MULTIDIMENSIONAL POVERTY IN FORCED DISPLACEMENT:
A COMPARISON OF SYRIAN AND NATIVE HOUSEHOLDS IN TURKEY

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DECLARATION OF ORIGINALITY

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ABSTRACT

Multidimensional Poverty in Forced Displacement: A Comparison of Syrian and Native Households in Turkey

This study addresses the limitations of traditional measures of poverty that focus solely on income or consumption expenditure and instead adopts a multidimensional approach inspired by Amartya Sen's capabilities perspective. Combining various statistical approaches with normative considerations, a multidimensional poverty index (MPI) is constructed for Syrian refugees in Turkey, a context that has received relatively less attention in the literature compared to other host countries. Using the Turkey Demographic and Health Survey (TDHS) 2018, the study examines and compares the diverse deprivations faced by displaced and non-displaced households. A dimension on financial security is incorporated in addition to three standard dimensions used in the literature (education, health, and living standards). The analysis reveals significant disparities, with Syrian households experiencing a seven times higher incidence of multidimensional poverty compared to native Turkish households. The overall MPI score for the refugee community is 33 percentage points higher than the host community. Particularly, informal employment emerges as a nationwide issue. The findings contribute to the understanding of the well-being of Syrian refugees in Turkey and highlight the urgent need for targeted policies and interventions to address the simultaneous deprivations they face.

ÖZET

Çok Boyutlu Yoksulluk ve Zorunlu Göç: Türkiye'de Suriyeli ve Yerel Hanehalklarının Bir Karşılaştırması

Bu çalışma, yalnızca gelir veya tüketim harcaması üzerine odaklanan geleneksel yoksulluk ölçümlerinin sınırlamalarını ele almaktadır ve bunun yerine Amartya Sen'in kapasiteler perspektifinden esinlenerek çok boyutlu bir yaklaşım benimsemektedir. Normatif düşüncelerle çeşitli istatistiksel yaklaşımları birleştirerek Türkiye'deki Suriyeli mülteciler için bir çok boyutlu yoksulluk endeksi oluşturulmuştur. Bu bağlam literatürde diğer ev sahibi ülkelere kıyasla daha az dikkat çekmiştir. Türkiye Nüfus ve Sağlık Araştırması 2018 verileri kullanılarak, çalışma mülteci ve yerli Türk hanelerinin maruz kaldığı çeşitli yoksunlukları incelemekte ve karşılaştırmaktadır. Literatürde standart olarak kullanılan üç boyutun yanı sıra (eğitim, sağlık ve yaşam standartları), finansal güvenlik boyutu da dahil edilmiştir. Analiz, Suriyeli hanelerin çok boyutlu yoksulluk oranının yerli hanelere kıyasla yedi kat daha yüksek olduğunu ortaya koymaktadır. Mülteci topluluğunun genel MPI skoru, ev sahibi topluluktan yüzde 33 daha yüksektir. Özellikle, gayri resmi istihdam ülke genelinde bir sorun olarak ortaya çıkmaktadır. Bulgular, Türkiye'deki Suriyeli mültecilerin refahının anlaşılmasına katkıda bulunmakta ve karşılaştıkları eşzamanlı yoksunluklarla başa çıkmak için hedefe yönelik politika ve müdahalelere acil ihtiyaç olduğunu vurgulamaktadır.

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ABBREVATIONS

AF method: Alkire-Foster method

BMI: Body Mass Index

CTT: Classical Test Theory

EFA: Exploratory Factor Analysis

HDI: Human Development Index

KMO measure: Kaiser-Meyer-Olkin measure

MCA: Multiple Correspondence Analysis

MPI: Multidimensional Poverty Index

OPHI: Oxford Poverty and Human Development Initiative

PCA: Principal Component Analysis

TDHS: Turkey Demographic and Health Survey

TECs: Temporary Education Centers

UN: United Nations

UNDP: United Nations Development Program

WFP: United Nations World Food Program

WHO: World Health Organization

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CHAPTER 1
INTRODUCTION

Traditional measures of poverty use income or consumption expenditure to establish a poverty line cut-off, which is then used to categorize individuals as either poor or non-poor. While they are relatively easier to construct, this conventional approach has faced increasing criticism due to its unidimensional focus on monetary poverty and the classification of people into a rather simple dichotomy. In response, Amartya Sen's capabilities perspective has laid the groundwork for a multidimensional approach to poverty (Sen, 1993; 1995). Subsequently, numerous scholars have examined poverty as a complex phenomenon manifesting in various degrees and forms, adopting a more comprehensive approach to its measurement.

Recently, various scholars have applied multidimensional poverty analysis to the forced displacement contexts. Considering the simultaneous deprivations displaced populations face, such as malnutrition and limited access to health and education, a deeper understanding of the well-being of these vulnerable groups is crucial. The expected increase in forced displacement, driven by factors like climate change, disasters, human rights violations, and conflicts, underscores the importance of studying the well-being of displaced communities (Admasu et al., 2021). While several studies have constructed multidimensional poverty measures for Syrian refugees in Jordan and Lebanon, there remains a noticeable research gap regarding Syrian refugees in Turkey.

To address this research gap, the present study aims to construct a multidimensional poverty index focused on Syrian refugees in Turkey, a context that has received relatively less attention compared to other host countries. By utilizing a representative dataset for both populations, this study examines and compares the diverse deprivations faced by both displaced and non-displaced households. For this purpose, the study combines insights from related literature with various statistical approaches to construct a comprehensive and contextually relevant MPI. This approach aligns with the methodology employed by Vollmer and Alkire (2022) and

Alkire and Kanagaratnam (2020), who demonstrate the effective integration of both normative and technical considerations in multidimensional poverty analysis.

Using the Turkey Demographic and Health Survey (TDHS) 2018, two MPIs for Syrian and native households are calculated. Given the widely acknowledged importance of education, health, and living conditions to overall well-being, these three dimensions are included in this analysis. Within the context of Syrian refugees, these dimensions take on greater importance due to the numerous challenges they face in accessing education and health services. Additionally, a fourth dimension on financial security is employed to capture the employment status, home ownership, and subjective financial situation of the households. In total, the study incorporates 12 indicators across the dimensions of education (years of education and school attendance), health (nutrition, child mortality, early marriage), living conditions (basic asset ownership, housing conditions, overcrowding), and financial security (employment, formal employment, house ownership, subjective financial situation).

The results of the analysis indicate significant disparities between Syrian refugee and native Turkish households. Syrian households experience a much higher incidence of multidimensional poverty, with 72.2% classified as poor compared to only 7.2% among native households. The overall MPI score for the refugee community is 33 percentage points higher than the host community. Particularly, informal employment seems to be a nationwide issue while almost 98% of Syrian households do not have a member working formally. The headcount ratios for all indicators are higher for the refugee community, except for the employment and flooring indicators.

This paper is structured as follows. Chapter two presents a review of related studies and provides background information on the conditions of Syrian refugees in Turkey. Additionally, it introduces the Alkire-Foster methodology as the framework for constructing the MPI. Chapter three focuses on the data and methodology, explaining the MPI construction process. Chapter four presents the results and discussion section, which highlights the findings of the study, including regional results. Finally, Chapter Five concludes.

CHAPTER 2
LITERATURE REVIEW

Multidimensional measures of poverty have originated from the capabilities approach proposed by Amartya Sen (Sen, 1993). Rather than instrumentalizing a low level of income, Sen has conceptualized poverty as the deprivation of basic capabilities that are intrinsically important for human well-being, such as access to basic education and healthcare (Sen, 1995). Subsequently, this approach was adopted by the UNDP in calculating the Human Development Index (HDI), which evaluates poverty based on three dimensions (Duclos & Tiberti, 2016). Today, numerous studies have been conducted on multidimensional poverty measures, the most influential method being the double cut-off approach proposed by Alkire and Foster (2011) at the Oxford Poverty and Human Development Initiative (OPHI) (Tekgüç & Akbulut, 2022).

The Alkire-Foster methodology is also used by the OPHI and UNDP to calculate the global Multidimensional Poverty Index (global MPI) for more than 100 developing countries (UNDP & OPHI, 2022). The global MPI serves as a complementary measure to conventional metrics, such as 1.9$ per day, by forming international criteria to assess multiple deprivations. For this purpose, the index utilizes micro-data at the household level, encompassing three dimensions – education, health, and living standards – and ten indicators (Alkire, Kanagaratnam, & Suppa, 2022). In addition to facilitating cross-country and regional comparisons, the MPI supports the identification and comparison of different population groups within a country (Alkire et al., 2015, chapter 5).

While the MPI framework has been adopted for various country contexts and cross-country comparisons, its application to forcibly displaced communities is a relatively recent development and mostly focuses on internally displaced populations. Admasu et al. (2021) constructed a cross-country MPI to capture the deprivations faced by internally displaced groups in Ethiopia, Nigeria, Somalia, South Sudan, and Sudan. The authors include four dimensions (education, health, living standards, and financial security) with 15 indicators and equal weights. Except for Nigeria, displaced and host communities are found to be significantly different in terms of multidimensional poverty. Temgoua, Sharma, and Wai-Poi (2020) explore the relationship between internal displacement in Iraq and multidimensional poverty, calculated in accordance with the global MPI. The authors also found substantial differences in the multidimensional poverty of internally displaced and non-displaced populations. Loaiza Quintero, Muñetón Santa, and Gabriel Vanegas (2018) evaluate the effect of forced displacement on multidimensional poverty in Antioquia, Colombia, in order to reveal the social costs related to the armed conflict.

Several studies have employed multidimensional poverty analysis for the case of Syrian refugees in Jordan and Lebanon. Lyons, Kass-Hanna, and Montoya Castano (2022) use the Alkire and Foster methodology to construct a Multidimensional Livelihood Index (MLI) for Syrian refugees in Lebanon. The MLI consists of 21 indicators grouped under five dimensions (education, health, living standards, employment, security, and social inclusion). The authors apply two weighting schemes in which they first assign equal weights to each dimension and then to each indicator. The results indicate employment to be a nationwide issue, while health deprivation is a significant problem in the governorates of Akkar and North Lebanon, and living standards and education are critical in the governorates of Baalbek-El Hermel and Bekaa. With regards to Syrian refugees in Jordan, Assaad, Boustati, and Jamkar (2022) calculate an MPI in accordance with the global MPI to identify vulnerable refugees. The authors then assess how the MPI scores affect refugees' access to different cash assistance and food voucher programs. Coban (2023) examines the relationship between gender and multidimensional poverty in Lebanon. For this purpose, the author adds a dimension on financial security to the three core dimensions identified by Alkire and Foster (2011). The findings reveal a higher MPI for refugee households compared to Lebanese households.

2.1 Brief background on the conditions of Syrian refugees in Turkey

The civil war that began in Syria in 2011 resulted in a significant displacement of its population, leading to a surge in the number of Syrians in neighboring countries. As the conflict escalated, Turkey became the host of the largest number of Syrian refugees, with its Syrian population reaching about 2.5 million by the end of 2015 (DGMM, 2021; Kırdar, Koç, & Dayioğlu, 2021). This number reached 3.6 million in 2018, the year that TDHS was collected, and stayed relatively stable in the following years.[1] While initially settled in camps near the border, the majority of refugees moved to urban areas and only 4.3% was living in camps in 2018 according to TDHS (HUIPS, 2019). Syrians in Turkey were given a temporary protection status in 2014 for purposes such as access to free health and education (Directive no. 2014/6883; published in Official Gazette on 2/10/2014).[2] As opposed to the universal regulation of refugee status in the United Nations (UN) Refugee Convention, temporary protection status is not internationally defined and regulated.

Before 2016, Syrian refugees were generally barred from formal employment in Turkey, with exceptions for circumstances like starting a business, which resulted in a limited number of work permits issued (Demirci & Kırdar, 2023). With the implementation of Law 8375 in 2016, Syrian refugees under temporary protection became eligible to obtain work permits under specific conditions. However, this legislative change had only a small impact on formalization and only 116.000 work permits were granted up to 2018 (Refugees Association, 2020). Hence, an overwhelming majority of refugees continue to work primarily in informal jobs, mostly in the agriculture, textile, and construction sectors (Düvell, 2018; Aracı, Demirci, & Kırdar, 2022). TDHS dataset illustrates that almost all (98.4% and 98.7%, respectively) of Syrian men and women who were employed in the last 12 months preceding the survey were working informally. Precarious working conditions are prevalent in informal employment and Syrian workers have been

[1] Since 2021, the number of Syrian refugees under temporary protection has shown a decrease to about 3.3 million in May 2023

[2] As defined by the UN Refugee Convention, the term refugee refers to Syrians in its broadest sense for convenience in this paper.

reported to work long hours while earning below the minimum wage (İçduygu & Diker, 2017; ILO, 2021; Dayıoğlu, Kırdar, & Koç, 2021).

Even though various social assistance programs, such as Emergency Social Safety Net (ESSN), are provided to Syrian refugees, monetary poverty remains prevalent. WFP (2016) interviewed 1562 Syrian refugee households residing off-camp and 93% of them were found to be living under the national poverty line. Furthermore, high levels of poverty and limited regular employment opportunities were found to be contributing to food insecurity among refugees. The findings reveal that nearly one-third of surveyed households were food insecure whereas two-thirds were at risk of food insecurity (WFP, 2016).

During the initial years of their displacement, Syrian refugee children residing in camps received education with camp administrators' initiative (Dayıoğlu et al., 2021). In 2014, Temporary Education Centers (TECs) were established, which initially adhered to the Syrian curriculum and used Arabic as the medium of instruction. The same year, as Syrians received temporary protection status, children were also able to attend public schools. In 2016, the curriculum for TECs was expanded to include 15 hours of Turkish sessions per week while these students were aimed to transfer to public schools (Dayıoğlu et al., 2021; Emin, 2016). This transfer was almost completed in the 2019-2020 academic year, hence most Syrian students started to attend public schools (MoNE, 2021). Accordingly, public schools offer free education for 12 years to all children, including refugee children with temporary protection status. Mandatory schooling in Turkey consists of 12 years that is divided into four years for each primary, lower-secondary, and upper-secondary level since the 2012-2013 school year (Kırdar et al., 2021). In Syria, compulsory education includes primary education for six years and lower-secondary education for three years (Emin, 2016).

Despite national and international efforts, the educational engagement of Syrian children remains a concern. Kırdar et al. (2021) reported that for the academic year 2018-19, the same year the TDHS survey was administered, the enrollment rate of

Syrian children aged 7-17 was 61.4%. Although this represents a significant increase from the strikingly low 20.4% in the 2014-15 academic year, the progress since then has been relatively stagnant. As of the 2020-2021 academic year, 64.2% of Syrian children attended school.

The low enrolment rate partly reflects the widespread incidence of child labor among Syrian refugees. With most families struggling to make ends meet, children are highly relied upon to contribute to the household income (Fehr & Rijken, 2022). Syrian children start working at a younger age compared to Turkish children and work for very long hours while earning low earnings (Fehr & Rijken, 2022). Using the 2018 TDHS data, Dayıoğlu et al. (2021) reveals that almost half (45.1%) of Syrian boys aged 15-17 were working in a paid job. Remarkably, among working children aged 12-17, only less than 3% were enrolled in school.

Finally, early marriage is a significant concern particularly for Syrian girls in Turkey, as it may be increasingly adopted as a coping strategy in response to the challenges of forced displacement (AFAD, 2014; Williams, Coşkun, & Kaşka, 2020). Early marriage is often associated with early pregnancy, which can, in turn, limit access to education and employment opportunities, leading to a heightened reliance on family support systems (Admasu et al., 2021).

2.2 Alkire - Foster (AF) Method

The AF method employs a simple counting approach to estimate multidimensional poverty (Pacifico & Poege, 2017; Alkire & Foster, 2011; Alkire et al., 2015, chapter 5). In the first step, individuals below the deprivation cutoffs for each indicator are considered deprived in that indicator. Then, individuals are identified as multidimensionally poor if their deprivation scores exceed the value specified by the second cut-off.

2.2.1 Identification of the poor

Consider a sample of individuals represented by N and at least two deprivation indicators, $D \geq 2$, which may be grouped under deprivation domains. The Y matrix is an $N \times D$ matrix where the entry y_{ij} represents the achievement level of person i for indicator j. The deprivation cutoffs of the D indicators are gathered in a d-dimensional vector $z = (z_1, ..., z_D)$. A deprivation cutoff z_j is specified for each indicator j, which shows the lowest level of achievement in order to be classified as non-deprived. Hence, the deprivation occurs when $y_{ij} < z_j$, thus when the i^{th} individual's achievement in indicator j is strictly below the related cutoff, z_j.

The 1 $\times D$ vector $w = (w_1, ..., w_D)$ contains the weights for each indicator D and can be adjusted with different weight structures. The deprivation matrix g^0 is an $N \times D$ matrix with entities represented by $g^0_{ij} = w_j$ when $y_{ij} < z_j$, and 0 otherwise. Thus, for each individual, the row sum of the deprivation matrix illustrates the number of weighted deprivations: $i : c_i = \sum_{j=1}^{D} g^0_{ij}$.

The poverty cutoff k is a value between 0 and 1 and categorizes an individual as MPI poor if the extent of weighted deprivations is above the specified value of k. Hence, the AF method utilizes both indicator thresholds and a poverty cutoff to classify an individual as multidimensionally poor, justifying the usage of the concept of dual-cutoff approach to refer to the method.

The identification function is defined as $p_k(y_i, z)$, taking the value of 1 when $c_i > k$ and 0 otherwise. Accordingly, it transforms the entries of the deprivation matrix g^0 as $g^0_{ij} p_k(y_i, z)$, so that when the i^{th} person is not classified as MPI poor, all elements in the row vector g^0_i are set to zero. The modified matrix is referred as the censored deprivation matrix, $g^0(k)$.

2.2.2 Measurement of multidimensional poverty

In the Alkire-Foster (AF) approach, the most basic metric for evaluating poverty is the multidimensional headcount ratio (H), which shows the incidence of poverty by dividing the number of multidimensionally poor individuals to the population size:

$$H = \frac{\sum_{i=1}^{N} p_k(y_i, z)}{N} = \frac{q}{N} \tag{2.1}$$

While the headcount ratio offers a simple measure in the AF framework, it fails to adhere to the measurement principle of dimensional monotonicity. This implies that if a poor individual start to experience deprivation in another dimension, H would not increase.

In order to define an index that satisfies this property, Alkire and Foster (2011) first identify the intensity of poverty (A) using the censored deprivation matrix, $g^0(k)$. First, $|g^0(k)|$ is defined as the sum of the elements of $g^0(k) : \sum_{i=1}^{N} \sum_{i=j}^{D} g_{ij}^0(k)$. Accordingly, the index A is calculated by dividing the number of deprivations experienced by the poor individuals ($|g^0(k)|$), by the number of poor individuals in the population (q):

$$A = \frac{|g^0(k)|}{q} \tag{2.2}$$

Finally, the multidimensional poverty index (MPI) or the adjusted multidimensional headcount ratio, M_0, is derived by multiplying the headcount ratio (H) and the average number of deprivations faced by MPI poor people (A), reflecting both the incidence and intensity of simultaneous deprivations:

$$M_0 = H \times A = \frac{|g^0(k)|}{N} \tag{2.3}$$

The adjusted headcount ratio can be broken down according to different population subsets and indicators. This implies that an overall index can be calculated by taking a weighted average of subgroup poverty indexes ($M_{0,g}$), in which the respective subgroup population shares (N_g) are taken as weights:

$$M_0 = \sum_{g=1}^{G} \frac{N_g}{N} M_{0,g} \tag{2.4}$$

Additionally, the percentage contribution of group g can be calculated by $C_{0,g} = (N_g/N)(M_{0,g}/M_0)$.

In order to decompose at the indicator level, first, the j column entries of $g^0(k)$ is collected under $|g_j^a(k)|$. Then, M_0 can be written in the following way:

$$M_0 = \sum_{j=1}^{D} |g_j^a(k)|/N \tag{2.5}$$

Then, the percentage contribution is $CI_{0,j} = |g_j^a(k)|/(N \times M_0)$ for each indicator. Similarly, for a set of indicators, the contribution is equal to the total of each individual indicator's contributions.

CHAPTER 3
DATA AND METHODOLOGY

This study employs the 2018 Turkey Demographic and Health Survey (TDHS), which is carried out every five years by the Institute of Population Studies at Hacettepe University.[3] In addition to the national sample, this latest round of TDHS uniquely incorporated a distinct module (TDHS-S) for Syrian refugees residing in Turkey. Both modules utilized the same questionnaires, with the Syrian sample incorporating additional questions related to migration history. Furthermore, both are representative of their respective populations, with response rates of 95 and 79%, respectively (HUIPS, 2019). The national sample comprises 11056 households and 7346 women, whereas the Syrian sample comprises 1826 households and 2216 women (HUIPS, 2019).

The TDHS collects data using two main questionnaires, namely the household questionnaire and the women's questionnaire (HUIPS, 2019). The former includes basic demographical and employment indicators for each household member, along with questions on the ownership of a diverse range of consumer goods. The latter, the women's questionnaire, targets women aged 15-49 years within the household and obtains more detailed information on health aspects while providing more comprehensive data on the labor market activities of both the interviewed women and their husbands. Considering these, the 2018 TDHS is one of the rare representative datasets that enable comparisons between large refugee and native populations across various demographic and health indicators (Demirci, Foster, & Kırdar, 2022).

3.1 Construction of the MPIs for the refugee and native communities

Two main MPIs are constructed for the Syrian and native households in Turkey following the steps described in Section 2.2, as initially outlined by Alkire and Foster (2011) and Alkire and Santos (2014). The first step included the specification of dimensions and indicators, as well as the deprivation thresholds for each indicator.

[3] The interviews for TDHS were conducted between October 2018 and February 2019 (HUIPS, 2019).

The selection process employed a combination of statistical results, normative reasoning, and related studies, and details for each indicator is provided in the subsequent section. The MPIs cover three core dimensions used in the most multidimensional poverty studies: education (years of education and school attendance), health (nutrition and child mortality), and living conditions (basic asset ownership and housing conditions). In addition to these basic deprivations that are mostly based on internationally recognized thresholds, additional indicators are employed to reflect the specific challenges faced by Syrian refugees in Turkey. First, a dimension on financial security is added, compassing indicators on employment status, house ownership, and subjective financial situation. Second, the health dimension is expanded to include early marriage. The living standards dimension now covers overcrowding as well. The final set of 12 indicators is provided in Table 1.

Table 1. Dimensions, Indicators, and Respective Weights

Dimensions	**Weights**	**Indicators**
Education	1/8	Years of schooling
	1/8	School attendance
Health	1/12	Nutrition
	1/12	Child mortality
	1/12	Early marriage
Living Standards	1/12	Basic assets
	1/36	Sanitation
	1/36	Flooring
	1/36	Heating
	1/12	Overcrowding
Financial Security	1/16	Employment
	1/16	Formal employment
	1/16	House ownership
	1/16	Subjective financial situation

Determining the weighting of dimensions is another key step in the AF method. Drawing from established practices within the MPI literature, equal weights are assigned to each dimension and the indicators within each dimension. This assumes four dimensions having equal importance, each weighted at 0.25. As Atkinson, Cantillion, Marlier, and Nolan (2002) noted, this approach also has an intuitive advantage in interpreting the MPI measures for a set of indicators. An alternative approach would be to employ statistical methods like Principal Component Analysis (PCA) to assign weights to indicators based on their factor loadings. However, these techniques are mainly utilized to minimize the joint deprivations experienced by poor individuals, which contradicts the essential goal of the MPI. At the same time, it must be acknowledged that the method of equal weighting is not without drawbacks and can lead to double counting when there are multiple indicators that reflect similar functionings of a population (Tekgüç & Akbulut, 2022). This consideration is especially pertinent when it comes to income or expenditure indicators, which, while absent from the TDHS, are frequently subject to debate in this context.

In light of these linkages, the selection process of indicators carefully considered the respective weights for indicators under a dimension. In particular, three indicators - sanitation, flooring, and heating - were found to be proxies for housing conditions across the pooled sample of Syrian and native samples, as will be shown in Section 3.2.2. Consequently, a housing conditions subdimension was established, treated as a single indicator in the weighting process. Thus, the education indicators are weighted at 1/8 each, the health and living standard indicators each carry a weight of 1/12, and the financial security indicators are weighted at 1/16 (see Table 1).

The analysis is conducted at the household level. While AF methodology allows for an individual-level analysis that could reflect intra-household inequalities, TDHS does not provide a diverse set of variables in each dimension to compare female and male individuals (particularly, in the health dimension). Observations for indicators under the living standards dimension are already provided at the household level and they are assumed to be public goods accessible to all household members (Klasen & Lahoti, 2016; Vijaya, Lahoti, & Swaminathan, 2014; Espinoza-Delgado & Klasen, 2018; Tekgüç & Akbulut 2022).

On the other hand, observations for almost half of the indicators were collected only for a subpopulation of the sample, such as the ever-married women or household members aged 18 and above. These indicators include all the education and health indicators, as well as employment. For these indicators, households with no eligible members are considered non-deprived in that indicator (Alkire et al., 2015, chapter 7). Intuitively, a household consisting solely of male individuals cannot be deprived of the dimension of early marriage, as this information is only provided for women. For these indicators, the identification of deprivation for individuals is made based on household achievements following the global MPI methodology. The main idea relates to the positive and negative externalities shared within the households, highlighting the interconnected nature of household well-being. For instance, if at least one school-age child is not attending school, all household members are considered deprived in this indicator, regardless of their individual school attendance status. The final step included the specification of the poverty cut-off, k, which is taken as 0.33 in accordance with the majority of applications of MPI[4] Hence, if a household's weighted deprivation score is equal to or above this value, the household is identified as multidimensionally poor.

3.1.1 MPI Dimensions and Indicators

Education

The significance of education in human development and its role in reducing the intergenerational transmission of poverty is widely recognized (Admasu et al., 2021; Tekgüç & Akbulut, 2022; Sen, 1993). In order to capture the educational attainment of refugee and native households, two indicators of years of education and child school attendance are employed similarly to the global MPI (Alkire, Kanagaratnam, & Suppa, 2020). The years of schooling indicator classifies a household as deprived if no one in the household (aged 14 years or older) has completed at least eight years of education. Eight years of education is chosen to offer a more consistent threshold across both samples, given that the compulsory education in Syria is nine years and it increased from five to eight years in 1997 in Turkey, and to 12 years in 2012. Given this difference, a more consistent threshold across both samples was opted for. The

[4]Examples include Lyons et al., 2023; Alkire et al., 2022; Tekgüç & Akbulut, 2022.

options under consideration were five and eight years, but given the pooled sample mean of 7.27 years of education (for individuals aged 14 and above) across both samples, eight years is taken as a more appropriate and stringent[5] threshold. The youngest eligible individuals are identified as members aged above 14 at the time of the survey since this is the age at which people in Turkey and Syria would typically complete grade eight. The second indicator – child school attendance – categorizes a household as deprived if any child in the age range of 6 to 14 is not attending school. This age range is chosen given the common official school starting age, which is 6 years in both countries, coupled with the established eight-year education threshold.

Health

In the health dimension, the two indicators are nutrition and child mortality, which are employed in accordance with the global MPI methodology. The critical role of these deprivations in determining people's overall health and well-being is well-established (IFPRI, 2016). Particularly for women of reproductive age, malnutrition can have more severe consequences, increasing the risks of adverse pregnancy outcomes and negatively affecting both their own health and the health of their children (Ibid.). Adequate nutrition is also crucial for a child's development, particularly from birth to two years, as it significantly impacts growth, health, and overall development while reducing risks of common childhood illnesses and deficiencies (UNICEF, 2013).

Three distinct variables for different age groups of women and children are employed following the definitions provided by the World Health Organization (Bloem, 2007; Alkire et al., 2022). First, children younger than 60 months are considered undernourished if they are stunted (height-for-age) or underweight (weight-for-age).[6] Females aged 15 to 19 years (181 to 228 months) are considered

[5]using five years as a threshold yielded 8.5% and 5.8% deprivation shares for Syrian and native samples

[6]Stunting, assessed via height-for-age, signifies being shorter than expected for a given age, indicating insufficient linear growth and cumulative growth deficits. Underweight, determined by weight-for-age, implies having a lower weight than expected for a specific age. Children with height-for-age or weight-for-age z-scores more than two standard deviations (SD) below the mean of the WHO Child Growth Standards are classified as stunted or underweight, respectively. In order to identify stunted or underweight children, z-scores found in the original DHS data files, which are

undernourished if their Body Mass Index (BMI) for age is two standard deviations below the median. Women aged 20 to 49 are undernourished if their BMI is below 18.5 kg/m². Assuming a negative externality, a household is considered deprived if at least one member of the household is undernourished (Alkire et al., 2022). Similarly, the second indicator, child mortality, categorizes all household members as deprived if any child under 18 years of age has died within the household during the five years preceding the interview date (Alkire et al., 2022, Dotter, 2017; Alkire & Santos, 2014).[7] Given the significance of early marriage in the context of Syrian refugees in Turkey, as discussed in Chapter Two, an indicator of early marriage is incorporated to emphasize the gendered implications of forced displacement and poverty. The same indicator is also employed by Admasu et al. (2021) to construct a cross-country MPI for displaced communities.

Living standards

The living standards dimension consists of indicators of asset ownership, housing conditions, and overcrowding, which are all provided at the household level. In order to construct more relevant proxies for the relevant populations, several statistical approaches are employed using the potential variables in the TDHS. First, the available asset variables were eliminated and consolidated under one asset ownership indicator, mainly following the methodological path suggested by Vollmer and Alkire (2022) to create a statistically validated asset indicator. Accordingly, three approaches are employed: Exploratory Factor Analysis (EFA), Multiple Correspondence Analysis (MCA), and Classical Test Theory (CTT). The construction of the asset ownership indicator is presented in Section 3.2.1. The final set of variables consists of 11 asset variables including television, computer, oven, microwave, dishwasher, washing machine, iron, vacuum cleaner, tea/coffee machine, kettle, and blender. In order to determine the threshold value, the pooled sample mean of the number of assets owned by households (5.5) was considered. However,

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calculated based on the WHO Child Growth Standards 2007 are applied following the DHS statistical guidelines.

[7] The child mortality indicator is derived from birth history data provided by interviewed women aged 15 to 49, hence relies on the values reported by mothers.

considering the significant gap between the populations in terms of the average total assets owned (less than 2% of the Syrian sample has more than 5 items), the threshold was chosen according to the peak of the joint distribution at two. Hence, households that do not own more than two of the aforementioned assets are considered deprived.

Secondly, to inform the selection of indicators related to housing conditions, another EFA was conducted with potential indicators that may reflect the housing conditions of different households. Further detail of this analysis is provided in Section 3.2.2. The final set of indicators consists of access to improved sanitation facilities[8], quality of flooring material[9], and type of heating facility[10]. The indicators on sanitation and flooring are also included in the global MPI. Other relevant studies that employ a flooring indicator include Assaad et al. (2022) and Dotter (2017), and for heating, they include Tekgüç and Akbulut (2022), Çoban (2023), and Yılmaz and Kılıç (2021).

Third, considering the prevalence of overcrowding among Syrian refugees, an indicator was constructed based on the number of people per sleeping room. Household crowdedness, defined by the number of occupants surpassing the available dwelling space, serves as a universal indicator of a detrimental home environment. Furthermore, forcibly displaced individuals may face an increased risk of residing in overcrowded houses with poor infrastructure, potentially leading to worse health outcomes (IOM 2020). Accordingly, the mean household sizes in the Syrian and native samples were six and 3.5, respectively. In order to measure the crowdedness of

[8]Deprivation occurs when a household lacks access to improved sanitation facilities or has access to improved facilities but they are shared with other households (Alkire et al., 2020). According to HUIPS (2019) and the UN SDG indicators, improved toilet facilities include flush/pour flush toilets to piped sewer systems, septic tanks, and pit latrines; ventilated improved pit (VIP) latrines; pit latrines with slabs; and composting toilets (DHS)

[9]The first variable, flooring, classifies households with natural material flooring as having inadequate flooring, based on the classification followed by the TDHS and global MPI (HUIPS, 2019; Alkire et al., 2022).

[10]A household is considered to have substandard heating if any type of stove (using natural gas, oil/gas oil, wood/coal, or dung) is employed for heating the house, indicating the absence of central or flat heating (Tekgüç & Akbulut, 2022). Electric heaters are also considered suboptimal as they only warm up a portion of the house. On the other hand, having an air conditioner is considered optimal due to its ability to regulate the temperature of the entire space more effectively

the house, the number of sleeping rooms is employed, following the UN definition. In order to classify households as deprived, the threshold is chosen according to the pooled sample mean. Accordingly, households with more than 2.45 people per sleeping room are considered deprived. The indicator is not categorized under housing conditions since the EFA revealed its different construct. In the related literature, Admasu et al. (2021) emphasize the use of a proxy for overcrowding in their analysis of multidimensional poverty in forced displacement contexts, although they do not include it in their study due to data limitations. Similarly, Tekgüç and Akbulut (2022) and Lyons et al. (2023) incorporate crowdedness as an additional indicator in their respective studies of Turkey and Syrian refugees in Lebanon.

Financial Security

An additional dimension is introduced to reflect the financial security of households. This dimension consists of four indicators on employment, formal employment, house ownership, and subjective financial situation. The emphasis on the employment aspect stems from its key role in shaping a sustainable livelihood for refugee families, beyond its apparent role as a means to earn income. The idea that employment significantly contributes to well-being through self-respect, social participation, and inclusion is more widely recognized recently (Tekgüç & Akbulut, 2022; Stiglitz, Sen, & Fitoussi, 2009; Lugo, 2007; Suppa, 2018; Fukuda-Parr, 1999). Beyond offering a level of economic stability, employment plays a key role in refugees' integration into society. Furthermore, forcibly displaced people may encounter additional obstacles that are related to identification documents, work permits, and cultural or language barriers (Lyons et al., 2023). Analyzing DHS 2018 points out the significance of employment for Syrian refugees: 40% of Syrian adult men and 82% of adult women have either never been employed or have not been employed in the year preceding the survey. Furthermore, as highlighted in Chapter Two, informal employment is highly prevalent in the Syrian refugee community. Strikingly, among those employed women and men, 98.4% and 98.7% respectively, were working without a work permit.

In order to capture the importance of informality separately, two indicators are employed. First, a household is deprived if no adult household member is employed. Second, using the formal employment indicator, a household is considered deprived if no adult household member is working with social security. Given that the figure for formal employment is strikingly low for the Syrian sample, the presence of only one person was considered more suitable for this indicator. Individuals who were not working are assumed to have no social security. To construct the two indicators, employment and social security data from the women's questionnaire is utilized, covering interviewed women and their husbands.

A second indicator of house ownership is added under the financial security dimension given several key considerations. Primarily, given that TDHS does not include relevant data on the value of the house, the mere fact of having a house is taken to signify a basic level of financial security that can provide stability in the face of unemployment or economic hardship. This is particularly relevant in forced displacement contexts where social inclusion might be limited and the safety net for those without employment may be lacking. In the face of increasing living costs, owning a home might provide a buffer against rent increases and other unexpected living expenses. Moreover, some studies have shown that homeownership has poverty-reducing and inequality-moderating effects in Turkey (Tekgüç, 2018; Acar, Anıl & Gursel, 2017).

TDHS includes two household-level variables on homeownership, which are combined to construct a single indicator. The first related question addresses whether the house is owned by any member of the household, while the second inquires if anyone within the household owns another house. A cross-tabulation of these two variables indicated that they identify unique sets of non-deprived households, with only 14 Syrian households (0.075%) owning both their residence and another property. The low correlation of 0.1 among these variables also suggested that these indicators might be complementary. Accordingly, households were classified as non-deprived if they met either of the two conditions: their house was owned by a member, or any member owned another house. [11] The women's questionnaire in TDHS also includes a question for interviewed women on whether they own a house and whether they own land. Crosstabulation of these variables revealed that only five women in the TDHS Syrian sample own a house or land on their own, and the share of women who has a house or land on their own or jointly with somebody else is only 3.5%. Given these exceptionally high deprivation levels among women, questions from the person questionnaire are employed.

A final indicator under the financial security dimension was added to capture aspects that may not be reflected in the two objective measures of financial security, namely employment and house ownership. The subjective financial situation indicator captures individuals' own perceptions of their financial situation, providing insights into their perceived economic stress and overall satisfaction. This aligns with the principles of subjective well-being literature, which acknowledges the significance of subjective assessments in gauging well-being. The related question was only asked for the interviewed women in the form of "How satisfied are you with the financial situation of your household?" on a scale from one to ten, where the latter represented complete satisfaction. The deprivation threshold was determined based on the pooled mean value of the variable in the dataset (3.9).

3.2 Selection of the indicators related to living standards dimension

3.2.1 Asset ownership

This section aims to design a statistically and normatively validated assets indicator that can effectively compare both refugee and native households. Accordingly, the analysis is conducted on the pooled Syrian and native samples. While TDHS includes 23 basic asset variables[12], these share only television and car ownership as common

[11] Consistent with Tekgüç (2018), households not paying rent were categorized as homeowners for the first question. Households living rent-free make up the 9% of the Syrian sample and 15% of the native sample. When rent-free living households were excluded, 0.44% of Syrian households and 62% of native households owned their homes.

[12] 23 asset variables in TDHS are deep freezer, gas/electric oven, microwave oven, dishwasher, garbage dispenser, washing machine, drying machine, iron, vacuum cleaner, LED/LCD television, home theatre, tea/coffee machine, kettle, generator, food processor/blender, paid TV services (Cable TV, Digiturk, D-smart, etc.), satellite TV, computer, internet connection, air conditioner, private car,

items with the global MPI. A selection among the available variables is made using three sequential statistical approaches, mainly following the methodological path offered by Vollmer and Alkire (2022). First, Exploratory Factor Analysis (EFA) is used to identify latent factors that explain the structure of the data and increase the internal reliability of the indicator. Then, Multiple Correspondence Analysis (MCA) is conducted with the retained variables to detect patterns and associations in the binary data more clearly. Finally, three alternative models are developed using the retained variables from the MCA and CTT is used to choose the optimal model.[13]

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) assumes the presence of multiple underlying factors that contribute to the observed variables through a linear combination (common variance) along with a residual component (unique variance) (Costello & Osborne, 2005; Vollmer & Alkire, 2022). While factor analysis is standardly conducted with Pearson correlations for continuous variables, since the asset variables in TDHS are Bernoulli-distributed, tetrachoric correlations are better suited to handle the skewness of these variables (Alkire et al., 2015, chapter 3; Uebersax, 2015).

An initial EFA was conducted including all variables, with the aim of the suitability of data for factor analysis. Nevertheless, this model yielded a Heywood case due to the singularity of the correlation matrix, implying the presence of improper solutions originating from a non-positive definite matrix (Farooq, 2022). A Heywood case typically occurs under the presence of missing values, items with zero variance, small sample size, or the existence of linear relationships among variables (Lorenzo-Seva & Ferrando, 2021).

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commercial vehicle, and tractor. The question is asked in the form of "Do you have the following in the household?".

[13]Confirmatory multivariate statistical approaches, such as Confirmatory Factor Analysis (CFA), are also commonly applied in the related literature. However, the multivariate normality assumption of this approach was rejected in our sample based on a Doornik-Hansen test for multivariate normality (chi2(46) = 4.27e+06, p <.0000). Hence, considering the binary nature of the data and the suggestions by Vollmer and Alkire (2022), statistical approaches are mainly utilized as exploratory tools in this study.

Having confirmed that the dataset is not hampered by the first three conditions, tetrachoric correlations between the variables are examined to assess the possibility of linear relationships among variables. In this process, a perfect correlation (correlation coefficient = 1.000) was observed between home theatre and washing machine variables. Further scrutiny of responses indicated that only 2% (268/12878) of households from the pooled Syrian and native samples owned a home theatre. This suggests that home theatre ownership may not be a standard deprivation indicator in the context of Turkey, as one might also expect. More notably, every household that owned a home theatre also possessed a washing machine. This implies that the inclusion of home theatre ownership does not contribute any unique information to the model and thus may be redundant. Consequently, the variable home theatre was removed from the analysis (Lorenzo-Seva & Ferrando, 2021; Farooq, 2022). Secondly, the paid TV variable was found to be highly correlated with TV (0.61) and the internet (0.69). Given that only 4% of paid TV subscribers do not own a TV, ownership of paid TV was excluded from the analysis.

The remaining 21 basic assets variables no longer produce a Heywood case. Moreover, two preliminary diagnostic tools that are frequently employed to evaluate the suitability of a dataset for factor analysis indicate sufficient reliability and validity of the model (Lorenzo-Seva & Ferrando, 2021; Vollmer & Alkire, 2022). First, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy reflects the degree of partial correlation among the variables and is equal to 0.82 for 21 variables, which is considered sufficient enough to commence with factor analysis. Secondly, Cronbach's Alpha is also equal to 0.82, suggesting that the variables are measuring the same underlying construct consistently.[14] Hence, these variables can now be used to detect any clustering or grouping among the variables.

In order to estimate the tetrachoric correlation matrix, positive semidefinite correlations are used (Vollmer & Alkire, 2022). Principal factor is employed as the extraction method since it does not assume multivariable normality and is mostly

[14]The null hypothesis that the variables are not intercorrelated was also rejected using Bartlett's test of sphericity.

preferred in multidimensional studies (Vollmer & Alkire, 2022). The number of underlying factors is decided according to the Kaiser criterion and examination of the scree plot. Table A1 reveals three eigenvalues exceeding one from the initial EFA, which is confirmed by the scree plot depicted in Figure B1. After the estimation, orthogonal or oblique rotation of factor loadings can be used to get a clearer pattern and ease of interpretation (Alkire et al., 2015, chapter 3). Given the likely correlation among the factors, oblique rotation is preferred since it allows factors to be correlated (Vollmer & Alkire, 2022; Guio, Gordon, & Marlier, 2012; Vaz, Alkire, Quisumbing, & Sraboni, 2013).

Using a three-factor solution and primary factor loading threshold of 0.5, 16 basic asset variables were decided to be kept in the analysis (Vollmer & Alkire, 2022). Table 2 illustrates the results of the first rotated EFA, marking the loadings above 0.5. Accordingly, five variables – deep freezer, drying machine, satellite TV, air conditioner, and commercial vehicle – do not have high loadings (>0.5) in any factors. Furthermore, the unique variances of these variables are higher than other items, exceeding 0.7 for the latest three variables, suggesting that the variables are not adequately explained by the three factors (Vollmer & Alkire, 2022). As these five items are also not considered essential in everyday life in Turkey, they are dropped from the analysis. Also, note that almost all observed variance (99%) is explained by the factor loadings of the first two factors.

For the set of 16 retained variables, a second EFA is conducted using a two-factor solution underlying asset deprivation (see the scree plot in Figure B2 and unrotated results in Table A2). Table 3 presents the oblique rotated results, revealing that the variables generator and garbage dispenser do not possess high loadings on any factor. Given that these assets are not considered essential for non-deprivation, they are excluded from further analysis.

A final EFA with the remaining 14 assets confirms the selection of related items, as can be seen in Table 4. A noteworthy observation is the high negative factor loading of the variable tractor on factor two. This negative loading can be attributed

Table 2. Rotated Factor Analysis with 21 Basic Assets

Number of Observations:	12,878
Method:	Principal Factors
Retained Factors:	3
Rotation:	Oblique promax
Number of Parameters:	60

Factor	Variance	Proportion
Factor1	8.41935	0.6611
Factor2	4.24511	0.3333
Factor3	1.90412	0.1495

Variable	Factor1	Factor2	Factor3	Uniqueness
Television	0.7782	-0.0548	-0.0473	0.4302
Computer	0.5717	0.1571	-0.4278	0.2952
Freezer	0.4432	0.0668	0.4477	0.6145
Oven	0.7468	-0.0460	-0.0264	0.4737
Microwave	0.5491	0.1582	-0.1387	0.5376
Dishwasher	0.8559	0.0017	-0.0894	0.2454
Garbage dispenser	-0.3046	0.9394	0.0936	0.3627
Washing machine	0.9945	-0.3554	0.1168	0.2473
Drying machine	0.1742	0.4647	-0.1976	0.5755
Iron	0.9315	-0.0528	-0.0056	0.1815
Vacuum	0.9629	-0.0573	0.1070	0.1308
Tea/coffee machine	0.5908	0.2213	-0.2164	0.3699
Kettle	0.6263	0.0770	0.0120	0.5517
Generator	0.1004	0.6188	0.2861	0.5537
Blender	0.8184	0.0091	-0.1280	0.2882
Satellite TV	0.4652	-0.1955	0.1495	0.8168
Internet	0.3618	0.1791	-0.5757	0.3497
Air conditioner	0.3456	0.1424	-0.0829	0.7901
Commercial vehicle	0.3168	0.1141	0.1650	0.8388
Tractor	0.0377	0.2131	0.8282	0.3539
Car	0.5369	0.2511	0.2063	0.5062

to an inverse relationship between the ownership of a tractor and the ownership of other retained variables, such as a computer and the internet. Upon further examination, this negative correlation vanishes when the correlation matrix is disaggregated for rural households in the Turkish sample. While this indicates that the tractor variable might not contribute positively to the internal consistency of the model, its high loading justifies its retention for further analysis. Hence, the retained variables for the MCA consist of television, computer, gas/electric oven, microwave oven, dishwasher, washing machine, iron, vacuum cleaner, tea/coffee machine, kettle, food processor/blender, car, and tractor.

Table 3. Rotated Factor Analysis with 16 Basic Assets

Number of Observations:	12,878
Method:	Principal Factors
Retained Factors:	2
Rotation:	Oblique promax
Number of Parameters:	31

Factor	Variance	Proportion	
Factor1	7.53664	0.7110	
Factor2	2.81798	0.2658	
Variable	**Factor1**	**Factor2**	**Uniqueness**
Television	0.7087	0.0635	0.4635
Computer	0.4924	0.5468	0.2777
Oven	0.7033	0.0414	0.4841
Microwave	0.5613	0.2386	0.5381
Dishwasher	0.8109	0.1335	0.2519
Garbage Dispenser	0.1397	0.2499	0.8946
Washing Machine	0.8548	-0.2161	0.3466
Iron	0.8922	0.0187	0.1924
Vacuum	0.9416	-0.0703	0.1530
Tea/Coffee Machine	0.6293	0.2887	0.3987
Kettle	0.6628	0.0293	0.5467
Generator	0.4707	-0.0645	0.7947
Blender	0.7789	0.1521	0.2906
Internet	0.2368	0.7193	0.3121
Tractor	0.3825	-0.7569	0.4751
Car	0.7183	-0.1164	0.5266

Multiple Correspondence Analysis (MCA)

MCA is a descriptive statistical approach that provides an application of the commonly used PCA to binary variables (Guio et al., 2012; Vollmer & Alkire, 2022). While EFA retains the unexplained variance by the latent factor (unique variance), all variables in MCA contribute to the latent concept. Accordingly, MCA provides a deeper examination of how each item's ownership or non-ownership contributes to the variance (inertia) in dimensions.

Table 5 presents the results of the MCA conducted on 14 selected variables. The Burt matrix is utilized to reveal the interplay between the ownership and non-ownership of variables. Additionally, principal normalization is applied to provide a more meaningful interpretation of both rows and columns in the same space (Vollmer & Alkire, 2022). It is noteworthy that the first dimension accounts for the vast majority of the total variance or inertia, representing 94.12%, while the second dimension explains a mere 1.11%. Thus, grouping these variables under a single dimension seems reasonable.

Table 4. Rotated Factor Analysis with 14 Basic Assets

Number of Observations:	12,878
Method:	Principal Factors
Retained Factors:	2
Rotation:	Oblique promax
Number of Parameters:	27

Factor	Variance	Proportion	
Factor1	7.20499	0.7887	
Factor2	3.25036	0.3558	
Variable	**Factor1**	**Factor2**	**Uniqueness**
Television	0.6896	0.0983	0.4606
Computer	0.4040	0.6205	0.2514
Oven	0.6825	0.0808	0.4836
Microwave	0.5395	0.2244	0.5619
Dishwasher	0.8008	0.1411	0.2485
Washing Machine	0.8501	-0.1483	0.3560
Iron	0.8822	0.0528	0.1818
Vacuum	0.9475	-0.0507	0.1381
Tea/Coffee Machine	0.5931	0.2975	0.4187
Kettle	0.6529	0.0432	0.5493
Blender	0.7538	0.1825	0.2884
Internet	0.1263	0.7996	0.2640
Tractor	0.4004	-0.6977	0.5762
Car	0.7111	-0.0953	0.5394

The biplot graph of the MCA analysis is shown in Figure 1 to detect the clustering and projection of the items more easily. The plot demonstrates the grouping of variables based on their relative locations in a two-dimensional space, determined by their Euclidean values. Data points situated at a greater distance from the origin suggest that the responses to those items have a stronger impact on the inertia of the corresponding dimension. Accordingly, two clusters emerge based on the "yes" or "no" answers to the asset ownership question. As can be seen more clearly from the coordinate values in Table 4, the non-ownership ("no") of six variables is ordered before their ownership (“yes”). Particularly, the non-ownership of washing machine, vacuum cleaner, and iron is situated farther from the origin, implying their comparatively high contribution to the variance of dimension one. On the other hand, for the remaining seven variables – computer, microwave oven, internet, coffee/tea machine, kettle, blender, and car –, ownership is ordered before their non-ownership. The only variable that is situated outside of both groups is the tractor variable, which has a contribution near zero for dimension one. While the ownership of it has a small effect on dimension two, this effect is negative as suggested by the previous EFA. Moreover, the variable has a lower overall quality (0.53) than other items (above 0.89). These suggest that the tractor variable may be incompatible with other variables, hence it is dropped from the analysis.

Classical Test Theory (CTT)

In the third step of the analysis, measures within the Classical Test Theory are used to assess the quality of alternative models. Table 6 and 7 provides the values for the KMO measure and Cronbach’s Alpha. The first alternative, conducted with 13 retained variables from the MCA, reveals an overall KMO measure of 0.90 and a Cronbach’s Alpha of 0.8504. Nevertheless, due to a high correlation (0.80) between the variables of the internet and computer, KMO values for these variables are relatively lower at 0.64 and 0.76. In order to understand their relative contribution and the optimal model for analysis, two additional models are constructed, each excluding either the internet or computer variable. The second alternative model, which retained the computer variable and excluded the internet, yielded an overall KMO value of 0.9615, with the KMO for computer showing a substantial increase to 0.9611. Cronbach’s Alpha is marginally decreased to 0.8463. On the other hand, the third model, which incorporated internet while excluding computer, generated lower values for both Cronbach’s Alpha (0.8379) and KMO (0.9512) compared to the first model. Taking these results into consideration, the second alternative model that includes the computer variable is chosen since it provides a higher internal consistency while decreasing Cronbach’s Alpha only slightly. Vollmer and Alkire

Table 5. MCA Statistics for 14 Basic Assets

Number of obs:	12,878
Total inertia:	.08788548
Method:	Burt/adjusted inertias
Number of axes:	2

Dimension	principal inertia	percent	cumul percent
dim 1	.0827199	94.12	94.12
dim 2	.0009743	1.11	95.23
dim 3	5.52e-06	0.01	95.24
Total	.0878855	100.00	

		Overall			Dimension 1			Dimension 2		
Categories		Mass	Quality	% Inertia	Coord	SqCorr	Contrib	Coord	SqCorr	Contrib
Television	No	0.025	0.976	0.054	0.432	0.975	0.056	0.018	0.002	0.008
	Yes	0.047	0.976	0.029	-0.231	0.975	0.030	-0.009	0.002	0.004
Computer	No	0.049	0.912	0.025	0.201	0.890	0.024	-0.031	0.022	0.050
	Yes	0.022	0.912	0.057	-0.448	0.890	0.054	0.070	0.022	0.111
Oven	No	0.020	0.981	0.054	0.487	0.977	0.056	0.030	0.004	0.018
	Yes	0.052	0.981	0.020	-0.184	0.977	0.021	-0.011	0.004	0.007
Microwave	No	0.058	1.003	0.008	0.110	0.992	0.009	-0.011	0.011	0.008
	Yes	0.013	1.003	0.036	-0.486	0.992	0.038	0.050	0.011	0.034
Dishwasher	No	0.031	0.947	0.065	0.419	0.947	0.066	0.006	0.000	0.001
	Yes	0.041	0.947	0.050	-0.319	0.947	0.050	-0.005	0.000	0.001
Washing Machine	No	0.003	0.986	0.030	0.865	0.947	0.030	0.175	0.039	0.104
	Yes	0.068	0.986	0.001	-0.042	0.947	0.001	-0.008	0.039	0.005
Iron	No	0.016	0.932	0.083	0.656	0.926	0.082	0.056	0.007	0.050
	Yes	0.056	0.932	0.023	-0.185	0.926	0.023	-0.016	0.007	0.014
Vacuum	No	0.015	0.925	0.084	0.680	0.915	0.081	0.071	0.010	0.075
	Yes	0.057	0.925	0.021	-0.174	0.915	0.021	-0.018	0.010	0.019
Tea/Coffee Machine	No	0.056	0.977	0.013	0.142	0.964	0.014	-0.016	0.012	0.015
	Yes	0.015	0.977	0.050	-0.529	0.964	0.051	0.059	0.012	0.055
Kettle	No	0.037	0.993	0.033	0.279	0.993	0.035	0.005	0.000	0.001
	Yes	0.034	0.993	0.035	-0.300	0.993	0.037	-0.005	0.000	0.001
Blender	No	0.039	0.955	0.049	0.326	0.955	0.050	-0.006	0.000	0.001
	Yes	0.033	0.955	0.058	-0.385	0.955	0.059	0.007	0.000	0.002
Internet	No	0.044	0.892	0.022	0.194	0.845	0.020	-0.045	0.046	0.093
	Yes	0.028	0.892	0.035	-0.309	0.845	0.032	0.072	0.046	0.148
Tractor	No	0.065	0.534	0.000	-0.002	0.007	0.000	0.016	0.527	0.016
	Yes	0.007	0.534	0.003	0.017	0.007	0.000	-0.150	0.527	0.156
Car	No	0.045	0.983	0.021	0.202	0.983	0.022	0.004	0.000	0.001
	Yes	0.026	0.983	0.037	-0.351	0.983	0.039	-0.007	0.000	0.001

(2022) note that the internet variable, as an intangible asset, is also conceptually distinct from the other tangible assets. Furthermore, the ambiguity inherent in questions related to the internet question, which could refer to either the infrastructure or accessibility of internet services, reinforces the exclusion of this variable.

Therefore, 12 asset items were statistically validated to be used in the MPI analysis. These variables are television, computer, oven, microwave, dishwasher, washing machine, iron, vacuum cleaner, tea/coffee machine, kettle, blender, and car. However, considering that the car, as an asset, demonstrates a different value profile

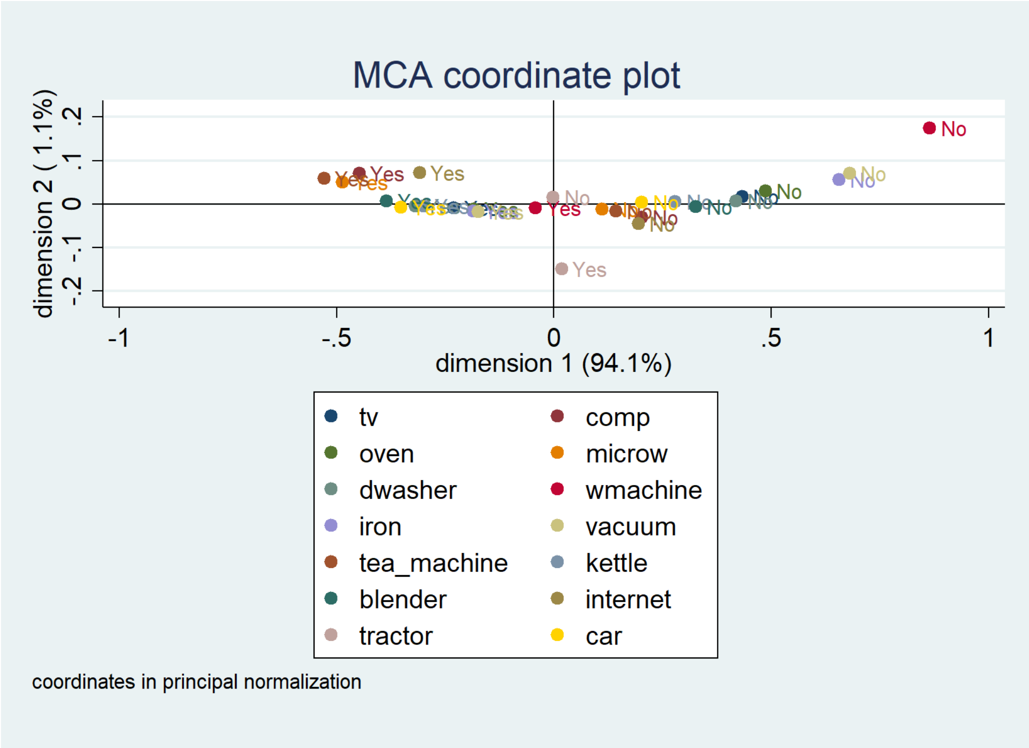

Figure 1. MCA Dimension Projection Plot for 14 Basic Assets

compared to the other assets, it was not deemed appropriate to aggregate the car as a basic asset along with the others. Exploratory cross-tabulations of alternative measures were conducted to understand the implications of including or excluding the car asset. These analyses revealed that including the car asset, coupled with other selected basic assets, in the form "Household owns a car or owns more than the sample average of the chosen small assets (excluding car)" would result in the reclassification of merely 359 households, or 2.8% of the sample, altering their status from non-deprived to deprived. Given this minor impact on the classification, it was decided to exclude the car asset from the asset ownership indicator. Consequently, the final set of assets included in the MPI analysis was adjusted to comprise eleven basic household assets.

Table 6. KMO Values for Three Alternative Models

	Alternative 1	Alternative 2	Alternative 3
Overall KMO	0.9017	0.9615	0.9512
Television	0.9812	0.9795	0.9787
Computer	0.7608	0.9611	
Oven	0.9699	0.9750	0.9722
Microwave	0.9027	0.9650	0.9549
Dishwasher	0.956	0.9512	0.9527
Washing Machine	0.9002	0.9499	0.9571
Iron	0.9144	0.9508	0.9533
Vacuum	0.8858	0.9490	0.9218
Tea/Coffee Machine	0.9266	0.9643	0.9435
Kettle	0.9648	0.9709	0.9661
Blender	0.9624	0.9643	0.9661
Internet	0.6376		0.8631
Car	0.9806	0.9786	0.9705

Table 7. Cronbach's Alpha for Three Alternative Models

	Alternative 1	Alternative 2	Alternative 3
Cronbach's Alpha	0.8504	0.8463	0.8379

3.2.2 Housing conditions

The TDHS dataset includes five potential indicators that may reflect the housing conditions of different households.[15] These are improved water resources[16] and sanitation facilities, improved quality of flooring material, substandard heating, and overcrowding (the number of people per sleeping room). In order to obtain statistical evidence on whether these conditions reflect the overall housing adequacy and can be aggregated under housing conditions, their correlation, and common variance were analyzed.

As presented in Table A3, high tetrachoric correlations were observed among the variables, signaling that some of these indicators may be redundant. In order to test the suitability of data for factor analysis, an initial EFA was performed with five potential indicators. Accordingly, the model fit for sampling adequacy resulted in a

[15] While data on the type of house is also provided in the TDHS dataset, this variable is not included among the potential indicators since there is no ideal definition for an improved house type for the whole country (potential answers include adobe, brick, stone, concrete, tent, container, and other).

[16] Household has drinking water with SDG standards (considering distance)

low KMO measure of 0.54, with a notably low value of 0.42 for the overcrowding indicator, reflecting its low proportion of variance that might be caused by latent factors. Table A3 further reveals that the variable exhibits negative correlations with both the water and flooring indicators, as opposed to the positive correlations amongst the others. Given these, overcrowding was removed from the original group of housing condition indicators for further analysis.

The remaining set of variables, excluding overcrowding, revealed a KMO value of 0.61. While its level is mediocre, this value is considered acceptable for factor analysis, suggesting the presence of moderate common variances among variables. Consequently, the first EFA is conducted with five indicators (water, sanitation, flooring, heating, and house type) using positive semidefinite correlations. The iterated principal factor extraction method was selected due to its capacity to produce more interpretable results, compared to the principal factor method (Vollmer &Alkire, 2022). Table 8 presents the unrotated results from this analysis, indicating the presence of a single latent variable. Despite the relative simplicity of a one-factor solution, the first factor accounts for 76% of the total variance, suggesting its potential in representing the quality of housing.

Table 8. Unrotated Factor Analysis for Housing Conditions Indicators

Number of Observations:	12,878
Method:	Iterated Principal Factors
Retained Factors:	3
Rotation:	Unrotated
Number of Parameters:	6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.48490	1.13098	0.7629	0.7629
Factor2	0.35392	0.24621	0.1818	0.9447
Factor3	0.10771	0.10789	0.0553	1.0001
Factor4	-0.00018	-	-0.0001	1.0000

Variable	Factor1	Factor2	Factor3	Uniqueness
Water	0.2259	0.4876	0.0533	0.7084
Sanitation	0.7405	0.1614	-0.1917	0.3888
Flooring	0.5366	0.0043	0.2607	0.6441
Heating	0.7730	-0.3001	-0.0129	0.3123

The results following oblique rotation are provided in Table 9. Notably, the only indicator with a factor loading below the recommended 0.5 threshold is access to improved water with 0.2 and it is eliminated from the indicators. Coupled with its exceptionally high uniqueness level of 0.96, the variable does not seem to adequately reflect the common factor with other housing condition indicators. In fact, among those households who were not classified as deprived by the other three indicators, the indicator on water classified only 21 out of 12878 households as deprived. A conclusive EFA was conducted with the remaining three indicators: sanitation, flooring, and heating. The results represented in Table 10 illustrate that each variable makes a substantial contribution to the factor. The Likelihood Ratio test offers robust evidence that the factor model fits the data better than the independent model (chi2(6) = 7971.20 Prob>chi2 = 0.0000). The KMO measure of sampling adequacy also increased to 0.65. These results support the idea that these three indicators may be used to reflect the housing conditions of different households.

Table 9. Rotated Factor Analysis for Housing Conditions Indicators

Number of Observations:	12,878
Method:	Iterated Principal Factors
Retained Factors:	1
Rotation:	Oblique promax (Kaiser off)
Number of Parameters:	4

Factor	Variance	Proportion
Factor1	1.36289	1.0000

Variable	Factor1	Uniqueness
Water	0.2008	0.9597
Toilet	0.7348	0.4601
Flooring	0.5305	0.7185
Heating	0.7080	0.4987

These three indicators – improved access to sanitation, flooring, and heating – are included as separate indicators under the subdimension of housing conditions. This modification aims to decrease their respective weights as they all reflect the housing conditions, in which a smaller percentage of the population is deprived (compared to other indicators). Hence, their respective weights reflect one-third of the overall weight for housing conditions. Another option could be creating a subindex for housing conditions to consider a household as deprived if they have unimproved sanitation or flooring or heating. This is not preferred since this approach obscures information on which housing dimensions are possibly more relevant to policy (Vollmer & Alkire, 2022). Secondly, considering that the overcrowding indicator does not directly reflect the physical structure of the house, as opposed to other variables, results represented here are taken as further signals not to classify the overcrowding indicator under housing conditions and it is added as a separate indicator under living standards dimension, making its weight equal to the weight of total housing conditions.

Table 10. Final Rotated Factor Analysis for Housing Conditions Indicators

Number of Observations:	12,878
Method:	Iterated Principal Factors
Retained Factors:	1
Rotation:	Oblique promax (Kaiser off)
Number of Parameters:	3

Factor	Variance	Proportion
Factor1	1.36289	1.0000

Variable	Factor1	Uniqueness
Toilet	0.6685	0.5530
Flooring	0.5208	0.7288
Heating	0.7875	0.3799

CHAPTER 4

RESULTS AND DISCUSSION

Table 11 provides the results for the MPI for refugee and native households based on the AF deprivation threshold (k=0.33) and equal weights for each dimension. The headcount ratios (H) show that the incidence of poverty among the refugee community is almost seven times higher than the native population. 72.2% of Syrian households experience multidimensional poverty, compared to 7.2% of native households. Secondly, the intensity of poverty (A) shows the average share of deprivations among the poor. Accordingly, on average, refugee households are deprived in 51.3% of the weighted indicators, while the native households have a lower average of deprivations at 40.3%. The main MPI measure, also called M_0, multiplies H and A to get a measure that illustrates both the incidence and intensity of poverty. While the headcount ratio simply provides the share of the deprived population, it does not increase as the weighted sum of deprivations suffered rises. On the other hand, MPI adjusts this measure to reflect the intensity of deprivation experienced by poor people.

The MPI for the refugee sample is found to be 33 percentage points higher than the native sample. While on average Syrians experience 37.4% of the total potential deprivations possible, this figure is 4.9% for the host community. It is important to observe that while headcount ratios (H and M_0) for the refugee and native households are significantly different, the intensity of poverty (A) for both samples is relatively closer to one another. This suggests that once an individual falls into

Table 11. Main MPI Measures for the Syrian and Native Samples

	Syrian Sample		Native Sample	
	Mean	Standard Error	Mean	Standard Error
Incidence (H)	0.731	0.020	0.121	0.005
Intensity (A)	0.513	0.005	0.403	0.003
MPI	0.375	0.012	0.049	0.002

poverty, the extent of their deprivation in terms of the number of dimensions tends to be similar in both samples, on average.

4.1 Decomposition by indicators

Unpacking the key statistics according to the indicators reveal important patterns among the Syrian and native population regarding the composition of multidimensional poverty. As reflected by the overall MPI measures discussed above, the refugee community shows consistently higher headcount ratios across almost all indicators, underlining their increased vulnerability to multidimensional poverty. Table 12 illustrates that the share of deprived households is the highest in formal employment indicators for both samples, while the situation is much more severe for the refugee community. Strikingly, 96.8% of Syrian households and 58.9% of native households did not have one member working with social security one year preceding the survey. Rather unexpectedly, the employment indicator is one area where the host community has a higher headcount ratio (29.008%) compared to the refugee community (18.916%), which may be related to the higher average household size of the Syrian sample. Another indicator in which the share of the poor Syrian sample was higher than the natives is the flooring indicator. This mostly stems from the fact that 8.64% of native households had wooden planks for flooring, which is classified as a non-permanent material according to the UN standards, as opposed to 1.86% of Syrian households.

Differences between the refugee and host community are more salient in some indicators. The greatest disparities are found in the indicators of asset and house ownership, reflecting the profound material deprivation faced by the refugee population. Regarding asset ownership, there is a 61 percentage point difference between the two samples. Hence, nearly 67% of the refugee community does not possess more than two of the following 11 assets: television, computer, oven, microwave, dishwasher, washing machine, iron, vacuum cleaner, tea/coffee machine, kettle, and blender. Similarly, in terms of house ownership, 91% of refugee

Table 12. Headcount Ratios of MPI Indicators

Indicator	Weight	Headcount Ratio	
		Syrian sample	Native sample
Domain 1			
Years of schooling	.12	35.755%	25.555%
School attendance	.12	24.638%	1.809%
Domain 2			
Nutrition	.08	15.082%	2.439%
Child mortality	.08	3.572%	0.498%
Early marriage	.08	52.870%	17.268%
Domain 3			
Sanitation	.03	2.698%	1.741%
Flooring	.03	2.302%	10.139%
Heating	.03	87.533%	43.731%
Overcrowding	.08	73.564%	20.337%
Assets	.08	67.191%	5.762%
Domain 4			
Employment	.06	14.847%	28.269%
Formal employment	.06	96.758%	58.850%
House ownership	.06	90.960%	22.185%
Subjective financial situation	.06	63.418%	38.002%

households do not own a house, compared to 22.2% of the host community. Moreover, the prevalence of overcrowding among the Syrian sample is 53.2 percentage points higher than the natives. Almost three third of (73.6%) the Syrian households had more than 2.16 people per sleeping room.

Regarding the education dimension, the gap among the populations is particularly pronounced in school attendance. About one-quarter of the refugee households had at least one child who did not attend school during the interview year, whereas all children in the overwhelming majority of native households (98.2%) attended school. While there is still a gap in years of schooling between the two populations, the difference is less significant with deprivation levels of 35.6% and 25.6% for Syrian and Turkish households respectively. This suggests that, while Syrians may have had access to basic schooling in the past, refugee children's current access to education is severely restricted compared to natives.

While the headcount ratios deliver insights into absolute deprivation, relative deprivation can be assessed by the contribution of each indicator to overall poverty.

Table 13. Contribution of Each Indicator (%)

		M_0	
Indicator	Weight	Syrian sample	Native sample
Domain 1			
Years of schooling	.12	0.116	0.247
School attendance	.12	0.081	0.032
Domain 2			
Nutrition	.08	0.031	0.013
Child mortality	.08	0.007	0.003
Early marriage	.08	0.101	0.060
Domain 3			
Sanitation	.02	0.002	0.005
Flooring	.02	0.002	0.014
Heating	.02	0.050	0.060
Overcrowding	.08	0.137	0.087
Assets	.08	0.129	0.076
Domain 4			
Employment	.06	0.021	0.095
Formal employment	.06	0.120	0.138
House ownership	.06	0.112	0.050
Subjective financial situation	.06	0.090	0.119
Total		1.000	1.000

These contributions are modulated by the respective weights of each indicator and sum to one, as illustrated in Table 13 and 14. For the Syrian sample, the highest contributor to the MPI is the overcrowding indicator with 13.7%. Given its relatively higher weight of 0.12, the indicator of years of education contributes most to multidimensional deprivation for the host community (24.7%).

Table 14. Contribution of Each Domain (%)

	M_0	
Domain	Syrian Sample	Native Sample
Education	0.197	0.279
Health	0.140	0.077
Living standards	0.320	0.242
Financial Security	0.343	0.403
Total	1.000	1.000

Table 15. Contribution of Each Indicator (%) by Residence Type

	Urban	Camp	Total
Education	0.116	0.121	0.116
Attendance	0.082	0.054	0.081
Nutrition	0.031	0.031	0.031
Mortality	0.007	0.008	0.007
Early marriage	0.102	0.089	0.101
Sanitation	0.001	0.012	0.002
Flooring	0.001	0.011	0.002
Heating	0.050	0.056	0.050
Overcrowding	0.137	0.142	0.137
Assets	0.128	0.158	0.129
Employment	0.019	0.060	0.021
Formal employment	0.120	0.126	0.120
House ownership	0.116	0.047	0.112
Subjective financial situation	0.090	0.086	0.090
Total	1.000	1.000	1.000

4.2 Decomposition by region and residence type

The results for the MPI are disaggregated considering the representativeness levels of the relevant TDHS modules of the Syrian and native populations. For the Syrian sample, the stratification was based on the residence type, hence the results are disaggregated by camp or non-camp populations. For the native sample, a regional breakdown is presented based on five broad regions (West, South, Central, North, and East).

Table 15 represents the related results for the Syrian sample. The relative share of the camp population is only 4.7%. The results show notable differences for some indicators among the households residing in camps and non-camp areas. As expected, the house ownership indicator exhibits a significantly higher contribution in the urban setting. Additionally, housing conditions indicators demonstrate higher contributions for camp households, reflecting their non-standard housing conditions. This observation is also supported by the high relative contribution of the living conditions dimension for the camp households, while employment contributes the most for non-camp households.

Table 16. Contribution of Each Indicator (%) by Region

	West	South	Central	North	East	Total
Education	0.272	0.244	0.265	0.293	0.199	0.247
Attendance	0.024	0.027	0.022	0.003	0.057	0.032
Nutrition	0.013	0.014	0.009	0.006	0.016	0.013
Mortality	0.001	0.003	0.002	0.002	0.007	0.003
Early marriage	0.064	0.054	0.041	0.027	0.076	0.060
Sanitation	0.003	0.005	0.005	0.007	0.007	0.005
Flooring	0.014	0.014	0.020	0.030	0.008	0.014
Heating	0.055	0.064	0.058	0.067	0.062	0.060
Overcrowding	0.067	0.087	0.062	0.029	0.137	0.087
Assets	0.074	0.083	0.088	0.072	0.068	0.076
Employment	0.098	0.096	0.119	0.143	0.067	0.095
Formal employment	0.137	0.138	0.147	0.161	0.130	0.138
House ownership	0.065	0.051	0.040	0.030	0.043	0.050
Subjective financial situation	0.114	0.119	0.121	0.130	0.123	0.119
Total	1.000	1.000	1.000	1.000	1.000	1.000

Table 16 represents the related results for the native sample. While the share of MPI poor households in sample is %12 for Turkey in total, substantially a higher share of households in the Eastern region cope with multidimensional poverty (%23). Furthermore, it is observed that the contribution of flooring in the northern region is significantly higher than in the other regions. This confirms the previous suggestion that the high percentage of wood plank houses in the Northern part may be the reason for the overall higher deprivation shares observed in the flooring indicator for the Turkish sample.

CHAPTER 5
CONCLUSION

Traditional measures of poverty, which solely focus on income or consumption, fail to capture the complex nature of poverty and the diverse deprivations faced by displaced populations. By employing the capabilities perspective and utilizing the Alkire-Foster methodology, this study constructs a comprehensive Multidimensional Poverty Index (MPI) for Syrian refugees in Turkey. In addition to the core dimensions included in most studies (education, health, living conditions), an additional dimension on financial security is added, consisting of indicators on employment, house ownership, and subjective financial situation.

The results of the analysis indicate significant disparities between Syrian refugee and native Turkish households. Syrian households experience a much higher incidence of multidimensional poverty, with 72.2% classified as poor compared to only 7.2% among native households. The overall MPI score for the refugee community is 33 percentage points higher than the host community. Particularly, informal employment seems to be a nationwide issue while almost 98% of Syrian households do not have a member working formally. The headcount ratios for all indicators are higher for the refugee community, except for the employment and flooring indicators. Regional variations show that the Eastern region has a higher share of multidimensional poverty, emphasizing the importance of addressing regional disparities in poverty alleviation efforts.

It is important to consider the limitations of the data when interpreting the findings. For nearly half of the indicators, the data collected in TDHS only includes a subgroup of the population, and the dimension of health is constructed using data exclusively on women and children. This lack of information on men's health has also restricted the analysis to the household level. Furthermore, since TDHS does not provide information on income or expenditure, it was not possible to compare the constructed MPI with traditional poverty measures. Future research could address these gaps and expand on the findings by incorporating individual level analysis.

APPENDIX A

TABLES FOR FACTOR ANALYSIS

Table A1. Unrotated Factor Analysis for 21 Basic Assets

Number of Observations:	12,878
Method:	Principal Factors
Retained Factors:	14
Rotation:	Unrotated
Number of Parameters:	203

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	8.55064	6.77361	0.6714	0.6714
Factor2	1.77703	0.61824	0.1395	0.8110
Factor3	1.15879	0.56225	0.0910	0.9020
Factor4	0.59654	0.20478	0.0468	0.9488
Factor5	0.39176	0.15888	0.0308	0.9796
Factor6	0.23289	0.01959	0.0183	0.9979
Factor7	0.21330	0.03442	0.0167	1.0146
Factor8	0.17888	0.03057	0.0140	1.0287
Factor9	0.14830	0.06137	0.0116	1.0403
Factor10	0.08694	0.01635	0.0068	1.0471
Factor11	0.07059	0.00518	0.0055	1.0527
Factor12	0.06541	0.04467	0.0051	1.0578
Factor13	0.02074	0.01680	0.0016	1.0594
Factor14	0.00394	0.03835	0.0003	1.0597

Table A2. Unrotated Factor Analysis for 16 Basic Assets

Number of Observations:	12,878
Method:	Principal Factors
Retained Factors:	10
Rotation:	Unrotated
Number of Parameters:	115

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.69391	6.33434	0.7258	0.7258
Factor2	1.35957	0.35700	0.1283	0.8541
Factor3	1.00257	0.45650	0.0946	0.9486
Factor4	0.54607	0.29898	0.0515	1.0002
Factor5	0.24710	0.09514	0.0233	1.0235
Factor6	0.15195	0.05758	0.0143	1.0378
Factor7	0.09437	0.03186	0.0089	1.0467
Factor8	0.06251	0.02230	0.0059	1.0526
Factor9	0.04021	0.02782	0.0038	1.0564
Factor10	0.01239	0.03450	0.0012	1.0576

Table A3. Correlation Matrix for Housing Conditions Indicators

	Variables				
	Water	Sanitation	Flooring	Heating	No overcrowding
Water	1.0000				
Sanitation	0.2358	1.0000			
Flooring	0.1372	0.3481	1.0000		
Heating	0.0275	0.5265	0.4102	1.0000	
No overcrowding	-0.0445	0.2605	-0.1190	0.4640	1.0000

APPENDIX B

FIGURES FOR FACTOR ANALYSIS

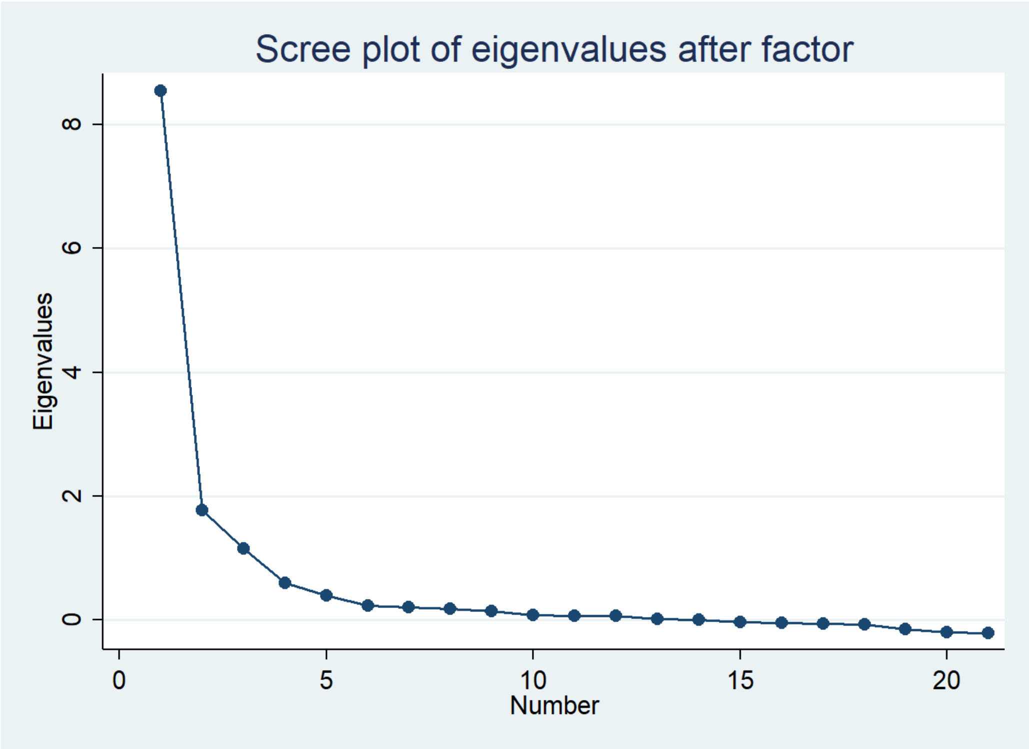

Figure B1. Scree Plot for Factor Analysis with 21 Basic Assets

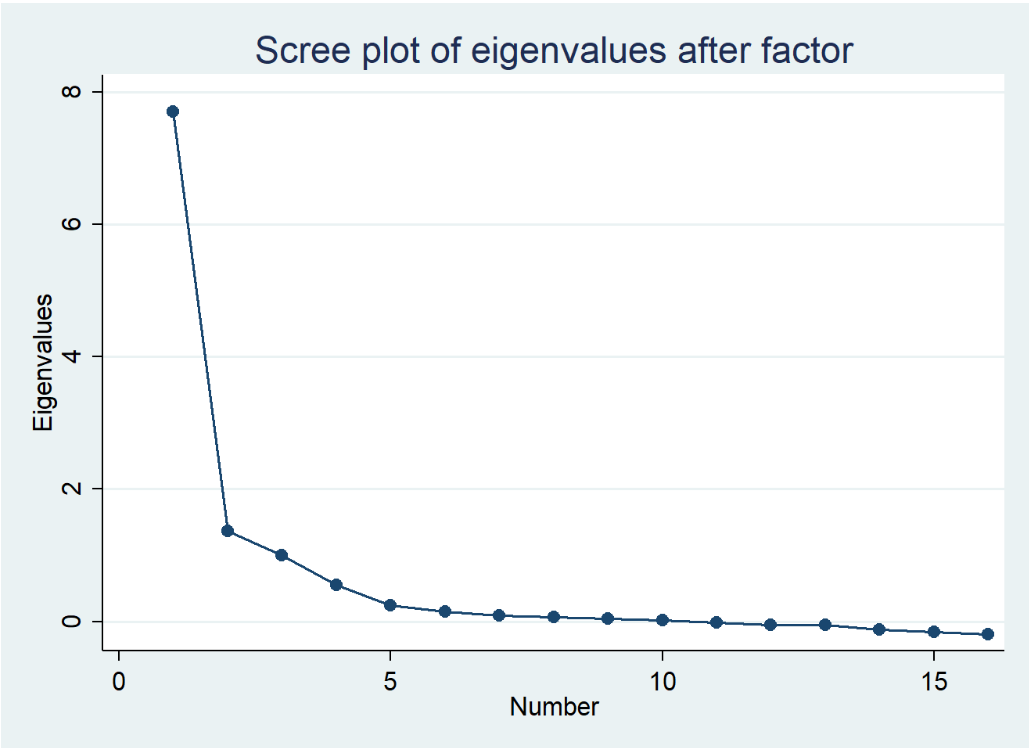

Figure B2. Scree Plot for Factor Analysis with 16 Basic Assets

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