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Abstract

This paper proposes two new approaches for targeting the beneficiaries of social benefit programs in Tunisia, such as the cash transfer and healthcare programs. The first approach is a mixed means test (MMT), which extends the proxy means test (PMT) model to explicitly combine both individual/household assessment and geographical targeting methods. The second approach is drawn from the identification step of the family of multidimensional poverty measures. Using the 2015 National Survey on Household Budget, Consumption, and Standard of Living, our results show that the targeting performances based on both approaches are considerably better than the existing programs. Specifically, the coverage rate of the poorest 10 percent using the MMT targeting model that combines individual/household and geographical scales is around 29 percent, nearly twice the coverage rate of the current PNAFN program. The MMT works well not only at the national level but also at the regional level. It allows us to minimize inclusion and exclusion errors for the poorest regions of Tunisia. Additionally, the proposed multidimensional approach identifies a higher number of beneficiaries compared to the selection process currently implemented in Tunisia. However, the inclusion of such a number of households in a social program may be constrained by the unavailability of monetary resources and the country's financial situation. For this purpose, the deprivation targeting approach allows us to categorize potential beneficiaries into three mutually exclusive and collectively exhaustive groups of households according to their degree of deprivation.

JEL Classifications: J1, I15, H2

Keywords: Social safety nets, targeting beneficiaries, Tunisia

ملخص

تقترح هذه الورقة نهجين جديدين لاستهداف المستفيدين من المزايا الاجتماعية في تونس مثل برامج التحويلات النقدية والرعاية الصحية. النهج الأول هو اختبار الوسائل المختلطة الذي يوسع نموذج اختبار الوسائل الوكيلة ليجمع صراحة بين كل من التقييم الفردي/ الأسرة "المعيشية" وطرق الاستهداف الجغرافي. والنهج الثاني المستخدم مستمد من خطوة تحديد أسرة تدابير الفقر متعدد الأبعاد . باستخدام المسح الوطني حول ميزانية الأسرة واستهلاكها ومستوى معيشتها لعام 2015، تظهر النتائج أن أداء الاستهداف القائم على كلا النهجين أفضل بكثير من البرنامج الحالى (أى البرنامج القومى لمساعدة العائلات الفقيرة فى تونس (PNAFN). يعمل اختبار الوسائل المختلطة بشكل جيد، ليس فقط على المستوى الوطني، ولكن أيضا على المستوى الإقليمي. فهو يسمح لنا بتقليل أخطاء الإدماج والاستبعاد إلى أدنى حد بالنسبة لأفقر المناطق في تونس. بالإضافة إلى ذلك، يحدد النهج متعدد الأبعاد المقترح عدد المستفيدين الأعلى مقارنة بعملية الاختيار المطبقة حاليا في تونس. بيد أن إدراج هذا العدد من الأسر المعيشية في برنامج اجتماعي قد يعوقه عدم توافر الموارد النقدية والحالة المالية للبلاد. ولهذا الغرض، يسمح نهج استهداف الحرمان بتصنيف المستفيدين المحتملين إلى ثلاث مجموعات من الأسر المعيشية حصرية بصورة متبادلة وشاملة بصورة جماعية وفقا لدرجة حرمانها.

1. Introduction

Effectively identifying the beneficiaries of a targeted social program is a challenging task compared to a universal program where everyone is covered without meeting specific eligibility criteria (Hana and Olken, 2018; Gentilini et al., 2020; Leseman and Slot, 2020). Although the universality of a social program provides an excellent way of reaching the poorest, the beneficiaries may include many people who do not need this form of public help, which generally means that resources are wasted (Brown, Ravallion, and van de Walle, 2018; Karlan and Thuysbaert, 2019). To ensure that the benefits of a program are concentrated on poor people and maximize its social impact with scarce resources, governments (mainly in developing countries) have tried many methods to select the appropriate recipients for aid programs.

In practice, three targeting methods have been commonly used (Coady, Grosh, and Hoddinott, 2004a). The first is categorical targeting, which refers to a method in which all individuals in a specified category, such as a particular age group or region, are eligible to receive benefits. It involves defining eligibility in terms of individual or household characteristics that are fairly easy to observe, difficult to falsely manipulate, and correlated with poverty (e.g., Ravallion and Wodon, 2007; Duflo, 2000). A second method is based on eligibility criteria to select households and individuals. The eligibility criteria can be defined using a direct measurement of income or consumption. This method, known as the means test, is dependent on the mechanisms used to check the quality of the potential beneficiaries' statements, which implies a highly developed administrative system (see, for example, Seleka and Lekobane, 2020). This type of verification is generally impracticable in developing countries (Lavallée et al., 2010; Alatas et al., 2012; Basurto, Dupas, and Robinson, 2019). Alternatively, the eligibility criteria can also be based on a score constructed from a set of variables reflecting the living conditions of households. This method is known as the proxy mean test (PMT), in which field workers collect demographic, asset, or housing information that can be used to roughly assess a household's poverty status (e.g., Kurdi et al., 2018; Stella et al., 2021; Premand and Schnitzer, 2021). A third method is the selection of program beneficiaries by local and regional commissions themselves, while the center controls the allocation of funds and quotas for each region (e.g., Crook and Sverrisson, 2001; Conning and Kevane, 2002; Bardhan and Mookherjee, 2005). Proponents of this targeting method have claimed that more information is available at the local level about who is poor. Local authorities tend to be more accountable to the locals and hence have an incentive to use locally available information to improve targeting performance (Galasso and Ravallion, 2001).

The performance of targeting methods is often a topic of active policy debates and research. In the literature, there is no consensus on this issue; Ravallion (2007), for example, argues that better targeting is not seen as desirable per se, but rather as an instrument for poverty reduction. Others argue that targeting should only be assessed against the program's eligibility criteria (Devereux et al., 2017). A common approach to analyzing the targeting performance of alternative transfer instruments is to compare the under-coverage and leakage rates (e.g., Coady, Grosh, and Hoddinott, 2004a; Stoeffler, Mills, and del Ninno, 2016; Bah et al., 2018). Analysis is often presented in terms of a two-by-two matrix (Cornia and Stewart, 1995). Under-coverage refers to exclusion errors and represents the proportion of poor households that are not included in the program. Leakage, however, represents the proportion of those who are reached by the program but are classified as non-poor (inclusion errors). Studies directly comparing alternative targeting methods based on their implementation in real-life settings are particularly rare in the literature (Premand and Schnitzer, 2021). For instance, Alatas et al. (2012) use random evaluation techniques to compare the targeting of PMT with methodologies that allow varying degrees of community inclusion in the decision-making process and are based on different conceptions of poverty in Indonesia. Some comparative studies are based on the implementation of one targeting method and the simulation of another, such as a PMT and selection by community leaders in Malawi (Basurto, Dupas, and Robinson, 2019); community-based targeting with five PMT procedures in northwest Burkina Faso (Schleicher et al., 2016); or geographic targeting followed by a household PMT and multidimensional targeting based on the deprivations of poor households in Mexico (Azevedo and Robles, 2013).

In Tunisia, the non-contributory social protection schemes represent a major component of the country's social protection system. In addition to universal energy and food subsidies that started in the 1970s, social safety nets include direct cash transfer schemes. Introduced in 1986 to mitigate the effects of structural adjustment programs, the flagship cash transfer program in Tunisia is the Assistance to Needy Families (PNAFN) program. This program offers unconditional financial assistance and access to healthcare programs either free of charge through the *Assistance Médicale Gratuite* (AMGI) program or at a reduced rate through the *Assistance Médicale à Tarifs Réduits* (AMGII) program (Machado, Bilo, Soares, and Osorio, 2018). The effectiveness of the targeting of these programs is currently gaining the attention of researchers, policymakers, and civil society organizations (CSOs). Research finds that the poor, who should be eligible, are often excluded from these programs. The exclusion rate reached around 50 percent among the poor and 40 percent among the extremely poor (Institut National de la Statistique, 2013; Nasri, 2020). Improving the selection of the poor and vulnerable households using better targeting can ensure lower subsidy costs and reduce inclusion and exclusion errors. This exercise is reasonably requested and necessary for Tunisia, especially in these very difficult circumstances characterized by the economy's weak recovery since the 2011 revolution. This is accompanied by the COVID-19 health crisis, the evolution of which remains unpredictable and the effects of which are heavy on the population, especially the poor and the most vulnerable households. However, the choice of targeting method is often a subject of active policy debate and research. This paper aims to compare the targeting accuracy of Tunisia's current social safety nets with two alternative targeting methods. The first model is an extended version of the PMT, called the Mixed Means Test (MMT), or a two-hierarchical/multilevel model that combines individual and geographic targeting approaches, and the second is a multidimensional targeting approach based on household deprivation. The comparison will be based on coverage as well as inclusion and exclusion error rates.

The structure of the paper is as follows. Section 2 presents a background on the social safety nets in Tunisia. Section 3 discusses the sample and data. Section 4 presents our empirical strategy. Section 5 discusses the main results, and section 6 concludes.

2. Background on social safety nets in Tunisia

Social safety nets in Tunisia are mainly based on a direct transfers scheme directed toward needy families, the elderly, and the disabled, known as the PNAFN, and on a health access program providing access to public medical institutions either free of charge or at a reduced rate. These programs, managed by the Ministry of Social Affairs (MAS), are based on a vast regional network of 24 regional divisions and 264 social promotion units spread over 264 delegations (administrative units) around the country.

The PNAFN is the most important cash transfer program in Tunisia. It accounted for around half (53 percent) of the total expenditures of the MAS, 1.9 percent of government spending, and around 0.5 percent of the gross domestic product (GDP) in 2016 (UNICEF, 2020). The PNAFN program was established by the MAS in 1986 to accompany the Structural Adjustment Program to provide regular, permanent, and unconditional assistance to needy families. It also provided them with free access to public healthcare through the AMGI program. Moreover, in the context of recognizing the rights of children from needy families to education and protection against failure and dropping out of school, Tunisia consolidated the PNAFN program by introducing an increase of 30 Tunisian dinars (TND) per child per quarter (with a limit of three children) granted to needy families with school-age children (UNICEF, 2014). In fact, conditional cash transfers in education are widely utilized social policy tools aiming to facilitate enrollment and regular school attendance. Among the international experiments using this conditional program type is the Tayssir program (cash transfer program for children) in Morocco (Benhassine et al., 2013); education fee waivers and student support grants in Sudan (Cooper, 2018); Oportunidades in Mexico; Red de Protección Social in Nicaragua; and Bolsa Família in Brazil (Handa and Davis, 2006; Takahashi, 2017; Brearley, 2016). The program benefits are granted based on requests made by families, and they involve several actors. The selection process generally flows as follows: (1) the family makes a claim for the cash transfer, declaring that their household income falls below the poverty threshold; (2) social workers carry out an investigation of the household income while considering the additional socio-economic criteria (eligibility criteria are listed in Table A.1. in the Appendix); and (3) a list of eligible families is prepared and sent to local and regional commissions, where a final list of beneficiaries and excluded families is prepared while taking into consideration the regional budget allocated by the MAS. However, the circular setting of these criteria states that it is not necessary for all these criteria to be met for the family to be eligible, leaving a discretionary margin to the social worker. The program addresses families that meet a certain set of criteria. First, their income must fall below the poverty line as assessed by the Tunisian Institute of Statistics (INS). Second, some additional socio-economic conditions are considered, namely household size; the number of household members with a disability and/or chronic health condition; household living conditions, such as dwelling and assets; and the inability of the head of the household to work due to a physical or mental impairment. Families are beneficiaries of the AMGII program if their annual income does not exceed the interprofessional guaranteed minimum wage (SMIG) if the family contains fewer than two persons, one and a half times the SMIG if the family is composed of three to five persons, and twice the SMIG if the family is composed of more than five persons.

In 2020, the total number of PNAFN beneficiaries reached 260 thousand compared to 124 thousand in 2010, representing an average annual growth rate of 7.7 percent. The average transfer per month has also increased from TND 56.7 in 2010 to TND 180 in 2020 (around USD 67 per month). In terms of coverage, the cash transfer program covers around 8.4 percent of the population, and around 24 percent have health coverage either through the AMGI program or at a reduced rate through the AMGII program.

Despite improvements in monthly allowances since the 2011 revolution, as well as in the coverage rates by region and by household standard of living, several studies mention the existence of clear signs of leakages and under-coverage in these programs. Together, the PNAFN and AMGII exclude 48.9 percent of poor families in Tunisia (Silva, Levin, and Morgandi, 2013). Arfa and Elgazzar (2013) also note that there is very little monitoring of the AMG program and that the eligibility criteria are not clear. These shortcomings make the program prone to leakages and inefficiency. Furthermore, the system is not efficient in terms of exclusion errors, as there is no official appeal system (Ibid.). By observing the distribution of the beneficiaries of the various programs according to the quintiles of expenditure, the INS, CRES, and AFDB (2013) also mention that half of the poor population and 39.4 percent of the population living in extreme poverty in Tunisia do not benefit from any component of the PNAFN program. The CRES and BAD (2017) study on the performance of the cash transfer program in Tunisia also shows that of 8.4 percent of households that were supposed to be covered by the PNAFN, 4.6 percent were not, which represents an exclusion rate of 53.1 percent. This study also highlights the difficulties associated with identifying needy households. Indeed, institutional weaknesses, poor coordination between different government services, and an increase in informality all make it difficult to identify low-income households, which increases the level of exclusion and inclusion errors.

In order to improve the performance of these social programs, the Tunisian partners (the government, UGTT, and UTICA), in collaboration with the International Labour Organization (ILO), have committed to implementing a new project (Social Contract) to promote social dialogue in Tunisia in accordance with Recommendation no. 202 of 2012.

To meet these objectives, the Tunisian government started a reform of the social protection system in 2013, one of the key issues of which is the review of the rules by which households are selected for the cash transfer program. A new program named Amen Social was created according to Organic Law no. 10-2019 of January 2019 (‘Amen Law’) for the promotion of poor and limited-income categories whose lack of resources affects their income, health, education, access to public services, and living conditions. It is a new and integrated social safety net program that covers most social assistance programs in Tunisia (the cash transfer program (PNAFN/AMGI) and the AMGII program, in particular) provided by the MAS. The purpose of Amen Social is to expand coverage and to achieve greater transparency, equity, and efficiency among social protection programs (Nasri et al., 2022). The PMT model was defined and officially selected as the basic targeting model to identify and validate beneficiaries of the direct cash transfers or the reduced free medical assistance as part of the Amen Social program (Article 8 of the Amen Social Law).

3. Data and descriptive statistics

The dataset used in this study comes from the National Survey on Household Budget, Consumption, and Standard of Living (EBCNV) of 2015.[4] The data are collected over a period of one year between May 2015 and May 2016 by the INS and can be downloaded from the INS website.[5] The 2015 EBCNV survey was initially based on a random sample of 27,108 households representing one percent of all the households in the country. Out of 27,108 households, 25,140 responded to the survey questionnaire, equivalent to 105,081 individuals. This represents a response rate of 92.7 percent.

It is a representative sample at the national level, covering both rural and urban areas and the seven economic regions of the country (Greater Tunis, North East, North West, Central East, Central West, South East, and South West). The 27,108 households were selected using two stages of stratified random sampling in each governorate. In the first stage, a sample of primary stage units (district) was selected with a probability proportional to their size (PPS) in the number of households. The district was defined by the 2014 General Census of Population as a geographic area that contains 70 households on average.[6]

The EBCNV aims to provide a picture of the structure and level of household expenditures, identify their living conditions, and identify the profiles of poor households and measure their poverty. It also highlights other aspects of household living conditions and access to public services, such as education, health coverage, and medical care. According to the 2015 survey, per capita spending per year was, on average, TND 3,871, compared to TND 2,601 in 2010, an increase of 48.8 percent over the 2010-15 period. The urban-rural gap in terms of spending remains large despite the improvement in per capita expenditure in rural areas compared to 2010 (Table 1).

[4] Ten surveys have been conducted since the independence: 1967, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, and 2015, with a sample of at least five thousand households distributed over the whole Tunisian territory and classified according to the main regions and areas (rural, urban). The 11th survey of 2021 is in progress. The 2021 survey includes, for the first time in Tunisia, an income section that is used to examine the various sources of household income, including those from agricultural and fishing activities.

[5] http://ins.tn/enquetes/enquete-nationale-sur-le-budget-la-consommation-et-le-niveau-de-vie-des-menages-2015.

[6] The Tunisian National Institute of Statistics has a database of approximately 40 thousand enumeration areas, or primary sampling units created for the 2014 General Census of Population and Housing. It constitutes the sampling frame for almost all surveys conducted by the INS, including the EBCNV survey.

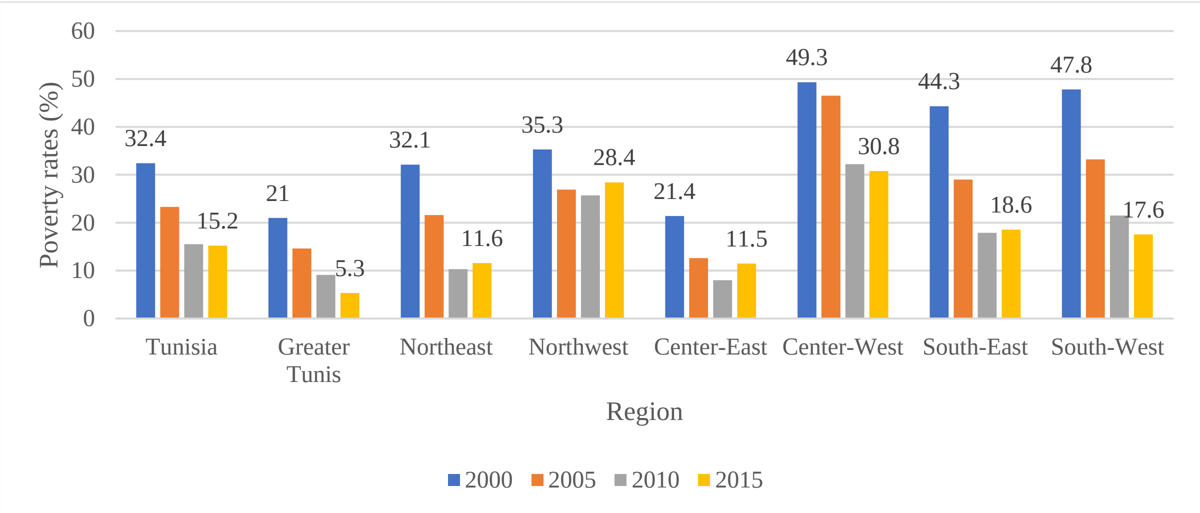
Table 1. Household and per capita expenditure, poverty, and welfare ratio by area

	2010	2015
Per capita expenditure (in DT)		
Urban	3,102	4,464
Rural	1,644	2,585
Total	2,601	3,871
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

Source: Authors' calculation using EBCNV surveys.

The poverty rate (share of households with expenditures below the poverty line) stood at 15.2 percent in 2015, compared to 32.4 percent in 2000. However, while the poverty rate shows an important decline of 17.2 percentage points in 15 years, it varies considerably between Tunisia's regions. The Central West and North West regions have the highest poverty rates, respectively 28.4 percent and 30.8 percent, followed by the regions located in the south of the Tunisian territory where the overall poverty rate reaches 18.6 percent, while the Greater Tunis region records the lowest rate of 5.3 percent. The rates in the North East and Central East regions are 11.5 percent and 11.6 percent, respectively (Figure 1).

Figure 1. Poverty rates at the national and regional levels



Source: Nasri et al. (2022).

4. Empirical strategy

Targeting refers to the set of mechanisms that allow policymakers to identify individuals or households that can benefit from resource transfers (Sabates-Wheeler, Hurell, and Devereux, 2015). It is a "process of defining who is eligible to receive social benefits and who is not, by setting eligibility criteria; identifying, verifying and registering eligible beneficiaries; and periodically validating and re-registering or de-registering program beneficiaries, because eligibility status can change over time" (Devereux, 2021). The most popular targeting methods can be classified into three groups (Coady et al., 2004): individual/household assessment (MT, PMT, hybrid means test (HMT)), categorical targeting, and self-targeting (see Table A.2. for a comparison between these methods). There is no perfect solution or model to follow, but each country chooses the model that best suits its needs and characteristics. Besley and Kanbur (1993) argue that moving from universal coverage toward narrowly targeted programs incurs an unavoidable trade-off between targeting costs and targeting accuracy.

Mixed Means Test (MMT)

Case studies on performance in terms of 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 used in Latin America and the Caribbean (Ficha CAS system in Chile, SISBEN in Colombia, Oportunidades Program in Mexico), in Asia (India, Indonesia, China, Thailand, and the Philippines), and in Africa (Burkina Faso, Ethiopia, Ghana, Malawi, Mali, Niger, Nigeria, Tanzania, Uganda (Brown et al. 2018), Egypt (Ahmed and Bouis, 2002), and Tunisia (CRES and World Bank, 2021; Muller and Bibi, 2010)). The results are very encouraging. For example, in Chile and Mexico, approximately 90 percent of social assistance reached the bottom 40 percent of the population when a PMT model was adopted (Sebastian et al., 2018; Castañeda and Lindert, 2005).

In the case of Tunisia, and in the absence of reliable and available data on household incomes and economic activities and the presence of a relatively high rate of informality,[7] the PMT can be used as an appropriate targeting model for the assistance programs (PNAFN and AMGII). However, the identification of poor households using the PMT model is based only on the households' own characteristics. Contextual or regional variables (characteristics of the area in which the household lives) are completely ignored. Given the spatial dimension of poverty in Tunisia (poverty is concentrated in the two regions of the North West and Central West), we use a new targeting model that explicitly combines individual targeting with geographic targeting. It is an MMT or a two-hierarchical/multilevel model where households (level 1) are nested within governorates (level 2).

This model, which combines individual and regional variables, was first developed by Bigman et al. (2000), who developed a method for targeting antipoverty programs and public projects to poor communities in rural and urban areas in Burkina Faso. They combine an extensive dataset from a large number of sources (demographic data from the population census; household-level data from a variety of surveys…etc.) to identify the key explanatory variables that determine the standard of living in rural and urban areas. Bigman et al. (2000) show that such targeting is an improvement over regional targeting in that it reduces leakage and under-

[7] In the fourth quarter of 2019, informal workers accounted for around 44.8 percent of the workforce - 38.3 percent without considering the agricultural sector (INS, 2020). Estimation de l'emploi informel en Tunisie pour l'année 2019 à partir des résultats de l'enquête trimestrielle sur la population et l'emploi.

coverage. Additionally, this mixed model properly accounts for the household survey design, including the analytic weights and the design structure (strata and primary sampling unit). Taking into account the hierarchical structure of the data, we can explicitly consider the different sources of variability in the data collected at the household level.

a. MMT methodology

Since developing countries generally do not have reliable surveys or information on household income, the most used measure of welfare is the per capita expenditure, which is considered a good predictor of neediness (Deaton, 1997; Gazeaud, 2020). To take into account the regional difference in living costs between households, we use the welfare ratio calculated as the annual per capita expenditure of household i at governorate j (y_{ij}) divided by the cost of living (the poverty line z_j) at governorate j. If the welfare ratio is above 1, the household could cover its basic needs. If the welfare ratio is below 1, then the household could not cover its basic needs (see Bigman et al., 2000 for more details). Formally, for household i at governorate j having 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 as follows:

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

where wr_{ij} represents the welfare ratio (in logarithm) of household i at governorate j, x_{ij} is the row vector of household characteristics (such as age, size, and education), and Q_j is the row of regional characteristics (unemployment rate, the share of agriculture activity, the share of manufacturing activity, poverty rate, the share of the population with higher education levels…etc.) of the governorate j. The deterministic part of the model ($\gamma_{00} + x_{ij}\gamma_{10} + Q_j\gamma_{01}$), contains all the fixed coefficients (γ_{00} is the overall mean of welfare ratio across governorates), while the stochastic component is in brackets in equation (1). The household level residuals e_{ij} are assumed to have a normal distribution with mean zero and variance σ_e^2; μ_{0j} is random error at the governorate level with an expected value of zero and variance $\sigma_{u_0}^2$. It is assumed to be independent of the household level residuals e_{ij} (see Goldstein, 1995; Raudenbush and Bryk, 2002; Kaplan, 2004 for more details on the mixed models).

The coefficients, which represent the weights, of equation (1), are estimated using the restricted maximum likelihood estimation (REML).[8] The fitted values (MMT score) of equation (1) ($\widehat{wr}_{ij}$) will be used to rank households from most eligible to least eligible for social assistance programs.

$$\widehat{wr}_{ij} = \hat{\gamma}_{00} + x_{ij}\hat{\gamma}_{10} + Q_j\hat{\gamma}_{01} \qquad (2)$$

[8] A multilevel logit model can be also used to estimate the MMT score using a binary indicator equal to one if the household's consumption falls below the poverty line and zero otherwise.

More specifically, a household is eligible for the program if its wr_{ij} score ($\widehat{wr}_{ij}$ in equation (2)) falls below a predetermined cutoff score.

b. Targeting performance

The performance of targeting models is always measured through standard indicators, including the coverage rate among the target population and the error rates (of inclusion and exclusion). The use of the targeting model as the MMT may lead some eligible households to be excluded from the program (exclusion errors) while other ineligible households are included (inclusion errors), also known as type I and type II errors, respectively (see Table 2) (Sebastian et al., 2018).

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

Source: Adopted from Sebastian et al. (2018).

Formally, these errors can be measured as follows (Brown et al., 2018):

Inclusion error rate (also known as the leakage rate):

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

Exclusion error rate (also known as the under-coverage rate):

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

Where w_i are the appropriate sample weights ($\sum_{i=1}^{n} w_i = 1$), and n is the total number of households in the sample. The IER gives the proportion of the non-poor households identified as poor, while the EER defines the proportion of the poor who are not identified as poor by the MMT model. If the predictions are perfect ($wr_{ij} = \widehat{wr}_{ij}$ for all households), both error rates must be zero ($IER = EER = 0$) (see Brown et al., 2018 for more details).

While both error measures are useful in evaluating the targeting model, their interpretation differs depending on the policy objectives set by the government. Indeed, if the budget allocated to the social assistance program is limited, the government can focus more on the inclusion error to avoid a non-poor household benefiting from a program allocated only for the poor.

4.1 Multidimensional targeting model

For this purpose, it is worth recalling that the PNAFN and AMGII programs, as indicated above, offer interventions in three dimensions: food, health, and education. These dimensions will be considered the main sources of deprivation for Tunisian households from which the potential beneficiaries will be identified. The eligibility criteria officially fixed for social safety nets will be also used as deprivation thresholds in the multidimensional targeting model.

The proposed targeting methodology is drawn from the identification step of the family of multidimensional poverty measures developed by Alkire and Foster (2007, 2011) based on the dual cutoff method. This family of measures satisfies a set of properties considered desirable in poverty measurement (Nasri and Belhadj, 2017). The identification implies (1) defining a cutoff point for each considered dimension, and (2) defining an across dimensions cutoff, as the number of dimensions in which the household should be deprived to belong to the poor group. The criteria for identifying the poor can range from 'union' to 'intersection.' The intersection criterion (k = d) identifies a household as poor only if it is deprived in all the considered dimensions. In contrast, the union criterion (k = 1) identifies a household as poor if it is deprived in any dimension and indicates the swath of society that risks poverty at some point in time. In other words, if the intention is to prevent poverty in the future, vulnerability to poverty must be considered in the anti-poverty program and the union approach is helpful (Nasri and Belhadj, 2018).

We consider $Y = |y_{ij}|$ a matrix of household achievements, where (y_{ij}) is the achievement of the i^{th} household in the j^{th} dimension for all $j = 1, \ldots, d$ and all $i = 1, \ldots, n$. The deprivation threshold for the j^{th} dimension will be indicated as (z_j) (Table A.3. in the Appendix). In this paper, each household is deprived in the food dimension if its achievement in this dimension is below the food threshold estimated by the INS for each stratum. This threshold is estimated at TND 1,085 in the metropolitan area; TND 1,050 in the municipal area, and TND 952 in the non-municipal area. The household is deprived in the education dimension if it includes a child between six and 16 years of age who does not pursue an education or training cycle. The household is deprived in the health dimension if its annual income does not exceed the SMIG, estimated at TND 314 if the family includes fewer than two persons; one and a half times the SMIG) if the family is composed of three to five persons; and twice the SMIG if the family is composed of more than five persons.

Corresponding to the matrix $Y = |y_{ij}|$, a (nxd), a dimensional deprivation matrix $g^0 = |(g_{ij}^0)|$is constructed. Each element of g^0 is equal to one when the i^{th} household is deprived in the j^{th} dimension and is equal to zero when the household is not deprived. In other words, each entry of the matrix g^0 can take only two values as follows:

$$g^0_{(ij)} = \begin{cases} 1 \;\; if \;\; y_{ij} < z_j \\ 0 \;\; if \;\; y_{ij} \geq z_j \end{cases}$$

Based on matrix g^0, we construct an n-dimensional column vector $c = |c_i|$ 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. Where Group_1, Group_2, and Group_3 represent the total number of potential beneficiaries living in three deprivations, two deprivations, and one deprivation, respectively. With the proposed multidimensional targeting, if a household is deprived in a dimension or in an additional dimension, then 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

We start our analysis by fitting a two-level empty model, also called the 'Random intercept model,' the 'null model,' or the 'intercept only' model. The empty model predicts the level 1 (household) intercept of the dependent variable (log of the welfare ratio) as a random effect of level 2 (governorate), without independent variables at level 1 or 2. The purpose of this step is to test for significant intercept variance, which tests the need for mixed modeling. If the intercept variance is not significant (no geographical differences in the welfare ratio of the households), it can be fixed for future steps. The following equation is estimated for the empty MMT model.

$$wr_{ij} = \gamma_{00} + [\mu_{0j} + e_{ij}] \quad (3)$$

Table 3 shows the results of the empty model for the two dependent variables: log of welfare ratio using the extreme poverty line (column 1) and the log of welfare ratio using the poverty line (column 2). The LR tests indicate that the mixed or multilevel model is more appropriate than the simple model (the LR tests are significant at the one percent level), which allows us to justify the use of this mixed modeling approach. The between governorate variance ($\sigma^2_{u_0}$) is non-zero for both dependent variables, showing that a geographical dimension is needed for the targeting process in Tunisia. This finding is supported by the intraclass correlation coefficients (ICCs) that revealed a considerable clustering of households ('extremely poor' or 'poor') within governorates.

Table 3. Empty model results

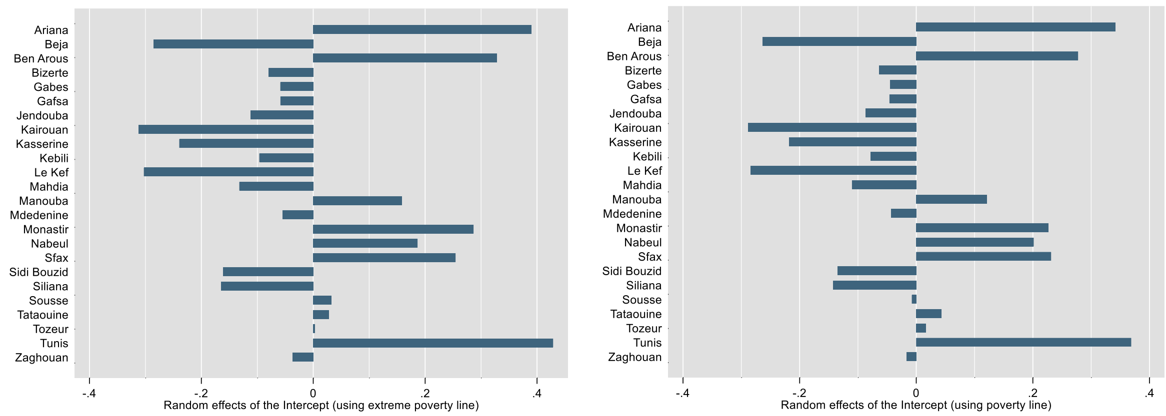
	Welfare ratio using extreme poverty line	Welfare ratio using poverty line
Intercept	1.05***	0.559***
Standard error	(0.045)	(0.039)
Variance of the error term at level 2 ($\sigma^2_{u_0}$)	0.048***	0.036***
Variance of the error term at level 1 (σ^2_e)	0.263***	0.259***
ICC = $\sigma^2_{u_0}/(\sigma^2_{u_0}+\sigma^2_e)$	15.33%	12.03%
Likelihood ratio test (chi2(1))	3,796***	3,046***
Log restricted likelihood	-18,950	-18,793

Notes: 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).
Source: Authors' calculations.

The variations across governorates in random intercept for both dependent variables are presented in Figures 2a and 2b, respectively. The coastal governorates (such as Tunis, Ariana, Manouba, Ben Arous, Monastir, Nabeul, and Sfax) have a comparatively higher welfare ratio, while non-coastal governorates (Beja, Kairouan, Kasserine, Le Kef, Siliana, and Sidi Bouzid) have a relatively lower welfare ratio.

Figure 2. Variation in random intercept of the empty model across governorates

(a) (b)



Source: Authors' calculations using the 2015 EBCNV survey.

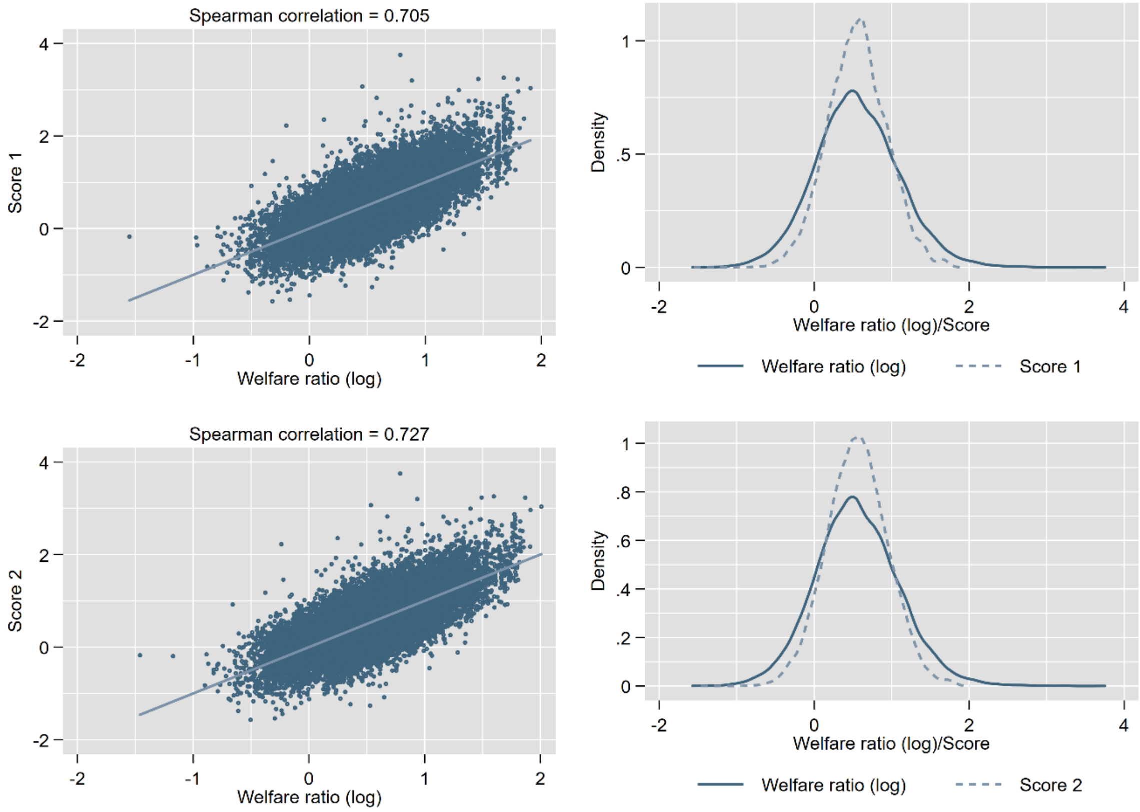
5.2 Results of the full MMT model

The next step consists of first introducing the set of variables related to the household (x_{ij}) and then the set of regional variables (Q_j). Since our main interest is to identify the appropriate specification for estimating the score to classify households according to their standard of living, we only present the goodness of fit of the two models: the MMT model with only household characteristics (MMT at the household level)[9] and the full MMT model that incorporates both sets of variables at both the household and governorate levels.

[9] The MMT model can be interpreted as a PMT model.

Figure 3 shows that the gap between the two distributions decreases for the full MMT that includes regional variables (the spearman correlation increases from 0.71 to 0.73) compared to the MMT at the household level.

Figure 3. Comparing distributions of scores and welfare ratio (log)



Source: Authors' calculations using the 2015 EBCNV survey.

Table 4 shows the distribution of beneficiaries by deciles of the true welfare ratio (rows) for six cutoff scores (columns) under the full MMT model (we present only the results for this model, which includes both household and regional explanatory variables). The MMT cutoffs are set at the 10th, 15th, 20th, 25th, 30th, and 40th percentiles of the welfare ratio distribution, implying that around 10, 15, 20, 25, 30, and 40 percent of the population with scores below the respective cutoffs are considered eligible for benefits. The first cutoff is close to the coverage of the existing PNAFN program (which covered nearly eight percent of the population in 2015). The second cutoff of 15 percent is close to the coverage of the AMGII program (it is also equal to the poverty rate in 2015) and the 25 percent cutoff is close to the coverage of both programs (AMGI and AMGII).

The first column in Table 4 gives the coverage of the PNAFN program and shows that 17.44 percent and 13.92 percent of the first (the poorest 10 percent) and second (the poorest 20 percent) deciles, respectively, are PNAFN beneficiaries. However, the results show that nearly five percent of the 7th decile and four percent of the 8th decile (which are generally non-poor households) also benefit from this program designed to primarily serve the poor population (inclusion errors). Using the full MMT model for a program that targets the poorest 10 percent of the population (based on the welfare ratio), the coverage rate of the poorest 10 percent equals 29 percent (with a coverage rate of 4.8 percent for all population), nearly twice the coverage rate of the current PNAFN program that covers an eligible population of eight percent. The coverage rate of the last five deciles does not exceed one percent (less than one percent of non-poor households benefit from this program, which covers the poorest 10 percent of the population). If we use the second cutoff of 15 percent (15 percent of the population below this cutoff would be eligible for benefits based on the full MMT model), more than 46 percent of the program's beneficiaries would come from the poorest decile, compared to 41 percent based on the current AMGII program. These results show that the targeting performance based on the full MMT model (combining individual and geographical targeting) is considerably better than the existing programs (PNAFN/AMGI and AMGII).

Table 4. Targeting performance of the full MMT model using different cutoff scores

Quantiles of the welfare ratio	PNAFN	AMGII	MMT cutoff 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

Source: Authors' calculations using the 2015 EBCNV survey.

Table 5 displays the distributions of program beneficiaries according to the different full MMT cutoff scores by welfare ratio deciles. It shows that 22.12 percent of the PNAFN beneficiaries are in the first poorest decile, 17.65 percent are in the second decile, and 15.33 percent are in the third decile, while 45 percent of the current PNAFN beneficiaries are distributed over the seven least upper deciles. If the PNAFN program was targeted based on the full MMT (cutoff 1-10th percentile), around 61 percent of the program's beneficiaries would come from the poorest 10 percent, which is three times the size of the current program. The last seven deciles contain only 12.7 percent of the beneficiaries, representing a very small proportion compared to that found for the current PNAFN program.

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

Quantiles of the welfare ratio	PNAFN	AMGII	MMT cutoff scores: 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

Source: Authors' calculations using the 2015 EBCNV survey.

We now turn to the inclusion and exclusion errors. Table 6 gives the results of these measures (under-coverage rates, leakage rates, and eligible shares) by the cutoff scores of the two models (the MMT model with only household characteristics and the full MMT model with household and regional characteristics). If we set the cutoff score at the 20th percentile, which would make 12.3 percent of households eligible (a little less than the poor population in Tunisia in 2015), the corresponding IER ranges between 33.9 percent for the MMT model to 34.2 percent for the full MMT model. These results imply that, for the MMT model, for example, 33.9 percent of those identified as poor by the MMT model are not, in fact, poor. This is a very acceptable rate of inclusion errors compared to the results found in other work using PMT as a targeting model. For example, Brown et al. (2018) show that the average rate of inclusion errors across their selected sample of countries[10] is around 37 percent, with an average exclusion error of 72 percent, for a fixed poverty level of 20 percent.

It is also important to note that both inclusion and exclusion errors decrease when increasing the cutoffs. For example, for the full MMT model, the inclusion error decreases from 39.3 percent for a 10th percentile cutoff (cutoff 1) to 26.6 percent for a 40th percentile cutoff, and the EER decreases from 70.7 percent to only 34.9 percent.

Table 6. Under-coverage and leakage rates and eligibility share by cutoff scores

Cutoff scores	MMT with only household characteristics: IER	EER	Eligible share	Full MMT with household and regional Characteristics: 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

Source: Authors' calculations using the 2015 EBCNV survey.

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

Given the spatial dimension of poverty in Tunisia, which is clustered in the two regions of North West and Central West, we calculate the inclusion and exclusion errors by region. The results for the MMT model with only household characteristics and the full MMT model are summarized in Table 7. The results show that regardless of the MMT cutoff scores, the eligible population shares are very low for the least poor regions (Greater Tunis and Central East), in contrast to the poor regions (North West and Central West). For example, if we set the cutoff score at the national level of the 20th percentile, 36.19 percent of the population of the Central West and 28.73 percent of the population of the North West will benefit from this program compared to only 1.86 percent for Greater Tunis and 8.97 percent for the Central East region.

It is also important to note that the inclusion and exclusion errors are much lower in the two poorest regions than in the less poor ones. The inclusion error ranges from 23.46 percent to 35.05 percent for the Central West region (the poorest region) and from 23.12 percent to 42.71 percent for the North West region. For the two poorest regions (the Central West and the North West), the exclusion rates are also very low, respectively at 35.68 percent and 41.98 percent for a 20th percentile cutoff score and only 15.72 percent and 20.82 percent for a 40th percentile cutoff. These results show that the full MMT targeting model combining individual and geographical scales works well not only at the national level but also at the regional level. It allows us to minimize inclusion and exclusion errors for the poorest regions of Tunisia.

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

	MMT with only household characteristics			Full MMT		
	IER	EER	Eligible share	IER	EER	Eligible share
Greater 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
North East						
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
North West						
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
Central 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

Table 7. Under-coverage and leakage rates and eligible share by cutoff scores and by region contd.

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
Central 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
South East						
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
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
South West						
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

Source: Authors' calculations using 2015 EBCNV survey.

5.3 Beneficiary identification using the multidimensional targeting model

The total number of potential beneficiaries is estimated at 1,213,939 households, which represents 43.64 percent of the total population in 2014. This includes all Tunisian households suffering from at least one deprivation. The results presented in Table 8 show that this proportion varies substantially between the Tunisian regions. It is estimated at 27.38 percent in Greater Tunis, and it is around 44.3 percent in the North East. However, this proportion is estimated at 56.43 percent in the North West, 64.89 percent in the Central West, and 56.99 percent in the South West. The proportion of potential beneficiaries living in the South East is 53.88 percent. The lowest proportion is estimated in the Central East (23.42 percent). There is clear evidence that the proposed targeting methodology identifies a higher number of beneficiaries compared to the selection process currently implemented in Tunisia. However, the inclusion of such a number of households in a social program may be constrained by the unavailability of monetary resources and by the financial situation of the country. For this purpose, the deprivations targeting approach allows us to categorize potential beneficiaries into three mutually exclusive and collectively exhaustive groups of households according to their degree of deprivation.

Table 8. Identifying potential beneficiaries using the household deprivations model

Regions	Total Head count	Group_1	Group_2	Group_3
Tunisia	1213939	8748	132053	1073137
	43.64%	0.31%	4.75%	38.58%
Greater Tunis	198767	250	9312	189204
	27.38%	0.03%	1.28%	26.06%
North East	175540	341	13206	161993
	44.30%	0.09%	3.33%	40.88%
North West	170443	1408	25085	143950
	56.43%	0.47%	8.30%	47.65%
Central East	253077	2011	26755	224309
	38.38%	0.31%	4.06%	34.02%
Central West	209,840	3838	38082	167919
	64.89%	1.19 %	11.78%	51.93%
South East	125617	653	11868	113093
	53.88%	0.28%	5.09%	48.51%
South West	80654	245	7742	72666
	56.99%	0.17%	5.47%	51.35%

Source: Authors' calculations using the 2015 EBCNV survey.

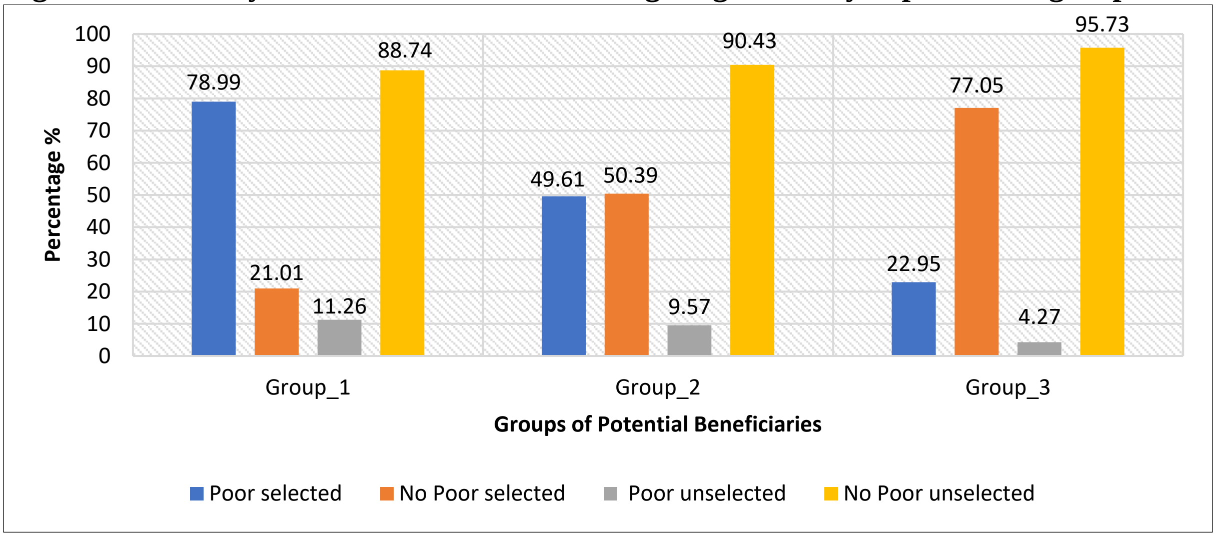
The first group includes potential beneficiaries who are in extreme deprivation. From the results of Table 8 (third column), 8,748 households are identified in this group (0.31 percent of the total population). The proportion of households included in this group varies considerably among the seven regions of Tunisia. The highest rates are estimated in the Central West (1.19 percent), the North West (0.47 percent), and the Central East (0.31 percent). The Greater Tunis region has the lowest rate (0.03 percent). The North East has the second lowest rate (0.09 percent), followed by the South West (0.17 percent) and the South East (0.28 percent). Therefore, there is an urgent need to target all dimensional interventions for all first group members without exception.

The second group includes potential beneficiaries suffering simultaneously and exactly from two deprivations. We identify 4.75 percent of the total population that should be included in this group; this is estimated at 4.06 percent in Central East, and it is around 3.33 percent in the North East. However, this proportion is estimated by 8.30 percent in the North West, 5.09 percent in the South East, and 5.47 percent in the South West. The proportion of potential beneficiaries in the Central West is 11.78 percent, which should be included in this second group. The lowest proportion is estimated in Greater Tunis (1.28 percent). The potential beneficiaries of this second group also need social interventions in two dimensions constituting the main causes of their deprivations. If public decision makers in Tunisia set multidimensional poverty alleviation as an objective, then there is an urgent need to prioritize the households included in these last two groups that suffer from multiple deprivations, even in the case of an austerity policy. However, to eradicate all deprivation forms, it would be useful to strengthen the targeting of the first two groups through a forward-looking policy targeting the proportion of households living in one deprivation. This proportion constitutes the potential beneficiaries of the third group. We find that this third group includes 1,073,137 Tunisian households living with a single deprivation, constituting around 38.58 percent of the total population. This proportion represents 34.02 percent and 40.88 percent of households living in the Central East and North East, respectively. The high proportions are observed in the Central West (51.93 percent), the South West (51.35 percent), and the North West (47.65 percent).

According to Table A.4. in the Appendix, targeting deprivations clearly cover more households compared to the selection process currently implemented in Tunisia. We estimate 1,213,939 Tunisian households as potential beneficiaries of the poverty reduction programs, 26.25 percent of which are officially identified as poor and 73.75 percent as non-poor. We find that 0.03 percent of households that aren't selected as potential beneficiaries are officially identified as poor. On the other hand, our results show that 99.97 percent of households not selected as potential beneficiaries are officially non-poor.

On estimating the targeting accuracy by potential beneficiary groups, we find that the methodology proposed in this research identifies 78.99 percent of poor households in the group of potential beneficiaries living in extreme deprivation and only 21.01 percent are non-poor people who were included in this group (Figure 4). The poor and the non-poor who were excluded from the first group are estimated at 11.26 percent and 88.74 percent, respectively.

Figure 4. Accuracy of the multidimensional targeting model by deprivations group



Source: Authors' calculations using the 2015 EBCNV survey.

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

6. Conclusion and policy recommendations

In this paper, we compare the targeting accuracy of social safety nets currently implemented in Tunisia with the MMT method and the multidimensional targeting approach based on household deprivation. Like most developing countries, Tunisia does not have reliable surveys or information on household income. In this case, the PMT model is often the most recommended targeting method for selecting the beneficiaries of social programs based on scores calculated from covariates that are highly correlated with household income or total consumption expenditure and difficult to manipulate. However, if the country sets the eradication of poverty in all forms as a strategic objective, a multidimensional targeting approach based on household deprivations would also be useful.

In the first part of this research, we estimate MMT models and test their performances. The targeting performance is evaluated from the distribution of households by deciles of the welfare ratio based on six cutoff scores. From our findings, there is clear evidence that the targeting performance based on the full MMT model is considerably better than the existing programs (PNAFN/AMGI and AMGII). We find that the coverage rate of the poorest 10 percent equals 29.26 percent using the full MMT model, which is almost twice the coverage rate of the current PNAFN program that covers only 17.44 percent (with a coverage rate of eight percent for the entire population). Moreover, we observe that both inclusion and exclusion errors decrease when increasing the cutoffs. Based on the full MMT model, the inclusion error decreases from 37.41 percent for a 15th percentile cutoff to 26.55 percent for a 40th percentile cutoff, and the exclusion error decreases from 61.47 percent to only 34.89 percent. By calculating targeting errors by region, the results show that the eligible population shares are very low for the least poor regions (Greater Tunis and Central East), in contrast to the poor regions (North West and Central West) regardless of the MMT cutoff scores.

On the other hand, we propose a targeting methodology using the multidimensional approach based on household deprivation. A divergence is 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 programs. There is clear evidence that the proposed targeting methodology identifies a higher number of beneficiaries compared to the current selection process. However, the inclusion of such a number of households in a social program may be constrained by the unavailability of monetary resources and by the financial situation of the country. For this purpose, the deprivations targeting approach allows us to categorize potential beneficiaries into three mutually exclusive and collectively exhaustive groups of households according to their degree of deprivation. On the other hand, targeting household deprivations is more accurate in including the officially poor and excluding the non-poor compared to the selection processes currently implemented in Tunisia.

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Appendix

Table A.1. 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 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.

Source: Circulars and decrees ministerial (MAS).

Table A.2. 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.	
PMT: Eligibility is 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 a way where it will be much higher among the poor than the non-poor	Low administrative costs.	May be difficult to find a means of delivering a large benefit.	Alatas et al. (2016) (Indonesia).

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

Table A.3. Dimensions and deprivation thresholds used for the household deprivation model

Dimensions	Deprivation Thresholds Description (Z_j)
Food	The household is deprived in this dimension if its achievement in this dimension is below the food threshold estimated by the INS for each stratum. This threshold is estimated at TND 1,085 in the metropolitan area; TND 1,050 in the municipal area, and TND 952 in the non-municipal area.
Education	The household is deprived in this dimension if the family includes a child between six and 16 years of age who does not pursue an education or training cycle.
Health	The household is deprived in this dimension if its income approximated by the total expenditure is lower than: * SMIG if household size ≤ 2 persons * 1.5*SMIG if 3 persons ≤ household size ≤ 5 persons * 2*SMIG if household size > 5 persons

Table A.4. Targeting models and poverty status

				Total	Poor	
					Yes	No
Multidimensional targeting			Yes	1213939	26.25 %	73.75 %
			No	1567621	0.03 %	99.97 %
Current process	Targeting	PNAFN	Yes	230223	23.24%	76.76%
			No	2551336	10.41%	89.59%
		AMGII	Yes	387399	28.22%	71.78%
			No	2394161	8.77%	91.23%
		Both Programs	Yes	597320	26.13%	73.87%
			No	2184239	7.47 %	92.53%