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Assessment of Multidimensional Poverty Alleviation Effort in Tunisia

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ABSTRACT

This paper assesses multidimensional poverty in Tunisia by applying the Alkire-Foster (A-F) methodology to household survey data, thus providing a direct and comprehensive approach to poverty measurement beyond traditional income-based indicators. Using data from the 2014 Tunisian Labor Market Panel Survey, the analysis captures deprivations across three dimensions: health, education, and living standards. It extends the framework by incorporating technology-related indicators to reflect poverty in the digital era. Results reveal that 12.8% of the Tunisian population is in acute poverty, with significant disparities across regions and governorates. Education emerges as the most critical contributor to deprivation, accounting for over half of the overall poverty measure.

Keywords: Poverty Alleviation, Dual-Cutoffs Method, A-F Model, Poverty Prediction, Household Survey

Classification JEL: C13, C18, I3, I32, O35.

INTRODUCTION

The eradication of all forms of poverty by the year 2030 is one of the global Sustainable Development Goals (SDGs) listed on the agenda for the United Nations Summit on Sustainable Development (UNSD). According to the United Nations Sustainable Development Goals (2021), it will be challenging to meet these goals by the deadline because an additional 120 million people will be living in poverty in 2020 compared to 2019. Additionally, the rate of extreme poverty will have increased for the first time since 1998, rising from 8.4% in 2019 to 9.5% in 2020. Hence, poverty poses one of the most serious challenges for the developing countries, and even for the entire world (Liu et al., 2017; Deng et al., 2020).

To alleviate poverty, it is essential to identify and classify people living in poverty and to define all its dimensions. Furthermore, poverty is not uniformly distributed geographically across a country, and different governorates may face unique challenges and needs. Consequently, measuring poverty by governorate is a crucial issue for effective policy development and implementation to address poverty and inequality.

Alkire and Foster (2011) proposed a general model to identify and measure poverty from a multidimensional framework (the AF Model). In addition to measuring the multidimensional poverty indexes, this model can also categorize them by population subgroup (such as geography or ethnicity) to illustrate the features of multidimensional poverty for each group —an important property for policymaking. Followed that, Alkire et al. (2017) using Alkire and Foster's (2011) multidimensional poverty indexes as a reference to conduct empirical research on data for Chile from 1996 to 2006 and developed a set of metrics to measure transitory poverty. Additionally, this kind of indicators can reduce the leakages from geographic targeting (Bigman and Srinivasan,

2002) and analysis focused on population subgroups, such as child poverty (Roelen et al., 2010). Indeed, for this reason that some countries use a score based on non-monetary indicators as eligibility criteria for their anti-poverty programs (Alkire et al. 2017). with this mindset, in the new era, China's efforts to reduce poverty have shifted focus from achieving the goal of “no worries about food and clothing and guarantees to have access to compulsory education, basic medical services and safe housing” (also known as “two no worries, three guarantees”) to addressing multidimensional relative poverty with unbalanced and inadequate development (Wang and Feng, 2020). Sen (1999) also defines poverty as deprivation of capabilities, more precisely as the “deprivation of basic capabilities rather than merely as lowness of incomes”. Basic capabilities include access to clean water, nutrition, education, healthcare among others (Sen 1982).

In Tunisia, the official poverty estimation is based on aggregating household consumption expenditure into one monetary component. Nevertheless, Tunisia’s system of direct social transfers is based on the concept of deprivation, which aligns more closely with the idea of multidimensional approaches. The inconsistency between the measurement of poverty and the policy pursued to address it can limit the effectiveness of the anti-poverty program (Nasri and Belhadj 2017).

More recently, a poverty map report was produced by the National Office of Statistics of Tunisia, in collaboration with the World Bank in September 2020. The poverty indicators were calculated based on datasets from the General Census of Population and Housing (RGPH) of 2014 and the National Survey on Budget, Consumption and Living Standards of Households (ENBCNV 2015). The calculation methodology, developed by C. Elbers, J. Lanjouw and P. Lanjouw (ELL 2000), was used to estimate poverty and inequalities.

However, in reality, policymakers in low- and middle-income countries (LMIC) like Tunisia charged with eradicating poverty, frequently lack the information necessary to utilize their resources wisely (Jerven, 2013). This lack of reliable data is a major obstacle to sustainable development, food security, and disaster relief. Furthermore, traditional methods used to obtain socioeconomic data are generally scarce, time-consuming, expensive, under-covered and labour-intensive.

Our contribution, compared to previous works, is threefold. First, to assess the utility of the 2014 Tunisian household survey for mapping poverty across the country, we conduct a comparative analysis between our findings based on the A-F model and the ELL approach (2000) used by the INS. Second, we pay particular attention to technical poverty. By including indicators related to access to technology, our analysis provides a more comprehensive understanding of poverty in the digital age.

The rest of the paper is structured as follows. Section 2 describes our data collection. Section 3 introduces our methodology. In this section, we will present the Alkire-Foster approach that we used to measure multidimensional poverty in Tunisia. while a final section concludes this communication.

Data Collection

Household Surveys

The last face-to-face household survey in Tunisia was conducted between December 24, 2013, and February 16, 2014, across the 24 governorates (Fig. 1). The questionnaire was designed to collect information on the size, composition, and characteristics of the population, as well as on buildings and dwellings at both regional and local levels. This information is essential for the development of national and regional economic development plans. In this paper, we use data from the Tunisian Labor Market Panel Survey (LMPS), conducted by the National Institute of Statistics (INS).

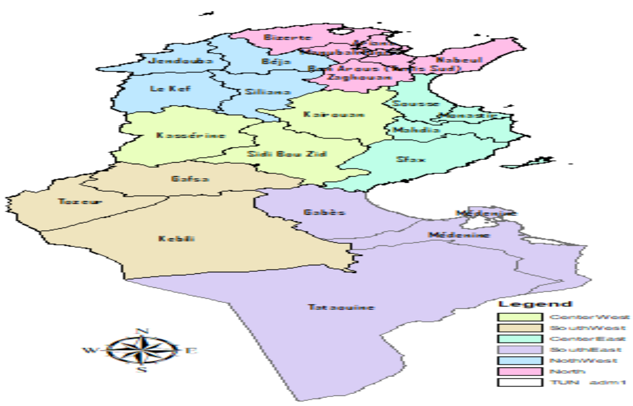

Figure 1. Map of Tunisia by Region and Governorate

METHODOLOGY

The Global MPI's Structure

How we measure poverty can importantly influence how we understand it, how we analyse it, and how we create policies to address it (Alkire and Foster 2011b).

There are basically two methods to measure poverty: the direct method and the indirect or income approach. According to Sen's capability approach, the direct technique reveals whether a person satisfies a list of defined basic needs, rights, or functionings. It has been used, for instance, in official measures to address unmet fundamental needs that have not been met in Latin America and in deprivation measures in Europe and the United States.

The income approach determines whether a person's income is below the poverty line, the threshold at which basic necessities can be met. This method is applied in most countries' official poverty measures.

It has been criticized by economists on the following points: First, consumption behaviour may not be uniform, so reaching the poverty line does not guarantee that a person will meet their minimum needs. Second, individuals may face different prices, which lowers the precision of the poverty threshold. Third, the ability to convert a certain amount of income into specific functions varies depending on factors such as age, gender, health, location, climate, and conditions like disability (Sen, 1979). Fourth, the market often fails to supply accessible, high-quality amenities such as water, healthcare, and education. Fifth, the use of the indirect method does not verify how income is distributed among households. Sixth, according to participatory studies, people living in poverty report that, in addition to low income, they also suffer from multiple deprivations. Lastly, income can be understood conceptually as a general means to achieving worthwhile ends. Even though income is important, measurement efforts should not exclude outcomes related to valuable ends (Alkire and Santos, 2014).

Prompted by the idea of implementing a direct method to measure poverty, and based on the Alkire and Foster measurement methodology, the Human Development Report Office of the United Nations Development Program and the Oxford Poverty and Human Development Initiative developed the Multidimensional Poverty Index (MPI) between 2009 and 2010. This new index aims to quantify acute poverty by using one of the poverty measures developed by Alkire and Foster (2011a), namely the Adjusted Headcount Ratio (M_0).

The MPI applies the M_0 measure to a set of ten indicators aligned with the Millennium Development Goals (MDGs). The indicators are grouped into three dimensions: health, education, and living standards. The health dimension includes indicators such as child mortality and nutritional status, the education dimension includes years of schooling and school attendance, and the living standards dimension includes access to clean water and electricity. Each indicator has a minimum acceptable threshold, referred to as the deprivation cut-off.

The M_0 measure was selected over other feasible alternatives as the foundation of the MPI structure for several reasons. First, the measure is robust when using either ordinal or cardinal variables, as it categorizes each individual's achievement into "deprived" and "non-deprived" groups. Second, M_0 maintains dimensional monotonicity (Alkire & Foster, 2011a), meaning that if a poor person becomes deprived in an additional indicator, the M_0 value increases—reflecting the greater intensity of poverty.

Third, the measure is decomposable by population subgroup. This allows for the calculation of the overall M_0 for the entire population as a weighted average of subgroup poverty rates, provided the subgroups are mutually exclusive and collectively exhaustive. This property enables meaningful comparisons across different population segments.

Finally, M_0 can also be decomposed by indicator. The percentage of the total population classified as poor and simultaneously deprived in a given indicator—weighted by the indicator's relative importance—can be used to compute the overall M_0. These percentages are referred to as censored headcount ratios, as opposed to uncensored headcount ratios, which represent the total deprivation rates regardless of poverty status. The decomposition by censored headcount ratios facilitates analysis of how each deprivation contributes to overall poverty, similarly to the subgroup decomposition approach (Alkire and Santos, 2014).

The table below presents a summary of the dimensions, indicators, thresholds, and weights used in the MPI. These were selected following extensive consultation with experts specializing in each of the three dimensions.

Table 1. Dimensions and Indicators of Poverty

Dimensions	Indicators	Cut-offs	Weight
Education	Years of schooling	No eligible household member has completed six years of schooling	1/6
	School attendance	Any school-aged child is not attending school up to the age at which he /she would complete class 8.	1/6
Health	Nutrition	Any person under 70 years of age for whom there is nutritional information is undernourished	1/6

	Child mortality	A chil under 18 has died in the household in the five-year period preceding the survey	1/6
Standard of living	Cooking fuel	A household cooks using solid fuel, such as dung, agricultural crop, shrubs, wood, charcoal, or coal	1/18
	Sanitation	The household has unimproved or no sanitation facility or it is improved but shared with other households	1/18
	Drinking water	The household`s source of drinking water is not safe or safe drinking water is a 30-minute or longer walk from home, roundtrip	1/18
	Electricity	The household has no electricity	1/18
	Housing	The household has inadequate housing materials in any of the three components: floor, roof, or walls	1/18
	Assets	The household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck	1/18

The Model

Alkire and Foster (2011) propose a new methodology for measuring multidimensional poverty which based on a "counting" method used to identify if an individual is poor and an adjusted FGT measure that reflect the breath, depth and severity of multidimensional poverty.

The identification method, denoted as ρ_k, is an extension of the traditional intersection and union approaches for measuring poverty. Instead of simply taking the intersection or union of a set of dimensions, the ρ_k method allows for the identification of poverty in different ways depending on the relative importance of the dimensions. Specifically, the method selects the k dimensions that are most important for identifying poverty based on a weighting scheme that reflects the researcher's preferences or societal values.

Let n represent the sample of individuals, and let $d \geq 2$ be the number of indicators related to these dimensions' health, education and living standards.

$$y = (y_{i,j})_{1 \leq i \leq n, 1 \leq j \leq d} \in M_{n,d}(\mathbb{K})$$

Where $y_{i,j} \geq 0$ is the achievement of individual $i = 1, 2, \ldots, n$ in variable (variables) used to determine the indicator $j = 1, 2, \ldots, d$ for each dimension.

Let $z_j > 0$ denote the deprivation cutoffs below which a person is considered to be deprived in indicator j.

An identification function ρ is used to determine if a person i is poor or not based on their achievement vector y_i and a cutoff vector z.

Let $y_i = (y_1, y_2, \ldots \ldots y_d)$ be the achievement vector of person i, where $y_{i,j}$, represents their achievement in indicator j.

Let $z = (z_1, z_2 \ldots, z_d)$ be the deprivation cutoff vector, where z_j represents the cutoff value for indicator j.

The identification function $\rho(y_i, z)$ is defined as follows:

If $y_{i,j} < z_j$ for at least one variable, then $\rho(y_i, z) = 1$ which means that the person is considered deprived.

For example, the health dimension can be identified in the data with two indicators such as: nutrition and child mortality, the person is considered deprived in the nutrition indicator if he is deprived for at least one variable used to define it.

In this paper, we consider that people living in poverty are more likely to suffer from malnutrition, chronic illnesses and mental health issues. Alike due, we suppose that the individual i is deprived if he has any kind of mental physical disability or if he has long standing illness or chronic diseases or if he has been limited in normal activities due to a health problem or if he had a work place injury or health problem in the past 12 months or if her health is fair, bad or very bad in general.

Otherwise, $\rho(y_i, z) = 0$, then the person is considered not deprived.

A methodology M for measuring multidimensional poverty is made up of an identification method and an aggregate measure (Sen, 1976). Following Alkire and Foster (2011), We consider that the aggregation step takes ρ as given and associates with the matrix y and the cutoff vector z an overall level $M(y; z)$ of multidimensional poverty index.

For any given y, let $g^0 = [g^0_{ij}]$ denote the nxd matrix of deprivations associated with y, whose entry g^0_{ij} is defined by $g^0_{ij} = 1$ if $y_{i,j} < z_j$ (when person i is deprived), while $g^0_{ij} = 0$ when person i is not deprived.

Let w be the 1xd vector assigned weights to each indicator based on their relative importance.

$w = (w_1, w_2, \ldots. w_d)$, with $0 \leq w_j \leq 1$ and $\sum_1^d w_j = 1$.

In this paper we consider that within each dimension, which are equally weighted, each indicator is noticed as having equal importance. Hence, all weights will be equal to $1/d$.

Let c_i be the deprivation score of each person i.

$$c_i = w_1 g_{i1}^0 + w_2 g_{i2}^0 + \cdots + w_d g_{id}^0$$

Let $0 \leq k \leq 1$ be the poverty cut-off, then an individual i is considered poor if $c_i \geq k$, let $c_i(k)$ be the censoring deprivation score of the poor, then:

$$\begin{cases} if\ c_i \geq k, then\ \ c_i(k) = c_i \\ \\ \qquad else\ c_i(k) = 0 \end{cases}$$

According to AF method, we use the Multidimensional Poverty Index (MPI) to measure acute poverty. The MPI takes into account two pieces of information which are the proportion (the percentage or the incidence) of people who are considered poor, and the intensity (the severity or depth) of their poverty.

The proportion of poverty in the population, measured by the multidimensional headcount ratio noted as H defined by:

$$H = \frac{q}{n}$$

Where q is the number of individuals who are identified poor in at least one dimension using the dual cutoffs (z & k), and n is the population size.

The intensity of poverty (A) given by:

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q}$$

The MPI's mathematical structure corresponds to one component of a family of multidimensional poverty measures proposed by Alkire and Foster (2007, 2011a), the M_0 or Adjusted Headcount Ratio that can be expressed as:

$$M_0 = H \times A$$

EMPIRICAL RESULTS

The application of the MPI by region to Tunisian data shows that 12.8% of the total population are in acute poverty. According to table 2, we constate that the average poor person is deprived in 36.6% of the weighted indicators and the proportion of weighted deprivations that the poor experience in Tunisia out of potential deprivations 4.7%.

When we include indicators related to technology, years of schooling, and assets, the H measure rises to 0.159, meaning that 15.9% of the Tunisian population is considered multidimensionally poor. The intensity of deprivation (A=0.399) increases the adjusted measure to 6.4%. However, the poverty rate calculated by the INS based on data from the 2014 General Population and Housing Census (RGPH) and the 2015 National Survey on Household Budget, Consumption and Standard of Living (ENBCNV), equals to 15.2%. The only region where our estimation results and those provided by the INS correspond is the southwest.

The Adjusted Headcount Ratio M_0 reveals that multidimensional poverty varies across Tunisia's six regions. The Center West and Center East are the poorest, both with M0 values of 7.8%. Southeast and Southwest follow at 6.8% and 6.4%, respectively. The Northwest has the third highest rate ($M_0 = 5.3\%$) followed by the North region with a rate equal to 4.1%.

Results at the level of Tunisian governorates show heterogeneity with regard to multidimensional poverty. According to the results shown in Table 3, Sidi Bouzid has the highest poverty rate (34.2%), while Kairouan has the highest poverty rate according to the National Institute of Statistics (34.9%). Our findings are consistent with what the INS found exclusively in the governorate of Manouba (12%). We explain this divergence as a result of the limitations of the household survey approach, which might introduce biases into the sample. Moreover, human subjectivity might have an impact on it.

Table 1. Multidimensional poverty measures by region.

Regions	H	A	M_0	H_{tech}	A_{tech}	$M_{0_{tech}}$	pop share in %	INS poverty rate (%)
All	0.128* (0.008)	0.366* (0.004)	0.047* (0.003)	0.159* (0.009)	0.399* (0.003)	0.064* (0.003)	100	15.2
North	0.078	0.346	0.027	0.106	0.387	0.041	23.2	8.9
North West	0.114	0.368	0.042	0.136	0.390	0.053	14.4	28.4

Center East	0.170	0.370	0.063	0.190	0.410	0.078	33.1	11.4
Center West	0.135	0.385	0.052	0.198	0.394	0.078	10.5	30.8
South East	0.130	0.377	0.049	0.163	0.417	0.068	11.4	18.5
South West	0.104	0.336	0.035	0.170	0.376	0.064	7.4	17.5

Table 2. Multidimensional poverty measures by governorate

Governorate	H	A	M_0	H_{tech}	A_{tech}	$M_{0_{tech}}$	INS poverty rate (%)
All	0.128* (0.008)	0.366* (0.004)	0.047* (0.003)	0.159* (0.009)	0.399* (0.003)	0.064* (0.003)	15.2
Tunis	0.080	0.337	0.027	0.102	0.372	0.038	3.5
Ariana	0.052	0.327	0.017	0.086	0.395	0.034	5.4
Ben Arous	0.037	0.324	0.012	0.056	0.357	0.020	4.3
Manouba	0.080	0.362	0.029	0.120	0.392	0.047	12.1
Nabeul	0.106	0.350	0.037	0.154	0.390	0.060	7.4
Zaghouan	0.148	0.378	0.056	0.148	0.432	0.064	12.1
Bizerte	0.042	0.381	0.016	0.042	0.452	0.019	17.5
Beja	0.032	0.375	0.012	0.042	0.428	0.018	32
Jendouba	0.113	0.363	0.041	0.161	0.391	0.063	22.4
El Kef	0.100	0.370	0.037	0.133	0.376	0.050	34.2
Siliana	0.221	0.362	0.080	0.234	0.388	0.091	27.7
Sousse	0.222	0.396	0.088	0.222	0.437	0.097	16.2
Monastir	0.086	0.348	0.030	0.114	0.421	0.048	8.3
Mahdia	0.145	0.380	0.055	0.157	0.414	0.065	21.1
Sfax	0.185	0.367	0.068	0.210	0.405	0.085	5.8
Kairouan	0.156	0.378	0.059	0.178	0.410	0.073	34.9
Kasserine	0.078	0.397	0.031	0.141	0.397	0.056	32.8
Sidi Bouzide	0.184	0.375	0.069	0.342	0.371	0.127	23.1
Gabes	0.174	0.379	0.066	0.228	0.421	0.096	15.8
Mednine	0.106	0.377	0.040	0.128	0.414	0.053	21.6
Tataouine	0.045	0.333	0.015	0.045	0.333	0.015	15
Gafsa	0.222	0.333	0.074	0.278	0.399	0.111	18
Tozeur	0.053	0.340	0.018	0.053	0.377	0.020	14.6
Kebili	0.092	0.348	0.032	0.173	0.370	0.064	18.5

Table 4 lists the dimensions of poverty for each region. Based on the estimation results, it is clear that the education dimension has the highest levels of poverty. (North: 6.7%, North West: 8.1%, Centre East: 12.6%, Centre West:13.5%, South East: 10.4%). From the results in table 4, we can conclude that the Education dimension is the main source of Tunisian deprivation with a contribution rate equal to 53.6%.

Table 3. Poverty decomposition by dimension across regions

Regions	Health	Education	Standard of Living	M_0
North	0.034*	0.067	0.022	0.041
Contribution %	27.7	54.5	17.8	100
North West	0.030	0.081	0.047	0.053

Contribution %	19	51	30	100
Center East	0.064	0.126	0.044	0.078
Contribution %	27.4	53.7	19	100
Center West	0.028	0.135	0.070	0.078
Contribution %	12.2	57.6	30.3	100
South East	0.062	0.104	0.038	0.068
Contribution %	30.7	50.8	18.5	100
South West	0.066	0.103	0.022	0.064
Contribution %	34.6	53.8	11.5	100

*equals to $M_0 \times (d = 3) \times Contribution(\%)$

CONCLUSION

The performance of a social poverty reduction program depends essentially on the effectiveness of the geographical targeting of the smallest territorial units concentrating the poorest households (INS 2020). In this article, we used a direct method based on the A-F model to measure multidimensional poverty by region and governorate in Tunisia through three dimensions which are health, education and standard of living. The empirical analysis using Tunisian data from 2014 shows that poverty rates vary significantly across governorates. We also found that the education dimension has the greatest impact on household poverty in Tunisia. In this regard, it may be necessary for the government to create a targeted program to reduce the main causes of poverty in different geographical areas by advancing educational techniques and giving them greater attention in the labour market.

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