 10%, 15%, 20%, 25%, 30%, and 40% of the population with scores below the respective cut-offs are considered eligible for benefits.

It is worth noting that the first cut-off is close to the coverage of the existing PNAFN program, which covered nearly 8% of the population in 2015. The second cut-off of 15% is near the coverage of the AMGII program, and it is

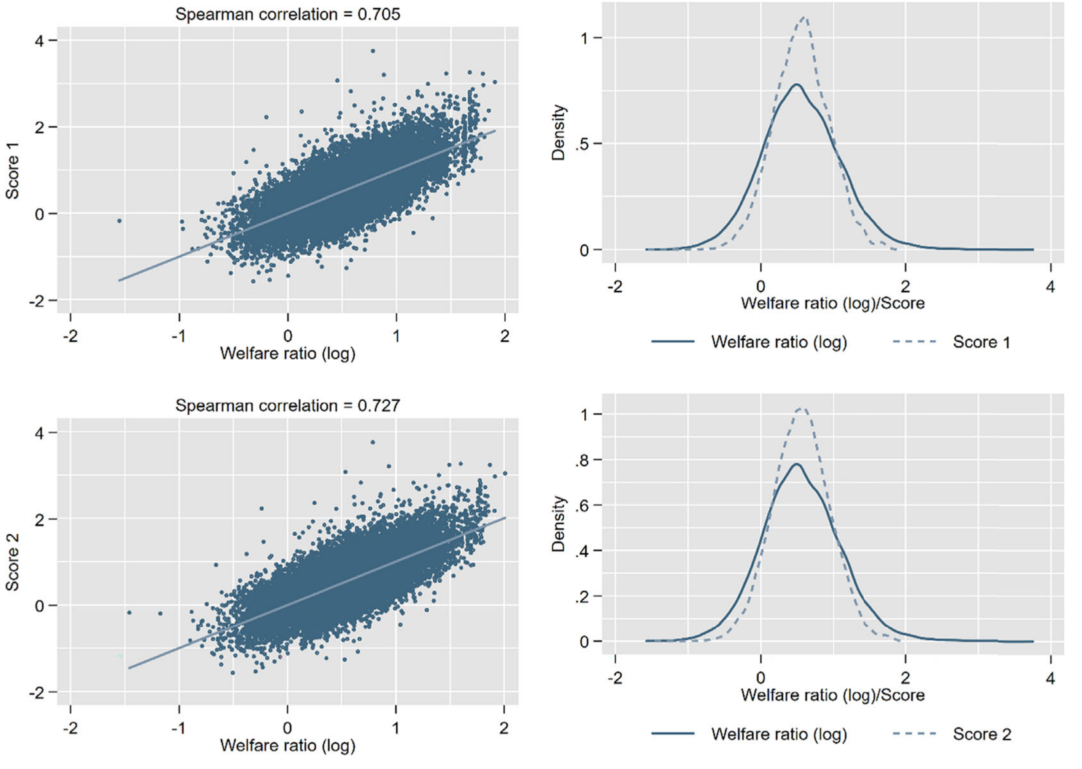

FIGURE 3 Comparing distributions of scores and welfare ratio (log). *Source*: Score 1 refers to the PMT model (MMT model with only household characteristics) and score 2 to the MMT model. Authors' calculations using 2015 EBCNV survey. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Targeting performance of full MMT model using different cut-off scores.

Quantiles of the welfare ratio	PNAFN	AMGII	MMT cut-off scores					
			Cutoff 1 (10th percentile)	Cutoff 2 (15th percentile)	Cutoff 3 (20th percentile)	Cutoff 4 (25th percentile)	Cutoff 5 (30th percentile)	Cutoff 6 (40th percentile)
Decile 1	17.44	41.16	29.26	46.25	58.15	67.60	75.86	88.89
Decile 2	13.92	28.06	9.35	19.56	31.21	41.01	52.13	70.5
Decile 3	12.09	22.03	3.47	9.92	17.09	25.55	34.97	55.71
Decile 4	9.16	18.06	2.68	7.36	12.16	18.97	26.54	45.34
Decile 5	7.79	13.93	1.81	4.38	8.07	12.37	18.03	34.06
Decile 6	5.96	11.38	0.59	2.34	4.67	7.12	12.11	24.89
Decile 7	4.99	8.56	0.43	1.53	2.57	4.09	6.72	17.91
Decile 8	4.14	5.52	0.19	0.54	1.13	2.4	4.22	10.79
Decile 9	2.25	4.62	0.18	0.23	0.31	0.73	1.64	4.36
Decile 10	1.13	1.71	0.23	0.23	0.39	0.55	0.7	2.13
All	7.9	15.51	4.82	9.23	13.58	18.04	23.29	35.46

Note: Authors' calculations using 2015 EBCNV survey.

also equal to the poverty rate in 2015. The 25% cut-off is close to the coverage of both programmes (AMGI and AMGII).

The first column of the table provides the coverage of the PNAFN program, which is the current approach for selecting PNAFN/AMGI beneficiaries. It indicates that 17.44% and 13.92% of the first (the poorest 10%) and second (the poorest 20%) deciles, respectively, are PNAFN beneficiaries. Interestingly, our findings align with the World Bank and CRES (2022), using the same 2015 survey, indicating that nearly 5% of the seventh decile and 4% of the eighth decile (generally non-poor households) also benefit from this program designed to primarily serve the poor population, thus revealing inclusion errors.[4]

Utilising the full MMT model for a program targeting the poorest 10% of the population based on the welfare ratio, the coverage rate of the poorest 10% amounts to 29%, with an overall coverage rate of 4.8% for the entire population. This is near two times the coverage rate of the current PNAFN program, which covers an eligible population of 8%. Importantly, the coverage rate of the last five deciles does not exceed 1%, indicating that less than 1% of non-poor households benefit from this program targeting the poorest 10% of the population.

If we consider the second cut-off of 15% (indicating that 15% of the population below this cut-off would be eligible for benefits based on the full MMT model), more than 46% of program beneficiaries would come from the poorest decile, compared to 41% based on the current AMGII program. These results underscore that the targeting performance based on the full MMT model, combining individual and geographical targeting, is considerably superior to existing programmes (PNAFN/AMGI and AMGII).[5]

Table 5 further illustrates the distributions of program beneficiaries according to the different full MMT cut-off scores by welfare ratio deciles. Notably, 22.12% of the PNAFN beneficiaries are in the first poorest decile, 17.65% in the second decile, and 15.33% in the third decile. In contrast, 45% of the current PNAFN beneficiaries are distributed over the seven least upper deciles. If the PNAFN program was targeted based on the full MMT (cut-off 1 – 10th percentile), about 61% of program beneficiaries would come from the poorest 10%, three times the current program's size. Conversely, the last seven deciles contain only 12.7% of the beneficiaries, representing a minor proportion compared to that found for the current PNAFN program.

TABLE 5 Distribution of beneficiaries using different MMT cutoff scores (full model).

			MMT cutoff scores					
Quantiles of the welfare ratio	PNAFN	AMGII	Cutoff 1 (10%)	Cutoff 2 (15%)	Cutoff 3 (20%)	Cutoff 4 (25%)	Cutoff 5 (30%)	Cutoff 6 (40%)
Decile 1	22.12	26.56	60.71	50.08	42.84	37.48	32.57	25.07
Decile 2	17.65	18.09	19.41	21.19	23.00	22.74	22.39	19.89
Decile 3	15.33	14.21	7.20	10.74	12.59	14.16	15.01	15.71
Decile 4	11.61	11.65	5.56	7.97	8.95	10.51	11.39	12.78
Decile 5	9.88	8.99	3.76	4.74	5.94	6.86	7.74	9.60
Decile 6	7.56	7.34	1.22	2.54	3.44	3.95	5.20	7.02
Decile 7	6.33	5.52	0.89	1.66	1.89	2.27	2.89	5.05
Decile 8	5.25	3.56	0.39	0.59	0.83	1.33	1.81	3.04
Decile 9	2.85	2.98	0.37	0.25	0.23	0.41	0.70	1.23
Decile 10	1.43	1.10	0.48	0.25	0.29	0.30	0.30	0.60
All	100	100	100	100	100	100	100	100

Note: Authors' calculations using 2015 EBCNV survey.

TABLE 6 Under coverage and leakage rates and eligible share by cutoff scores.

	MMT with only household characteristics			Full MMT with household and regional characteristics		
Cutoff scores	IER	EER	Eligible share	IER	EER	Eligible share
Cutoff 1 (10th)	40.76	74.20	4.36	39.29	70.74	4.82
Cutoff 2 (15th)	36.02	66.38	7.88	37.41	61.47	9.23
Cutoff 3 (20th)	33.96	59.32	12.32	34.16	55.32	13.58
Cutoff 4 (25th)	31.98	53.35	17.15	32.04	50.97	18.04
Cutoff 5 (30th)	31.26	47.15	23.07	30.04	45.68	23.29
Cutoff 6 (40th)	27.79	36.93	34.93	26.55	34.89	35.46

Note: Authors' calculations using 2015 EBCNV survey.

Table 6 presents the results of inclusion and exclusion errors, including under-coverage rates, leakage rates, and eligible shares, for cut-off scores of the two models: the MMT with only household characteristics and full MMT model with both household and regional characteristics.

For instance, if we set the cut-off score at the 20th percentile, making 12.3% of households eligible (less than the poor population in Tunisia in 2015), the Inclusion Error Rate (IER) ranges between 33.9% for the MMT model to 34.2% for the full MMT model. These results indicate that, for the MMT model, 33.9% of those identified as poor are not actually poor—an acceptable rate compared to other work using PMT as a targeting model. For example, Brown et al. (2018) show that the average rate of inclusion error across their selected sample of countries[6] is about 37%, with an average exclusion error of 72%, for a fixed poverty level of 20%.

It is also important to note that the inclusion and exclusion errors both decrease with increasing cut-offs; a cut-off of the 40th percentile, the inclusion error drops from 39.3% to 26.6% and the EER from 70.7% to only 34.9%.

Considering the spatial dimension of poverty in Tunisia, which is clustered in the north-west and central-west regions, inclusion and exclusion errors were calculated by region. Table 7 summarises the results for the MMT model with only household characteristics (PMT model) and the full MMT model. Regardless of the MMT cut-off scores, eligible population shares are notably low for the least poor regions (Great Tunis and Center East) compared to the poor regions (North-west and center West). For clarification, if the cut-off score is set at the national level of 20, approximately 36.19% of people in the center-west and 28.73% of people in the north-west will benefit from the program. In contrast, the coverage for Grant Tunis is only 1.86%, and for the central-east region, it is 8.97%. This distribution highlights the targeted approach of the full MMT model, directing more assistance to the regions identified as the poorest.

Importantly, the inclusion and exclusion errors are significantly lower in the two poorest regions compared to the less poor ones. Specifically, the inclusion error ranges from 23.46% to 35.05% for the center-west region (the poorest region) and from 23.12% to 42.71% for the north-west. The exclusion rates are also notably low for these two poorest regions, the center-west and north-west, with rates of 35.68% and 41.98% for a cut-off score of 20th percentile, and even lower at 15.72% and 20.82% for a cut-off of 40th percentile. These outcomes underscore the effectiveness of the full MMT targeting model, which combines individual and geographical factors, not only at the national level but also at the regional level. This model proves successful in minimising inclusion and exclusion errors, particularly for the poorest regions of Tunisia.

In addition, the results presented in Table A6 (Appendix) provide important insights into the main correlates of the potential beneficiary's profile selected by MMT based on the three cut-offs (10%, 15%, and 25%). Our results show that most of the selected potential beneficiaries are households living in rural areas led by married men, and the average size of these households is estimated to be more than six people. The educational level of more than 80% of these household heads does not exceed the primary level; approximately 30% are unemployed or inactive, and over than 30% are engaged in non-agricultural work.

TABLE 7 Under coverage and leakage rates and eligible share by cutoff scores and by region.

	MMT with only household characteristics (PMT model)			Full MMT		
	IER	EER	Eligible share	IER	EER	Eligible share
Great Tunis						
Cutoff 1	72.29	96.79	0.35	61.73	95.90	0.32
Cutoff 2	61.67	92.50	1.04	61.58	92.95	0.98
Cutoff 3	44.12	81.88	2.60	48.55	88.03	1.86
Cutoff 4	36.72	75.08	4.49	32.94	79.03	3.57
Cutoff 5	41.72	66.76	8.43	33.49	73.31	5.93
Cutoff 6	36.62	55.19	16.10	31.03	59.56	13.35
Northeast						
Cutoff 1	44.13	79.75	2.40	40.47	79.64	2.27
Cutoff 2	46.06	75.33	5.23	44.44	76.48	4.84
Cutoff 3	39.03	68.66	8.79	39.04	70.34	8.32
Cutoff 4	35.66	63.42	12.61	35.14	63.86	12.36
Cutoff 5	32.98	54.83	18.40	29.06	56.27	16.83
Cutoff 6	31.39	42.85	32.09	28.26	42.24	31.01
Northwest						
Cutoff 1	41.42	77.82	7.27	42.71	69.00	10.40
Cutoff 2	28.27	65.79	13.40	31.91	51.57	19.99
Cutoff 3	23.64	56.08	20.34	28.59	41.98	28.73
Cutoff 4	22.70	47.93	28.33	27.81	36.67	36.89
Cutoff 5	22.78	42.11	35.83	25.86	30.82	44.61
Cutoff 6	19.72	32.18	49.70	23.12	20.82	60.58
Center East						
Cutoff 1	33.85	79.07	2.45	30.04	76.46	2.61
Cutoff 2	29.92	72.69	4.44	34.34	66.78	5.76
Cutoff 3	35.82	68.13	7.67	35.88	62.77	8.97
Cutoff 4	32.58	61.82	11.71	32.67	60.64	12.09
Cutoff 5	32.31	56.09	16.79	31.77	56.05	16.68
Cutoff 6	30.34	45.18	27.55	28.46	43.40	27.70
Center West						
Cutoff 1	33.42	61.40	12.82	35.05	54.74	15.41
Cutoff 2	30.63	51.59	21.26	35.00	44.09	26.21
Cutoff 3	30.61	45.21	29.81	32.90	35.68	36.19
Cutoff 4	29.89	37.65	38.99	30.74	30.52	43.98
Cutoff 5	27.47	31.52	46.97	29.17	25.33	52.44
Cutoff 6	21.45	21.28	61.41	23.46	15.72	67.49
Southeast						
Cutoff 1	51.86	73.00	6.72	46.00	75.56	5.43
Cutoff 2	43.46	64.15	11.61	42.83	67.11	10.53
Cutoff 3	38.67	54.97	17.92	36.85	60.44	15.29

TABLE 7 (Continued)

	MMT with only household characteristics (PMT model)			Full MMT		
	IER	EER	Eligible share	IER	EER	Eligible share
Cutoff 4	37.32	50.49	23.24	35.94	53.98	21.14
Cutoff 5	35.84	44.02	30.53	34.13	46.92	28.20
Cutoff 6	31.48	31.98	45.88	30.09	35.20	42.84
Southwest						
Cutoff 1	53.09	72.57	6.44	55.19	78.82	5.20
Cutoff 2	49.49	63.22	12.61	49.44	67.84	11.01
Cutoff 3	42.73	52.00	19.99	36.79	57.44	16.06
Cutoff 4	39.79	44.07	27.07	37.77	51.26	22.83
Cutoff 5	36.13	36.15	35.56	32.34	41.64	30.67
Cutoff 6	29.99	25.41	50.86	26.01	28.63	46.05

Note: Authors' calculations using 2015 EBCNV survey.

TABLE 8 Identifying of Potential beneficiaries using Household' deprivations Model.

Regions	Total head count	Group_1	Group_2	Group_3
Tunisia	*1,213,939*	*8748*	*132,053*	*1,073,137*
	43.64%	*0.31%*	*4.75%*	*38.58%*
Great Tunis	*198,767*	*250*	*9312*	*189,204*
	27.38%	*0.03%*	*1.28%*	*26.06%*
North East	*175,540*	*341*	*13,206*	*161,993*
	44.30%	*0.09%*	*3.33%*	*40.88%*
North West	*170,443*	*1408*	*25,085*	*143,950*
	56.43%	*0.47%*	*8.30%*	*47.65%*
Central East	*253,077*	*2011*	*26,755*	*224,309*
	38.38%	*0.31%*	*4.06%*	*34.02%*
Central West	*209,840*	*3838*	*38,082*	*167,919*
	64.89%	*1.19%*	*11.78%*	*51.93%*
South East	*125,617*	*653*	*11,868*	*113,093*
	53.88%	*0.28%*	*5.09%*	*48.51%*
South West	*80,654*	*245*	*7742*	*72,666*
	56.99%	*0.17%*	*5.47%*	*51.35%*

Note: Authors' calculations using 2015 EBCNV survey.

5.3 | Beneficiaries identification using Multi-dimensional targeting model

The total number of potential beneficiaries is estimated at 1,213,939 households, constituting 43.64% of the total population in 2014. This percentage encompasses all Tunisian households experiencing at least one form of deprivation. The findings outlined in Table 8 reveal significant variations across different Tunisian regions. Specifically, it stands at 27.38% in Greater Tunis, approximately 44.30% in the Northeast, 56.43% in the North West, 64.89% in the West Center, and 56.99% in the South West. In the South East, 53.88% of households are potential beneficiaries, while the East Center has the lowest proportion at 23.42%. These results underscore that the proposed targeting methodology identifies a larger pool of beneficiaries compared to the existing selection process in Tunisia. The deprivation targeting approach effectively categorises potential beneficiaries into three distinct and comprehensive groups based on their level of deprivation.

The first group comprises potential beneficiaries experiencing deprivation in the three dimensions simultaneously. According to the results presented in Table 8 (Third column), 8748 households fall into this group, accounting for 0.31% of the total population. The proportion of households in this group varies significantly across the seven regions of Tunisia. The highest rates observed in Central West (1.19%), North West (0.47%), and Central East (0.31%). The Greater Tunis region reports the lowest rate (0.03%), followed by the North East (0.09%), South West (0.17%), and South East (0.28%). Consequently, there is an immediate imperative to target comprehensive interventions addressing all dimensions for all members of the first group without exception.

The second group comprises potential beneficiaries experiencing exactly two deprivations simultaneously. We have identified 4.75% of the total population that should be included in this group, with estimates of 4.06% in Center East and about 3.33% in the Northeast. However, this proportion is estimated at 8.30% in the North West, 5.09% in the South East, and 5.47% in the South West. In the West Center, 11.78% of potential beneficiaries should be included in this second group, while the lowest proportion is estimated in Greater Tunis (1.28%). Individuals in this second group require social interventions in two dimensions, addressing the primary causes of their deprivations. The potential beneficiaries of the third group make up this portion, totalling 1,073,137 Tunisian households or about 38.58% of the country's population. This percentage represents 34.02% and 40.88% of households in the North East and the Center East, respectively, with high proportions observed in the West Center (51.93%), South West (51.35%), and North West (47.65%).

Table A5 in the appendix indicates that the targeting deprivations covers more households compared to the current selection process implemented in Tunisia. We estimated 1,213,939 Tunisian households as potential beneficiaries of poverty reduction programmes, of which 26.25% are officially identified as poor, and 73.75% are non-poor. Our results show that 0.03% of households not selected as potential beneficiaries are officially identified as poor. On the other hand, 99.97% of households not selected as potential beneficiaries are also officially non-poor.

In estimating the targeting accuracy by potential beneficiaries' groups, our proposed methodology in this research identifies 78.99% of poor households in the group of potential beneficiaries living in extreme deprivation,

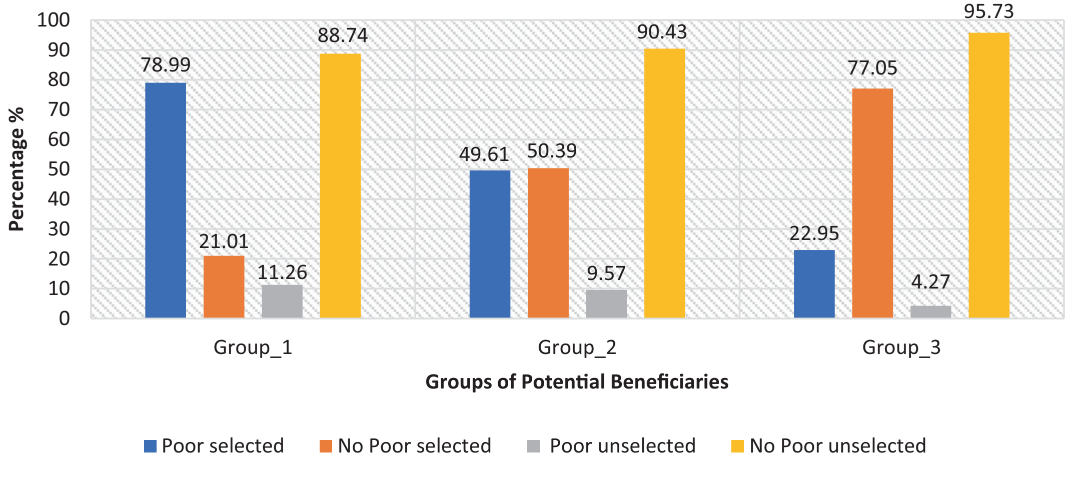

FIGURE 4 Accuracy of Multi-Dimensional Targeting Model by Deprivations Group. *Source*: Authors' calculations using 2015 EBCNV survey. [Colour figure can be viewed at wileyonlinelibrary.com]

with only 21.01% being non-poor individuals included in this group (Figure 4). The poor and non-poor excluded from the first group are estimated at 11.26% and 88.74%, respectively.

As shown in Figure 4, the proportion of non-poor households excluded from the second group is estimated at 90.43%, while the poor households excluded from this group, living with exactly two deprivations, represent only 9.57%. However, the proportions of poor and non-poor households selected as potential beneficiaries are similar and estimated at around 50%. Regarding the third group, the proportion of non-poor households is 77.05%.

From the results presented in Table A6 (Appendix), our findings indicate that most of the potential beneficiaries selected in the first group are households living in rural areas (81,84%), led by married men, and the average size of these households is estimated to be more than seven individuals. More than 35% of these household heads are unemployed, over 20% are engaged in agricultural work. However, in the second group, we observed that nearly 19.54% of potential beneficiaries are households headed by women, with approximately 19.40% of these household heads being unmarried. The average size of households included in the second group is five individuals. Unlike the first two groups, our results indicate a higher proportion of potential beneficiaries living in urban areas in the third group, estimated at 64.20%. Furthermore, the percentage of heads of households who are unemployed or inactive in this group is 26.43%.

6 | CONCLUSION AND POLICY RECOMMENDATIONS

In this paper, we compared the targeting accuracy of social safety nets currently implemented in Tunisia using the Mixed Means Test (MMT) method and multi-dimensional targeting based on household deprivation. Like most developing countries, Tunisia lacks reliable surveys or information on household income. In such cases, the PMT model is often the recommended targeting method to select program beneficiaries based on scores calculated from covariates highly correlated with household income or total consumption expenditure, which are challenging to manipulate. However, if Tunisia were to eradicate poverty in all forms as a strategic objective, multi-dimensional targeting based on household deprivations also appears valid.

In the first part of this research, we estimated MMT models and evaluated their performance. The targeting effectiveness is assessed based on the distribution of households by deciles of the welfare ratio using six cut-off scores. Our findings indicate that the targeting performance of the full MMT model is significantly better than the existing programmes (PNAFN/AMGI and AMGII). The coverage rate of the poorest 10% equals 29.26% using the full MMT model, nearly two times the coverage rate of the current PNAFN program, covering only 17.44 (with a coverage rate of 8% for all populations). Moreover, we observed that inclusion and exclusion errors decrease with increasing cut-offs. With the full MMT model, the inclusion error decreases from 37.41% for a cut-off of the 15th percentile to 26.55% for a cut-off of the 40th, and the exclusion error decreases from 61.47% to only 34.89%. Calculating targeting errors by region reveals that eligible population shares are very low for the least poor regions (Great Tunis and Center East) in contrast to the poor regions (North-west and center West), irrespective of the MMT cut-off scores.

On the other hand, we have proposed a targeting methodology using a multi-dimensional approach based on household deprivation. A divergence was observed between the selection process of social program beneficiaries and the official identification of poor households in Tunisia. The dimensions used are those of social safety nets currently implemented in Tunisia, and the deprivation thresholds are directly derived from the eligibility criteria used by the PNAFN and AMGII programmes. There is clear evidence that the proposed targeting methodology identifies more beneficiaries than the selection process currently implemented in Tunisia. To this end, the deprivations targeting approach allows categorising potential beneficiaries into three mutually exclusive and collectively exhaustive groups of households based on their degree of deprivation. Moreover, targeting household deprivations is more accurate regarding the inclusion of officially poor and non-poor households compared to the selection processes currently implemented in Tunisia.

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CONFLICT OF INTEREST STATEMENT

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in official website of ERF. Archive https://erf.org.eg/erf-micro-data-catalogue-nada/. And data in this study can be obtained by connecting with corresponding author.

ETHICAL APPROVAL

This article does not contain any studies with human participants performed by the author.

INFORMED CONSENT

This article does not contain any studies with human participants performed by the author.

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ENDNOTES

[1] Grosh et al. (2022) present a detailed literature review on targeting methods.

[2] The new data for the 2020–21 household survey have recently been made available on the website of the National Institute of Statistics. However, the variable relating to the administrative level of the governorate does not exist among the survey variables, although it is present in the questionnaire. The governorate variable represents the second level of the multilevel model and is required for the estimation of the MMT model. Given this limitation, it is recommended to keep using the estimates based on the 2015 survey until the necessary variable is available in the new data. An update of the proposed model can be pursued once the missing variable is included in the dataset, allowing for implementing the MMT model using the latest available survey data.

[3] The MMT model with only household characteristics can be interpreted as a PMT model.

[4] Based on the 2005 EBCNV survey, the World Bank (2015) reported that 8.2% of all PNAFN benefits accrue to the highest quintile (richest population), while 40% accrue to the lowest quintile. This coverage rate of the poorest population (the first quintile) in Tunisia, as indicated in this study, appears to be comparatively low compared to Argentina, the Dominican Republic, and Sri Lanka.

[5] The first two columns of Table 4 measure the targeting performance of the current approach used to select PNAFN and AMGII beneficiaries. This approach considers the geographical distribution of poverty by region. i.e. assigning quotas.

[6] Burkina Faso, Ethiopia, Ghana, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda.

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APPENDIX A

TABLE A1 Eligibility Criteria for social safety nets in Tunisia.

Programs	Eligibility criteria
PNAFN	Individual annual income work ability of the household head Loss of the head of the family, with the deterioration of the economic capacity of the family lack of bond from among children who are able to spend or the inability of the bond to provide the basic needs of the family The presence of people with disabilities or people with chronic or serious diseases within the family Low living conditions in terms of housing and health facilities
AMGII	Annual income Household size

Note: circulars and decrees ministerial, (MSA).

TABLE A2 Comparing targeting methods.

Targeting method	Advantages	Limitations	Example of case study
1. Individual/household assessment			
Means Test (MT): applied when complete income information is available and can be verified.	Very accurate	Requires high levels of literacy and documentation of economic transactions, preferably of income.	
Proxy means test (PMT): eligibility based on a score estimated using a set of observed variables that reflects the household's welfare.	Economically efficient, useful in situations with high levels of informality, captures multidimensional aspects of poverty.	The results of the PMT model depend on the quality of the available data (household survey), and on the estimation methods. Difficult to update quickly, less flexible to shocks.	Brown et al. (2018) (Burkina Faso, Ethiopia, Ghana, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda), Ahmed and Bouis (2002) (Arab Republic of Egypt).
Hybrid means test (HMT): Combination of MT and PMT	Provides the ability to predict hard-to-verify income based on a statistical model.	Requires detailed information on the different sources of income.	
2. Categorical targeting			
Geographical targeting: beneficiaries are generally selected according to their geographic location (poverty mapping can be used).	Administratively simple and can be combined with other methods.	Poor performance when poverty is not spatially concentrated.	
3. Self-targeting			
Program open to all but designed in such a way that take-up for it will be much higher among the poor than the nonpoor	Low administrative costs.	May be difficult to find a means of delivering a large benefit.	2012 (Indonesia)

Note: The first three columns are based on Coady et al. (2004).

TABLE A3 Descriptive Statistics of household characteristics and regional variables.

Variable	Mean	SD	Min	Max
Individual/household variables				
Area of residence (= 1 if urban)	0.684	0.465	0	1
The size of the household	4.727	1.733	1	22
Gender of the head (= 1 if male)	0.888	0.315	0	1
Household composition				
1 to 2 adults with 1 to 2 children	0.180	0.384	0	1
1 to 2 adults with 3 or more children	0.166	0.372	0	1
3 or more adults with 0–1 child	0.428	0.495	0	1
3 or more adults with 2–3 children	0.117	0.321	0	1
3 or more adults with 4 or more children	0.020	0.139	0	1
Household with 1 active member	0.389	0.488	0	1
Household with 2 active members	0.318	0.466	0	1
Household with 3 or more active members	0.210	0.407	0	1
Education level of the head				
With no education	0.224	0.417	0	1
Primary	0.395	0.489	0	1
Secondary	0.274	0.446	0	1
Tertiary	0.107	0.309	0	1
Status of the head				
Employed	0.660	0.473	0	1
Unemployed	0.029	0.167	0	1
Pensioners/retired	0.145	0.352	0	1
Others	0.165	0.372	0	1
Dependency ratio	0.441	0.230	0	1
Dwelling characteristics				
Low-quality housing	0.107	0.309	0	1
High-quality housing (flat)	0.214	0.410	0	1
Apartment	0.522	0.500	0	1
Access to drinking water (= 1 if yes)	0.872	0.334	0	1
Access to natural gas (=1 if yes)	0.219	0.413	0	1
Dwelling with bathroom (= 1 if yes)	0.724	0.447	0	1
Dwelling with kitchen (=1 if yes)	0.979	0.143	0	1
Regional variables				
Population density	596.845	1057.996	3.843	3667.524
Urbanisation rate	68.233	21.885	27.100	100
Share of population with no education	19.192	7.765	10.300	35
Share of population with primary education	32.027	3.211	26.600	36.900
Share of population with secondary education	36.967	4.682	26.900	44.200
Share of population with highly education level	12.119	4.579	6	22.200
Poverty rate	14.929	8.880	4.600	33.600

TABLE A3 (Continued)

Variable	Mean	SD	Min	Max
Unemployment rate	15.114	4.588	9.100	27.100
Share of employment in the agricultural sector	10.980	8.352	0.612	28.582
Share of employment in the industrial sector	17.422	8.915	4.237	37.040

Note: dependency ratio is the ratio of dependents (people younger than 15 or older than 64) to the working-age population (those ages 15–64 years).

TABLE A4 Dimensions and Deprivation Thresholds used for Household Deprivations Model.

Dimensions	Deprivation thresholds description (Z_j)
Food	Household is deprived if his achievement in this dimension is below the food threshold estimated by INS for each stratum. This threshold is estimated at 1085 TND in the metropolitan area; at 1050TND in the municipal area and 952 TND in the non-municipal area.
Education	Household is deprived in this dimension if there is in the family a child aged between 6 and 16 years who does not pursue an education or training cycle.
Health	Household is deprived in health if its income approximated by the total expenditure is lower than: * SMIG if household size ≤2 persons * 1.5 SMIG if 3persons ≤ household size ≤5 persons * 2 SMIG if household size >5 persons

TABLE A5 Targeting models and poverty status.

				Poor	
			Total	Yes	No
Multi-dimensional Targeting		Yes	1,213,939	26.25%	73.75%
		No	1,567,621	0.03%	99.97%
Current Targeting Process	PNAFN	Yes	230,223	23.24%	76.76%
		No	2,551,336	10.41%	89.59%
	AMGII	Yes	387,399	28.22%	71.78%
		No	2,394,161	8.77%	91.23%
	Both Programs	Yes	597,320	26.13%	73.87%
		No	2,184,239	7.47%	92.53%

TABLE A6 Beneficiaries profiles by targeting method.

		Multi-dimensional targeting model			Mixed means test model		
		Group_1	Group_2	Group_3	Cutoff (10%)	Cutoff (15%)	Cutoff (25%)
Location	Rural %	81.84	61.04	35.80	77.44	71.15	62.71
	Urban %	18.16	38.96	64.2	22.56	28.85	37.29
Demographic Characteristics	Female HH %	11.33	19.54	14.49	5.33	6.35	6.81
	Male HH%	88.67	80.46	85.51	94.69	93.65	93.19
	H size mean	7.05	5.32	4.57	7.51	6.95	6.41
	H age mean	49.26	56.18	53.08	50.39	51.06	51.62
	Household head married%	86.91	80.6	83.95	94.35	94.01	92.79
	Household head not married %	13.09	19.4	16.05	5.65	5.99	7.21
Employment Status of household head	Unemployed /inactive %	38.83	39.65	26.43	35.69	32	28.81
	Retired %	0.2	4.69	9.78	1.97	2.97	3.51
	Working in Agricultural sector %	21.36	16.26	9.89	20.10	19.81	18.32
	Working in non-agricultural sector %	29.58	27.45	32.98	30.81	32.64	34.08
	Senior and middle managers of the liberal professions and other employees %	10.03	11.95	20.92	11.43	12.57	15.28
Education of household head	No Schooling%	47.92	47.12	29.07	45.88	42.81	37.33
	Primary %	47.96	40.86	43.2	47.62	48.92	50.30
	Secondary%	4.12	11.32	23.10	5.3	8.11	12.13
	Higher education level %	00	0.7	4.63	0.2	0.16	0.24