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A MACHINE LEARNING APPROACH TO TARGETING HUMANITARIAN ASSISTANCE AMONG FORCIBLY DISPLACED POPULATIONS[1]

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Abstract

Increasing trends in forced displacement and poverty are expected to intensify in coming years. Data science approaches can be useful for governments and humanitarian organizations in designing more robust and effective targeting mechanisms. This study applies machine learning techniques and combines geospatial data with survey data collected from Syrian refugees in Lebanon over the last four years to help develop more robust and operationalizable targeting strategies. Our findings highlight the importance of a comprehensive and flexible framework that captures other poverty dimensions along with the commonly used expenditure metric, while also allowing for regular updates to keep up with (rapidly) changing contexts over time. The analysis also points to geographical heterogeneities that are likely to impact the effectiveness of targeting strategies. The insights from this study have important implications for agencies seeking to improve targeting, especially with shrinking humanitarian funding.

Keywords: poverty, forced displacement, refugees, humanitarian assistance, machine learning.
JEL Classifications: I3, I32, I38, O1, O19, O53, R23, H1.

ملخص

من المتوقع أن تزداد في السنوات القادمة اتجاهات التشريد القسري والفقر. يمكن أن تكون نُهج علم البيانات مفيدة للحكومات والمنظمات الإنسانية في تصميم آليات استهداف أكثر قوة وفعالية. تطبق هذه الدراسة تقنيات التعلم الآلي وتجمع بين البيانات الجغرافية المكانية وبيانات المسح التي تم جمعها من اللاجئين السوريين في لبنان على مدى السنوات الأربع الماضية للمساعدة في تطوير استراتيجيات استهداف أكثر قوة وقابلية للتنفيذ. تسلط النتائج التي توصلنا إليها الضوء على أهمية وجود إطار شامل ومرن يجسد أبعاد الفقر الأخرى جنبًا إلى جنب مع مقياس الإنفاق الشائع الاستخدام، مع السماح أيضًا بإجراء تحديثات منتظمة لمواكبة السياقات المتغيرة (بسرعة) بمرور الوقت. ويشير التحليل أيضا إلى أوجه عدم التجانس الجغرافي التي يحتمل أن تؤثر على فعالية استراتيجيات الاستهداف. الرؤى من هذه الدراسة لها آثار مهمة على الوكالات التي تسعى إلى تحسين الاستهداف، خاصة مع تقلص التمويل الإنساني.

1. Introduction

The United Nations High Commissioner for Refugees (UNHCR) estimates that there are more than 100 million forcibly displaced persons (FDPs) worldwide (UNHCR, 2023). At least 70% of these populations live in conditions of extreme poverty, without access to food, water, and basic services (e.g., InfoMigrants, 2021). Humanitarian support to address these basic needs is primarily provided by international agencies such as the UNHCR, the World Food Programme (WFP), and UNICEF. However, forced displacement is increasingly becoming protracted and the efficacy of cash-based assistance as a response strategy is reaching its limits such that current levels of support are no longer sufficient (Lyons, Kass-Hanna, & Molena, 2021; Lyons, Kass-Hanna, & Montoya Castano, 2023). As a result, agencies are needing to redesign and implement cash-based assistance programs that more efficiently identify and target the most vulnerable families.

Targeting models used by government and humanitarian agencies mostly rely on a proxy means testing (PMT) approach, where support programs target families whose estimated consumption levels fall below a certain threshold (e.g., Altındağ et al, 2021; Brown et al., 2018; Chaaban et al., 2018; Chaaban et al., 2020; Lyons, Kass-Hanna, & Montoya Castano, 2023; Moussa et al., 2021; Schnitzer, 2019; Verme & Gigliarano, 2019). Advocates of this method have long contended that the PMT method provides a relatively accurate and cost-effective tool to target the poor, that is suitable for large-scale assistance programs and is less prone to manipulation (Mills et al., 2015). However, these models have some important limitations that are not often recognized. First, PMTs are based on expenditures, which are highly susceptible to variations in prices, especially in countries with rising inflation or where the prices of goods and services differ considerably across regions. Second, PMTs are the best available tools if poverty is only based on a monetary measure such as income, or more commonly, consumption expenditures. However, there may be segments of the population who are not consumption poor, but who are nevertheless poor. Such populations may experience deprivations in other dimensions. They may, for instance, experience hardships related to food insecurity, inadequate housing, or a lack of employment opportunities. They could also have little or no access to essential services and resources, including healthcare, education, sanitation, and clean water. If a more comprehensive definition of poverty is used (e.g., a multidimensional measure of social welfare), then expenditure-based PMTs are not very accurate predictors of poverty. Third, even if the best metric for defining poverty is expenditure and the PMT is the best tool to measure it, the predictions are not very accurate. Some have even suggested that such methods are largely arbitrary and akin to a "lottery" (Kidd et al., 2017; Kidd & Wylde, 2011).

The main objective of this paper is to propose a more effective targeting strategy that: (1) is less susceptible to price fluctuations, (2) does not rely on a measure that is solely based on expenditures, and (3) enhances the precision and accuracy of the targeting mechanisms. To construct and test our methodology, we use data collected from Syrian refugees in Lebanon. The Syrian refugee crisis is one of the largest mass displacements in recent years, and one of the worst humanitarian crises of our time. For over a decade, Lebanon has hosted an estimated 1.5 million Syrian refugees. The majority live in precarious conditions in the most impoverished areas of Lebanon where they represent more than 20% of the population – the highest per capita proportion of refugees in the world (Chaaban et al., 2020; Government of Lebanon & United Nations, 2020). The prolonged nature of the conflict, coupled with the COVID-19 pandemic and Lebanon's dire economic conditions and political crises, have resulted in deteriorated living conditions for the refugees. According to UNHCR, UNICEF, and WFP (2021), more than 90% of Syrian refugee households in Lebanon live in extreme poverty, below the Survival Minimum Expenditure Basket (SMEB).

As such, Lebanon provides a novel case for researchers to simultaneously investigate current targeting mechanisms used by humanitarian agencies and propose methods for improving them (Altındağ et al, 2021; Chaaban et al., 2018; Inter-Agency Coordination Lebanon, 2021; Lyons, Kass-Hanna, & Montoya Castano, 2023). In particular, research has focused on the selection of variables to better predict poverty, as well as the inclusion of analytical tools and criteria to classify those households who are most in need of assistance. For instance, Altındağ et al. (2021) proposed a low-cost methodology that used limited administrative data and machine learning (ML) techniques to predict household expenditures with accuracy comparable to that of survey-based models that have used PMT. Verme and Gigliarano (2019) used data from Syrian refugees in Jordan, a neighboring country of Lebanon that also experienced a similar influx of refugees, and proposed that researchers use ROC (Receiver Operating Characteristics) curves to define the optimal poverty cutoffs that reduce leakage and increase coverage. Despite the valuable contributions of these studies, they measure poverty only in terms of expenditures per capita. Other approaches such as Chaaban et al. (2018) move beyond monetary measures to include non-monetary measures such as food security. Yet, challenges remain on how to effectively combine these different measures into a single indicator of poverty that can identify households who are most in need of assistance.

Lyons, Kass-Hanna, and Montoya Castano (2023) have proposed one of the most comprehensive multidimensional approaches. They constructed a multidimensional poverty index (MPI) akin to that of Alkire and Foster (2011) and Alkire and Santos (2014) to classify poor refugee households that are deprived in several dimensions of human life, including health, food security, education, living standards, employment, personal security, and social inclusion. While the approach identifies more precisely which households and geographical locations are vulnerable to experiencing protracted poverty, the index requires data that are not readily available to agencies and costly to collect, which makes it challenging to operationalize.

This study contributes to the literature on poverty and targeting mechanisms for forcibly displaced populations in three key respects. First, we substitute expenditures per capita as the variable to measure poverty with a multidimensional metric. To keep it simple and practical, our metric is based on three variables: expenditures, food security, and coping strategies. As such, it brings some elements from the multidimensional poverty literature (Aaberge & Brandolini, 2015; Alkire & Foster, 2011; Alkire & Santos, 2014; Lyons, Kass-Hanna, & Montoya Castano, 2023; Ravallion, 2011; World Bank, UNDP, & UNICEF, 2021). Unlike the traditional expenditure-based PMT approach, our measure acknowledges that households face different costs to achieve the same standards of living and that higher expenditures are not an exact indicator for satisfying all basic needs. We use a distance function to measure the distance between each household and the "poorest profile" and show that the classification of households who are poor is highly sensitive to the definition of poverty.

Second, we follow a rigorous methodology using machine learning (ML) techniques to better predict which households are more likely to be classified as poor based on a set of sociodemographic characteristics. In our analysis, we highlight some of the potential problems that arise in defining and using socioeconomic variables to predict PMT scores. We expect that these insights will help future researchers and international organizations to more accurately calculate PMT scores. Data science approaches have recently been used to address poverty and economic vulnerability in general (e.g., Abdul Rahman et al., 2021; Coromaldi & Drago, 2017; Yoder et al., 2021). However, relatively few studies have applied ML techniques to assist in the targeting of humanitarian assistance for forcibly displaced populations (Altındağ et al., 2021). ML analysis improves upon traditional econometric methods, as it does not require strong assumptions about the distribution of the data. At the same time, it enables the interaction of the variables that explain poverty (to create clusters) in flexible ways, which is not possible with linear methods.

Third, we include geospatial covariates in our ML models. The work of Lyons, Kass-Hanna, and Montoya Castano (2023) highlighted the importance of taking into consideration not only people-based poverty, but place-based poverty as well. Lebanon is a country that exhibits considerable heterogeneities across geographical locations in terms of land use, climate, employment opportunities, economic growth, etc. There are clear geographical heterogeneities that need to be taken into consideration in the construction of current and future targeting algorithms. We found only a few studies that use geospatial data to provide insights into anti-poverty interventions and the targeting of humanitarian aid. These studies focus primarily on the usage of mobile phone data (Aiken, Bedoya, Blumenstock, & Coville, 2022; Aiken, Bellue, Karlan, Udry, & Blumenstock, 2022). The work of Chi et al. (2022) stands out as one of the first studies to use a broader range of geospatial indicators and ML techniques to generate micro-estimates of the relative wealth and poverty of the populated surface of low- and middle-income countries (LMICs). In this context, our research also contributes to this emerging field by including a comprehensive set of geospatial indicators as predictors of poverty in ML models specifically tailored for refugee populations. We compare our results over time to assess the stability of the expenditure-based PMT and the multidimensional-based PMT methods over a four-year period that includes a pre- and post-COVID timeframe.

In the end, the ultimate goal of this study is to show in a systematic way how ML techniques can be combined with a multidimensional approach to improve traditional PMT targeting mechanisms. Increasing trends in poverty and displacement are expected to intensify in coming years due to population growth, climate change, economic inequality, and increased conflicts. Our findings show how governments and humanitarian organizations can use a data science approach to design more robust and effective targeting mechanisms in the face of increasing poverty and displacement, along with more limited resources. This work is particularly timely given the current Russo-Ukrainian crisis, where more than 7.9 million refugees have fled the country, 4.9 million have registered for temporary protection, and over 7 million are estimated to have been displaced internally within Ukraine (UNHCR, 2022a, 2002b, & n.d.). The results from this study using data on Syrian refugees in Lebanon can help to inform resource allocation decisions related to this and other forced displacement crises in the future.

The remainder of this paper is structured as follows. The next section describes the data. The third section presents our methods for constructing our multidimensional poverty measure using the distance formula and for using machine learning to generate our poverty predictions. The fourth section presents the results from the various comparisons of the traditional expenditure-based PMT with our multidimensional-based PMT (MD-PMT) approach. The final section summarizes the key findings and highlights implications for humanitarian and development organizations seeking to improve current targeting mechanisms, especially given increasing poverty and displacement and limited humanitarian funding.

2. Data

We used survey data taken from the *Vulnerability Assessment of Syrian Refugees (VASyR)* jointly gathered by the UNHCR, WFP, and UNICEF for the years 2018, 2019, 2020, and 2021. The *VASyR* is a nationally representative survey of Syrian refugee households in Lebanon that includes detailed information on: (1) individual and household demographics, including work and schooling; (2) shelter, utility, sanitation, and settlement conditions; (3) income, expenditures, assets and debts; (4) food consumption and dietary diversity; (5) health and safety; and (6) coping strategies (UNHCR et al., 2018, 2019, 2020, 2021). The UN agencies use the results from this annual survey to inform the distribution of humanitarian assistance and other interventions.[7]

[7] In each survey year, data were collected from Syrian refugee households who were randomly selected from the 26 administrative districts across the eight governorates of Lebanon. To ensure representativeness at the district and governorate levels, sampling was based on a two-stage cluster approach whereby clusters (villages, neighborhoods, or towns) were selected within each district, and then refugee cases were randomly selected within each cluster. Specifically, probability proportionate to size (PPS) methodology was used, where clusters with larger concentrations of refugees were more likely to be selected. Weights were also constructed at the district level based on the refugee population in each district. See UNHCR, UNICEF and WFP (2018, 2019, 2020, 2021) for more details about the sampling and survey methodology.

We supplemented the *VASyR* data with official administrative data on the types, amounts, and duration of cash and non-cash assistance provided to refugee families who are registered with the humanitarian agencies. We then merged all the data with the PMT scores that were internally generated for each household by the humanitarian agencies. The PMT scores were generated using a proprietary algorithm that predicts households' consumption expenditures based on the most updated administrative data. Households with PMT scores below a certain expenditure level (usually the Minimum Expenditure Basket - MEB) were classified as poor by the UNHCR. A household's PMT score largely determines its eligibility for cash and food assistance and other interventions.

Our analysis was conducted at the household level and by survey year and governorate. The initial sample size included 18,551 refugee households for all four survey years (4,434 in 2018, 4,670 in 2019, 4,480 in 2020, and 4,967 in 2021). Households with heads less than 15 years old or who had missing information about their educational attainment or other key explanatory variables were excluded from the sample. The final sample consisted of 18,196 refugee households (4,281 in 2018, 4,534 in 2019, 4,427 in 2020, and 4,954 in 2021).

The merged data were used to construct standard PMT scores that approximated expenditures per capita (expenditure-based PMT). We also constructed our multidimensional-based PMT (MD-PMT) scores, which captured three key dimensions: (1) expenditures per capita, (2) food consumption scores (FCS), and (3) reduced coping strategies (rCSI). These three factors are most often used by UNHCR and WFP to measure vulnerability among the refugees.

Other variables included in our study accounted for the household's family structure in terms of its household size, dependency ratio, proportion of female-headed and single-parent households, and the share of household members by age, gender, education, employment status, health and disability, and residency status. We also included variables that identified households that had received cash for food and/or multipurpose cash assistance. Additional factors were included to capture other dimensions of vulnerability to poverty and household deprivations related to basic living standards and social welfare.

Table 1 presents the descriptive statistics for the variables by survey year; p-values are reported to identify which variables differed significantly across the years[8]. The mean values for our key variables used to define poverty were found to significantly vary across the years. Expenditures per capita more than doubled between 2018 and 2021, due to severe currency depreciation and

[8] For this purpose, we use the R Package compareGroups. The p-values are calculated using t-tests by category when the variables are continuous. These t-values are then adjusted for multiple pairwise comparisons following the Benjamini- Hochberg method. When the variables are categorical, the p-values are based on a chi-square test.

surging inflation.[9] Refugee households' use of reduced food coping strategies increased between 2018 and 2021, while food consumption scores (FCS) decreased. Both indicators suggest a rise in food insecurity, which is not surprising given recent events and reports by the humanitarian agencies (e.g., UNHCR et al., 2021). Most of the other variables were also found to vary significantly over time, except for those related to the dependency ratio, the share of household members by age, the share of working-age males, along with female-headed and single-parent households. See Table A1 in the Appendix for a complete listing of all variables and how they were constructed.

A unique set of geospatial covariates were also included in our models to assess the importance that these factors may play in predicting poverty and the extent to which there may be place-based poverty. The extraction of the geospatial attributes was conducted using the district administrative units. The geographic boundaries for the twenty-six districts in Lebanon were used. First, we calculated the average elevation and its standard deviation for each district using the USGS/NGA Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) at the resolution of 30 arc-seconds (approximately 1 km at the equator).[10] We then extracted the fraction area coverage for four different land cover types, namely built-up area, crops, permanent water area, and seasonal water area.[11] These data were gathered using the annual 100m global land cover maps in raster format available from the Copernicus Global Land Service (CGLS) portal.[12] The fractions of land area coverage for the five land cover types were calculated for each of the 26 districts and averaged across the available years. Also, included was the Normalized Difference Vegetation Index (NDVI), a standardized measure of healthy vegetation and how sensitive the vegetation in a particular area may be to drought. The average Normalized Difference Vegetation Index (NDVI) per district was extracted from the CGLS, which includes the NDVI Collection 300m (Versions 1 and 2). In addition, we extracted the monthly nighttime light intensity using the Visible Infrared Imaging Radiometer Suite (VIIRS) V10 produced by the Earth Observation Group (EOG) at the resolution of 15 arc second (approximately 500m at the equator).[13] Light intensity was averaged over each district to provide a proxy for economic development. Finally, the total population count was extracted from the WorldPop rasters, where the population counts were adjusted to match the UN population estimates.[14] See again Table A1 in the Appendix for a listing of the geospatial variables and their definitions.

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[9] Lebanon's local currency has lost more than 95% of its value, driving inflation to triple digits since July 2020 and impacting mostly the poor and vulnerable (World Bank, 2022). Note that the rise in expenditures due to depreciation and inflation does not impact our empirical results, as we use a distance formula and estimate the results for each year separately. Details on our methodology are presented in the next section.

[10] https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation

[11] Initially, we also extracted data on snow covered areas, but the averages were zero for all districts and so this indicator was excluded from the analysis.

[12] https://land.copernicus.eu/global/

[13] https://eogdata.mines.edu/products/vnl/

[14] https://www.worldpop.org/

3. Methodology

3.1.A distance approach to measuring multidimensional poverty

As previously mentioned, the traditional PMT approach defines poverty using a unidimensional measure of expenditures. In this paper, we define a simple multidimensional measure of poverty using three dimensions: expenditures (Exp), food consumption score (FCS), and reduced coping strategies (rCSI). We use a distance function to combine these three dimensions and approximate a multidimensional poverty score (MD poverty score). Specifically, we estimated the distance of each household to the poorest profile in our sample by calculating the weighted average of the distances to the average of the fifth percentile in each dimension.[15] We preferred using the Manhattan distance function[16], as its values better resembled a normal distribution (see Figure A1 in the Appendix).

We estimated the distance assuming equal weights for each of the three dimensions (33/33/33). As a robustness check, we employed a second weighting scheme (50/25/25), where we assigned a weight of 50% to expenditures to emphasize its importance as an indicator of poverty. Then we split the remaining 50% equally across the other two dimensions (25% for FCS and 25% for rCSI). Equation (1) shows the estimated distance ($DIST_i$) for the *i*th household, where W_x denotes the weights of each component and $\overline{X_{5\%}}$ is the average of the fifth percentile for each dimension X:

$$DIST_i = W_{Exp}|Exp_i - \overline{Exp_{5\%}}| + W_{FCS}|FCS_i - \overline{FCS_{5\%}}| + W_{rCSI}|rCSI_i - \overline{rCSI_{5\%}}|. \quad (1)$$

As a final step, we adjusted the distances such that households closer to the poorest profile received the highest values, while households not considered to be as poor received values closer to 0. Equations (2) and (3) show the inverse distance of each household to the poorest profile, whereby higher scores were assigned to households experiencing greater poverty and in greater need of humanitarian assistance:

$$MD\ Poverty\ Score_i = Max(DIST_i) - DIST_i \quad (2)$$

$$MD\ Poverty\ Score_i = Max(DIST_i) - (W_{Exp}|Exp_i - \overline{Exp_{5\%}}| + W_{FCS}|FCS_i - \overline{FCS_{5\%}}| + W_{rCSI}|rCSI_i - \overline{rCSI_{5\%}}|). \quad (3)$$

[15] Note that the weighted average of the distances to the average of the fifth percentile in each dimension was calculated by year and not by region or governorate. Therefore, our calculations account only for temporary changes in the socioeconomic conditions.

[16] As a robustness check, we also analyzed the Euclidian and Minkowski distance functions. See Figure A1 in the Appendix for a comparison of the distributions of the Manhattan, Euclidean, and Minkowski distance formulas.

Distance functions have been previously used to estimate which households fall into multidimensional poverty. To our knowledge, there have been two main applications in the literature. The first application follows the concept of Sen's functionings or capabilities, where households seek to guarantee a certain level of capabilities, such as good housing conditions or a high level of education. These capabilities can be achieved using inputs, such as income, savings, or assets. In this sense, this first approach uses distance functions, typically used in the analysis of production efficiency, to measure the number of inputs necessary to achieve a certain level of capabilities (Deutsch & Silber, 2005; Ramos, 2008). The second approach is the use of cluster analysis to classify households into poverty levels or predict which households are more likely to be poor based on a set of socioeconomic characteristics (Otoiu et al., 2014; Sani et al, 2018; Usmanova et al., 2022). Implicitly, clustering algorithms use distance functions to measure the dissimilarity between observations and to classify them into clusters.

Our methodology differs from both approaches, as our goal was not the classification of households into clusters, but the use of distances to create an indicator of poverty that resembles the standard expenditure-based PMT approach. To this end, we used a metric that quantifies how far a certain household is from not being poor (and from not being eligible for assistance), which is the inverse of each household's distance to the poorest profile. In this sense, higher scores are associated with households who were more multidimensionally poor and thus more in need of humanitarian assistance[17]. Furthermore, we used inputs (i.e., socioeconomic characteristics) to predict out the likelihood of households to be poor, just as the standard PMT approach does. We argue that our approach is more flexible than the expenditure-based PMT, because it allows us to include other dimensions of poverty with varying weights. One possible scheme is to assign a 100% weight to expenditure and zero for all other dimensions, which would be similar to the expenditure-based method.

Note that the distance approach does not address the fact that the main problem with multidimensional measures of poverty is that they are hard to operationalize. They require data that are often unavailable or costly to obtain, and they require a clear definition of the weighting scheme, etc. (Lyons, Kass-Hanna, & Montoya Castano, 2023). Also, it is not certain whether the assistance provided by humanitarian organizations can help to reduce all deprivations included in more traditional multidimensional definitions of poverty (Lyons, Kass-Hanna, & Montoya Castano, 2023). For example, it is unlikely that more humanitarian assistance will increase the level of education of adult members in the household, an indicator commonly used by the multidimensional poverty index designed by Alkire and Foster (2011), among others. To address these concerns, we opted for a measure of poverty that includes a reduced set of variables which

[17] This approach is consistent with typical multidimensional poverty indices where a larger value indicates a higher level of poverty. It differs, however, from the PMT approach, where a lower score indicates a lower level of consumption expenditure and thus a higher level of poverty. To make comparisons across the two methods in identifying the poorest households, we multiply the MD poverty scores by (-1) so that the bottom X^{th} percentile of the distribution would refer to the poorest X%, as is the case for PMT.

can be influenced by the humanitarian assistance. As such, our measure can be more easily calculated and predicted with available information and can, thus, be more practically operationalized by humanitarian organizations.

3.2.Machine learning and poverty predictions

To predict traditional PMT scores (PMT), we used expenditures per capita. To predict multidimensional-based PMT scores (MD-PMT), we used our multidimensional poverty scores (MD poverty score) calculated in Equation (3). Using both methods, we predicted poverty for all refugee households using machine learning (ML) techniques. Our training protocol and cross-validation strategy can be described as follows (see also Han, Kamber, & Pei (2012)). We compared the performance of three ML models: Lasso Regression (Lasso), Random Forest (RF), and Gradient Boosting (GB). The models were trained to predict poverty based on the distance from the poorest five percent. Models were fitted using R statistical language (version 4.2). The predictors of poverty included in our models were described in the data section. These variables were selected, because they are included in some form in UNHCR's official administrative data collected for all refugees and so are readily available to humanitarian organizations. We added to the models the set of geospatial indicators that are available for all refugees.

To prevent overfitting, we used a repeated K-fold (K=5) cross-validation strategy to evaluate the performance of our models.[18] We divided the data into five equal folds and trained the models using four partitions and then tested the models using the remaining partition. This process was repeated three times. Modeling and cross validation were implemented using the R Package Caret (version 6.0) (Greenwell et al., 2022; Liaw & Wiener, 2002).

The models were calibrated to identify the best model at predicting the PMT scores using expenditures per capita and the MD-PMT scores using our MD poverty score. Five accuracy metrics were used to evaluate the performance of the three models – namely, the absolute error (Abs. Error), the Pearson correlation coefficient (Correlation), the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), and the R-squared. See Equations (4)-(8):

$$\text{Abs. Error} = \sum |y_i - \hat{y}| \tag{4}$$

$$\text{Correlation} = \sum(x_i - \bar{x})\,(y_i - \bar{y}) \,/\, \text{sqrt}(\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2) \tag{5}$$

$$\text{Mean Squared Error (MSE)} = \sum(y_i - \hat{y})^2 / \text{N} \tag{6}$$

$$\text{Root Mean Squared Error (RMSE)} = \text{sqrt}(\sum(y_i - \hat{y})^2 / \text{N}) \tag{7}$$

$$\text{R-squared} = 1 - \text{(sum of squared residuals / total sum of squares).} \tag{8}$$

[18] Overfitting happens when the model memorizes the training dataset and performs well in terms of goodness of fit. However, model quality degrades when applied to external data other than the training dataset (e.g., an out of sample testing dataset). The solution for overfitting is using cross-validation, which is a resampling method that uses different portions of the data to test and train a model on different iterations (Han, Kamber, & Pei, 2012).

Table 2 presents the results for the five metrics for the three ML models estimated for our PMT and MD-PMT scores. The models were estimated separately for each year. In comparing the five metrics, the results were similar for all three models. When predicting the MD-PMT scores (top panel of Table 2), Gradient Boosting (GB) performed slightly better than the Lasso and Random Forest (RF) for the years 2020 and 2021, whereas Random Forest (RF) performed slightly better for the years 2018 and 2019. When predicting the PMT scores (bottom panel of Table 2), the results were again comparable across the three ML models, with Gradient Boosting (GB) performing slightly better than Random Forest (RF) for half of the years (2018 and 2020). It is worth noting, but not surprising, that the predictions for the PMT scores resulted in slightly better results compared to the predictions for the MD-PMT scores (higher values for R squared and higher correlations). The ML models used to predict the PMT scores did not need to account for the interactions between the three-dimensional poverty measure.

From here, Gradient Boosting (GB) was used to refine the calibration of the models.[19] The Gradient Boosting (GB) method relies on a more complex decision tree algorithm that is more flexible and often more accurate than that used by Random Forests (RF).[20] Using Gradient Boosting (GB), we performed a parameter grid search to obtain the best values of parameters. The parameter search was done for interaction depths of 1, 5 and 10, and the number of trees ranged from 10 to 200, with a step of 10 (Kuhn, 2022).

Figure 1 presents the GB results for our PMT and MD-PMT scores across the four years. The figure reveals the covariates that were the top predictors of poverty and the importance of each in explaining the prediction of the models. Three key findings are worth noting. First, the key predictors of poverty vary considerably when comparing the results for both approaches. For the GB model that predicted the expenditure-based PMT, we observe that the top three predictors were household-level covariates. These predictors included: the number of household members, the percentage of household members working, the percentage of males aged 20 to 49, and the percentage who had previously received cash for food. Some geographical covariates were identified as important predictors as well. The fraction of land area covered with crops was the most consistent geospatial predictor across all years, followed by nighttime light intensity, which is a proxy for urbanization and economic performance. The NDVI, a proxy for agricultural activity within an administrative unit, and land elevation, a proxy for geographic accessibility and climate conditions, were also found to be important predictors, even if to a lesser extent and not consistently across all years.

[19] The results for the Lasso and Random Forest models were similar and are available upon request.

[20] Gradient boosting (GB) often outperforms other methods, because it follows a sequential training model that constructs the decision trees using a gradient descent algorithm, where each decision tree is trained to minimize the errors in the predictions of the previous one. The prediction trees in other models such as Random Forest are first trained independently and then combined at the end.

Second, the most important predictors of poverty using the MD-PMT exhibited greater variation across the survey years. Among these indicators, geospatial factors, specifically the Normalized Difference Vegetation Index (NDVI) and the proportion of land area covered with crops, emerged as the most significant predictors. Additionally, elevation indicators, both in terms of average and within-district variation also were of importance, although to a lesser extent. Similar to the expenditure-based PMT models, the percentage of household members working emerged as the most consistent and reliable predictor among the sociodemographic factors for all of the survey years. Following this, the percentage of males aged 20 to 49 ranked as the subsequent significant predictor.

Interestingly, the governorate of North Lebanon was the most important predictor for three of the four survey years. Figures A2 and A3 in the Appendix provide some insights into this interesting finding. Figure A2 in the Appendix presents the distribution of the real MD poverty scores and the predicted values for the MD-PMT scores by year and governorate. For the most part, we see that the distributions are similar over time. However, the distributions of the real and predicted scores for governorate 7 (North Lebanon) are skewed to the right, indicating that households in this governorate tend to be clustered more towards high levels of multidimensional poverty. Figure A3 in the Appendix presents the distributions for each of the three dimensions in the MD poverty score used to generate the MD-PMT scores. We see that the distributions for expenditures per capita and the food consumption score are similar across years and across governorates. However, some anomalies for reduced coping strategies (rCSI) can be observed. In particular, we see that for governorate 7 (North Lebanon) a larger share of the distribution relies on reduced food coping strategies compared to the other governorates. This observation suggests that food insecurity levels are higher for this specific governorate. At first glance, this finding may appear surprising, considering that other governorates such as Bekaa, Baalbek-El Hermel, and Akkar are known to have higher poverty rates among both host and refugee communities. However, a closer examination of the heterogeneities across different geographic locations in Lebanon and the ensuing economic dynamics offers a plausible explanation. Despite being characterized as some of the poorest areas, these governorates encompass large agricultural areas, unlike North Lebanon.[21] As refugees tend to have employment opportunities in the agriculture sector, they are less prone to food insecurity in these governorates. However, in the case of North Lebanon, which primarily consists of urban areas and mountainous regions, refugees encounter more significant obstacles in terms of food production and access. This circumstance likely contributes to North Lebanon being identified as a key predictor of the MD- PMT scores in the GB model.

[21] The average fraction of cropland in Bekaa, Baalbek-El Hermel, and Akkar is approximately 28%, 23% and 21%, respectively. In contrast, the average proportion of land utilized for crop production in the North is less than 7%. It is worth noting that the Bekaa and Baalbek-El Hermel governorates encompass the fertile “Bekaa Valley” known to be Lebanon’s foremost agricultural region, where crop areas account for over 60% of the country’s total crop land.

Thirdly, the significance of location in predicting poverty is evident, whether considering covariates at the governorate level or geospatial attributes at the district level. There are inherent place-based factors related to poverty that previous research has struggled to adequately capture. Among the 20 predictors presented for each GB model in Figure 1, the geospatial attributes accounted for roughly half of the top predictors for three out of the four survey years for both the expenditure-based PMT and the MD-PMT models. Moreover, these attributes constituted at least 50% of the top ten predictors in 2018, 2019, and 2021 when the model predicted the MD-PMT scores. They also accounted for nearly 50% of the top predictors in 2018, 2019, and 2020 when the PMT scores were predicted. These results suggest that when predicting a more complex definition of poverty that extends beyond expenditure-based measurements, the models prove more effective in identifying spatial correlations among observations across different spatial scales (e.g., governorate, district).

Figures 2A and 2B present geographical visualizations of poverty, illustrating the percentage of refugee households in each district that fell within the bottom 30% of the distribution based on predicted PMT and MD-PMT scores.[22] When poverty was defined solely based on expenditure, the districts in the Northern and Eastern regions, adjacent to the Syrian border, tended to have the highest concentrations of impoverished refugee households. As expected, these districts included the poorest governorates of Akkar, Baalbek-El Hermel, and Bekaa. However, when the multidimensional measure was used, the Northwest districts, particularly the governorate of North Lebanon, emerged as the areas with the highest concentrations of poverty.[23]

Taken together, the three aforementioned findings highlight the considerable heterogeneity observed between the two models and over time. These findings underscore the pressing need for humanitarian organizations to be consistently and regularly updating their definition of poverty and the algorithms used to predict poverty for the entire refugee population.

4. Results

4.1 Overlap between the PMT and MD-PMT scores

We employed several methods to compare the PMT and MD-PMT models. First, we examined the overlap between refugee households identified as the poorest using our MD-PMT method and those identified as the poorest using the expenditure-based PMT. To do this, we took the 10th, 20th,

[22] Figures A4 and A5 in the Appendix present the geographical mappings of poverty based on the real values for expenditure and our multidimensional poverty score (MD score). The visualizations generated using the real values look almost identical to the mappings generated using the predicted PMT and MD-PMT scores in Figures 2A and 2B.
[23] Figure 2B shows that in 2018, two districts within the North Lebanon governorate (Zgharta and Batroun) exhibited notably higher concentrations of multidimensional poverty. This finding is consistent with research conducted by Lyons, et al. (2023), who developed a comprehensive multidimensional poverty index encompassing 21 indicators across five dimensions to assess poverty among Syrian refugees in Lebanon. Lyons et al. (2023) similarly observed that Zgharta and Batroun had a larger proportion of refugees with higher deprivation scores, as indicated by their extensive multidimensional poverty index.

30th, 40th, and 50th percentiles for both methods and calculated the percentage of households in the X^{th} percentile of the distribution of MD-PMT scores that also belonged to the X^{th} percentile of the distribution of PMT scores. For example, in 2018, among households whose predicted MD-PMT scores ranked in the 10th percentile, 16.6% had predicted expenditure-based PMT scores that also ranked in the 10th percentile. In other words, 16.6% of households predicted to be the poorest based on the multidimensional measure were also predicted to be the poorest based solely on expenditure. Our results showed that households classified as the poorest differed significantly depending on the poverty metric used, as demonstrated by the overlap between the two measures for both the real and predicted values presented in Table 3.[24]

Similarly, the overlap varied considerably from year to year. Specifically, for 2019 and 2021, there was minimal or no overlap between those predicted to be the poorest (10th percentile) using the PMT versus the MD-PMT method (0.0% and 0.2%, respectively). This result is unfortunate, as an accurate targeting scheme should be able to identify the extremes of the distribution correctly (i.e., the households that are the worst off and the relatively better off). We would expect differences between the two approaches to emerge in the middle of the distribution, where it is less clear which households are worse off. Additionally, we observed that food insecurity, as measured by the FCS and rCSI, did not necessarily correlate with expenditures. Comparing the real values reported in Table 3, we found that for the bottom 10th percentile, the overlap between the two approaches in 2019, 2020, and 2021 was less than 30%.

4.2 Comparison of relative efficiency at capturing other forms of deprivation

Next, we analyzed whether the predicted PMT and MD-PMT scores were correlated with other indicators of poverty. We identified households within the 30th percentile for both the distribution of the PMT and MD-PMT scores and calculated the proportion of these households that had experienced deprivations in other dimensions of poverty or social welfare. For example, in the first row of Table 4, we estimated the percentage of households within the 30th percentile according to both methods who: (1) had expenditures below the Survival Minimum Expenditure Basket (SMEB), (2) had an rCSI score equal to or higher than 19, (3) had an FCS below the acceptable threshold (less than or equal to 42), or (4) were deprived in all three dimensions simultaneously. To provide a point of comparison, we also calculated the percentage of the total refugee population that had experienced deprivation in each specific dimension of poverty or social welfare (the "Total" columns in Table 4). We would expect higher deprivation rates among the poorest households (using any of the methods) compared to the average of the total refugee population.

[24] Note that the results presented in Table 3 are based on a distance function where equal weight was assigned to each dimension. As a robustness check, the models were re-estimated assigning 50% weight to expenditure and 25% weight to each of the food consumption score (FCS) and the reduced coping strategies index (rCSI) (50/25/25). Not surprisingly, the results revealed that the overlap between the two models is greater when more weight is placed on expenditures. The results using different weighting schemes are available upon request.

Table 4 reveals that the predictions obtained using the expenditure-based PMT method did not accurately classify households experiencing deprivation in terms of rCSI and FCS. In fact, the percentage of the poorest households (the bottom 30%) in terms of expenditure who experienced deprivation in these two dimensions was lower than the average for the total population, for almost all years.

To expand this analysis, we included deprivations related to living standards. These deprivations encompassed various aspects such as having children of school age not attending school, relying on dung or charcoal for cooking, having inadequate access to electricity (less than 16 hours per day), living in overcrowded shelters with less than $4.5m^2$ per person, lacking access to adequate sanitation and drinking water, and having been exposed to security issues like robbery, kidnapping, and harassment. We sought to determine the correlation of these deprivations with both the expenditure-based PMT and MD-PMT methods. Our findings revealed that certain deprivations were more closely associated with the PMT method, while others exhibited stronger correlations with the MD-PMT method.[25] Moreover, in some cases, the percentage of the poorest households (bottom 30%) experiencing deprivations in living standards was not significantly different from that of the population as a whole. These outcomes indicate that there is potential to enhance the MD-PMT approach by incorporating additional dimensions of poverty, such as an index for living standards.

4.3 Comparison of refugee characteristics using both measures

We also extended our analysis to compare the characteristics of refugee households predicted to be poor using both the PMT and the MD-PMT. In Table 5, we divided the sample into 4 groups: those classified as poor according to both the PMT and MD-PMT methods (Both), those not classified as poor by either method (None), and those classified as poor according to only one of the two methods. To increase the sample size of the overlapping group classified as poor using both methods, we expanded the poverty classification to the 40^{th} percentile.

Significant differences were observed across all variables among the four categories. A few findings are particularly noteworthy. For example, household size and dependency ratio were more significant for refugees classified as poor based on the PMT, but were less significant when the MD-PMT was used. In other words, households solely identified as poor using the PMT score were more likely to be larger in size and to have a higher proportion of dependents compared to those solely identified as poor using the MD-PMT score. This difference could potentially be explained by considering economies of scale in the calculation of expenditures per capita, such as the decreasing marginal cost of food with an increasing number of household members, particularly with children.

[25] The PMT scores were more strongly correlated with deprivations in school attendance and shelter crowdedness for all years. On the other hand, the MD-PMT scores were more strongly correlated with deprivations related to water and electricity. For other deprivations in living standards, results were mixed across the years.

Additionally, we found that households only classified as poor using the MD-PMT score were more likely to have a female head of household, a higher percentage of male members aged 20-49, a disabled head, and/or family members with medical conditions, in comparison to those who were only classified as poor using the PMT. Households only classified as poor using the MD-PMT score were also more likely to utilize reduced coping strategies (higher rCSI) and to be food insecure (lower FCS). This finding should not be surprising, as rCSI and FCS were key dimensions used to define poverty in the multidimensional model.

Interestingly, the main differences in the characteristics between the two methods were associated with the households' location and whether they were receiving humanitarian assistance, specifically cash for food and multi-purpose cash. Households located in Baalbek-El Hermel and Bekaa were highly likely to be classified as poor using the PMT, but not when the MD-PMT score was used. Conversely, the opposite was observed for households in North Lebanon. Furthermore, households located in Mount Lebanon were less likely to be classified as poor according to the PMT, but a significant percentage of households in this governorate were identified as poor using the MD-PMT score. The latter result is particularly noteworthy, as the cost of living in Mount Lebanon is relatively higher compared to other areas of the country, thus resulting in higher expenditure levels. However, households in Mount Lebanon may still experience other forms of poverty, such as food insecurity. Not surprisingly, a larger proportion of households receiving assistance, both cash for food and multipurpose cash (MPC), were classified as poor according to the expenditure-based PMT compared to those classified as poor based on the MD-PMT score alone. In fact, the number of households receiving assistance and classified as poor solely using the MD-PMT score was notably low, almost as low as the households not classified as poor by either of the two measures. These findings, once again, underscore the significance of the geospatial component in understanding poverty. They also highlight that relying solely on expenditure to determine which households are in greatest need of assistance can result in households that are struggling with food insecurity being overlooked.

4.4 Comparison of the exclusion errors

Finally, we compared the exclusion errors using both the real values (expenditures per capita and MD poverty scores) and predicted values (PMT and MD-PMT scores). We estimated the exclusion errors (households who were predicted to be non-poor, when in reality, they were actually poor) for different percentiles using both methods. The upper panel in Table 6 presents the exclusion errors based on the real values of our MD poverty scores, while the lower panel presents the exclusion errors based on the real expenditures per capita reported by households.

As expected, when poverty was measured solely based on the real values of expenditures per capita, the predictions for the standard PMT resulted in lower exclusion errors. Conversely, when poverty was measured based on the real values of the MD poverty scores, the predictions using the MD-

PMT scores performed better (indicated by the italicized numbers in Table 6). Furthermore, when comparing these numbers across different percentiles (again, the numbers in italics), we found that the exclusion errors were relatively similar for both models, with the MD-PMT score occasionally outperforming the PMT score and vice versa.

In this regard, our multidimensional-based PMT methodology behaves similarly to the standard PMT in terms of exclusion errors, but only when the measure of poverty is multidimensional. For instance, in the top panel for the year 2018, we found that 18.9% of those who were multidimensionally poor (bottom 30% of the distribution of real MD poverty scores) were not predicted as multidimensionally poor. This implies that these households would be "excluded" from being classified as poor based on the bottom 30% of the predicted values. Similarly, in the bottom panel for the year 2018, we found that 19.9% of those who were poor based on expenditures (bottom 30% of the distribution of real expenditures per capita) were not predicted as poor using the standard PMT values for the bottom 30% of the distribution. Consequently, if international organizations were to target the bottom 30% of households to receive assistance, 19.9% of the 30% poorest households would be excluded from receiving assistance.[26] Therefore, in terms of exclusion errors, the MD-PMT method performs comparably to the expenditure-based PMT method, while offering more flexibility in how poverty is defined and measured.

It is important to note that the predictions presented in Figure 2B and Tables 3 to 6 assumed equal weights for the three dimensions included in the multidimensional poverty model. As part of a robustness check and for comparison purposes, we explored how the predictions might change if more weight was assigned to expenditures in the multidimensional-based poverty model. To this end, we re-estimated our models assigning 50% weight to expenditures and 25% weight each to the food consumption score (FCS) and the reduced coping strategies index (rCSI) (50/25/25). The results obtained from this modified weighting assignment were similar to those obtained when equal weights were assigned to each dimension. Figure 3 shows the distribution of our MD-PMT predictions by district, while Table 7 shows the overlap between multidimensional-based poverty and expenditure-based poverty.

5. Conclusions

This paper uses data from Syrian refugees in Lebanon to construct a multidimensional poverty score. The score was derived by calculating a weighted average of the distances to the poorest profiles across the three dimensions: expenditures per capita, the food consumption score (FCS), and the reduced coping strategies index (rCSI). Initially, models were estimated with equal weights assigned to each dimension, and subsequently with 50%, 25%, and 25% weights assigned to the dimensions, respectively. The results were then compared with those generated by the traditional

[26] We also calculated the inclusion errors, which reveal similar, albeit opposite, patterns. When exclusion errors were lower, inclusion errors were found to be higher. These results are available upon request.

expenditure-based PMT method used by humanitarian agencies to predict households' consumption expenditures.

The comparison revealed that the results obtained from the PMT method align closely with the multidimensional-based PMT results when expenditure is assumed to have a 100% weight. This comparison underscores the sensitivity of classifications to the definition of poverty. The decision to adopt either unidimensional or multidimensional definitions and measures of poverty significantly influences targeting strategies and determines which households are included or excluded from assistance programs. Solely relying on a unidimensional, monetary measure to target assistance may inadvertently leave behind households experiencing critical deprivations in other dimensions, such as food insecurity.

From this perspective, our approach offers greater flexibility as it allows researchers and organizations to incorporate multiple dimensions of poverty, capturing heterogeneities that the expenditure-based PMT formula may not fully capture. In this study, we identified the profiles of households that tended to be excluded from receiving assistance based on the scores generated by the traditional PMT method used by humanitarian organizations, in comparison to our proposed multidimensional approach. Furthermore, we examined the results across multiple years, encompassing periods before and after major shocks such as the COVID-19 pandemic and Lebanon's compounded economic and political crises. Adding this time element to our analysis highlights the consistency of our methodology over time and its ability to capture changing socio-economic conditions.

Humanitarian crises exist in conditions that are dynamic and in states of constant turmoil and flux. As such, humanitarian organizations must regularly update their targeting mechanisms, typically on an annual basis. Our approach can serve as a stable method for identifying households in greater need of assistance, especially during periods of rising inflation. The findings have important implications for government and international agencies seeking to develop robust and effective targeting mechanisms, particularly in a world where predicting future changes has become increasingly challenging. In such a context, targeting strategies need to be designed to be flexible, allowing for regular adjustments and updates.

The findings from this study also highlight the significance of considering the geographical element in poverty analysis. Although the geographic units were represented as dummy variables in our algorithm, their importance was evident during the model training process, especially for the years where there was significant economic instability. This suggests that geographical heterogeneities should be taken into account when constructing future algorithms for classifying poverty and determining eligibility for assistance. That said, further research is needed to gain a better understanding of the specific place-based elements of poverty that this study and previous research have yet to explore. By adopting a multidimensional approach, organizations can adapt their targeting mechanisms to address the evolving needs of vulnerable populations and ensure that assistance reaches those who need it most effectively.

It is important to acknowledge some limitations of our work. Our models and predictions are reliant on the available data. Without access to longitudinal data, we cannot fully capture how poverty changes over time and within and across refugee households. Also, the lack of geo-coordinates for individual refugee households limits our ability to conduct more rigorous geospatial analysis. We also do not have access to the administrative data or specific algorithms used by the humanitarian organizations to generate the expenditure-based PMT scores. These data restrictions impede our ability to test and refine our models for more accurate and consistent predictions aligned with internal methods currently being used by humanitarian organizations to rank the refugee households and prioritize needs in the face of limited resources.

Nevertheless, our study benefits from several years of data, which we have linked to information on humanitarian assistance received, the actual PMT scores generated internally by UNCHR, and a robust set of geospatial attributes at the district level. Furthermore, we are among the first to apply a data-science based approach to developing and testing a more comprehensive and adaptable targeting mechanism that goes beyond expenditure-based measures and can accommodate different definitions and priorities associated with poverty. In this regard, we view our paper as a "road map" that can "guide" other researchers and humanitarian organizations in more rigorously designing, testing, and updating current targeting methods. This work is particularly relevant in the current context of various ongoing crises such as the Russo-Ukrainian crisis, the Sudanese conflict, and increasing displacement resulting from climate change. As a result, our findings have broader applicability beyond the specific case of Lebanon. They can inform and guide humanitarian organizations in making critical decisions on how to allocate limited resources among forcibly displaced populations in various crisis situations. By better understanding the multidimensional nature of poverty and incorporating geographical considerations, our research can contribute to the development of more effective and targeted assistance strategies in diverse humanitarian contexts.

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Table 1. Descriptive statistics by year

Variables	2018 (N=4,281)	2019 (N=4,534)	2020 (N=4,427)	2021 (N=4,954)	p-value
Expenditures per capita (LBP)	157,740 (114,886)	148,884 (106,154)	195,249 (151,120)	340,854 (259,794)	0.000
rCSI (#)	17.9 (14.4)	19.0 (15.2)	17.3 (13.7)	20.1 (14.3)	<0.001
FCS (#)	53.4 (20.1)	55.1 (18.8)	45.0 (18.3)	48.3 (18.2)	<0.001
Household size (#)	4.93 (2.22)	5.12 (2.42)	5.04 (2.19)	5.04 (2.17)	0.002
Dependency ratio	0.46 (0.23)	0.45 (0.24)	0.46 (0.24)	0.46 (0.23)	0.521
Female head	0.16 (0.37)	0.16 (0.36)	0.17 (0.37)	0.16 (0.36)	0.420
% HH members aged 0-4	0.17 (0.18)	0.17 (0.18)	0.18 (0.19)	0.18 (0.19)	0.054
% HH members aged 5-9	0.15 (0.17)	0.15 (0.16)	0.14 (0.16)	0.14 (0.16)	0.014
% HH members aged 10-19	0.18 (0.21)	0.18 (0.21)	0.19 (0.22)	0.19 (0.21)	0.390
% HH members older than 60	0.03 (0.13)	0.03 (0.13)	0.03 (0.13)	0.03 (0.13)	0.530
% Male members aged 20-49	0.21 (0.19)	0.21 (0.20)	0.21 (0.20)	0.22 (0.20)	0.345
% Female members aged 20-49	0.21 (0.15)	0.18 (0.14)	0.20 (0.15)	0.20 (0.14)	<0.001
% HH members education unknown	0.36 (0.25)	0.24 (0.22)	0.25 (0.23)	0.11 (0.14)	0.000
% HH members no education	0.12 (0.21)	0.07 (0.16)	0.07 (0.17)	0.37 (0.33)	0.000
% HH members primary education	0.15 (0.21)	0.29 (0.26)	0.28 (0.26)	0.22 (0.24)	<0.001
% HH members secondary education	0.09 (0.17)	0.09 (0.18)	0.11 (0.19)	0.09 (0.17)	<0.001
% HH members above secondary education	0.06 (0.16)	0.07 (0.18)	0.06 (0.17)	0.05 (0.15)	<0.001
% HH members inactive	0.09 (0.15)	0.34 (0.25)	0.30 (0.23)	0.25 (0.21)	0.000
% HH members studying	0.01 (0.06)	0.02 (0.06)	0.02 (0.07)	0.00 (0.03)	<0.001
% HH members working	0.17 (0.20)	0.16 (0.21)	0.16 (0.21)	0.20 (0.21)	<0.001
% HH members unemployed	0.10 (0.18)	0.07 (0.16)	0.09 (0.17)	0.07 (0.15)	<0.001
% HH members with disability	0.03 (0.09)	0.06 (0.15)	0.06 (0.15)	0.07 (0.16)	<0.001
% HH members with medical condition	0.17 (0.23)	0.15 (0.23)	0.15 (0.23)	0.16 (0.23)	0.051
Disabled head	0.04 (0.19)	0.08 (0.28)	0.10 (0.31)	0.11 (0.31)	<0.001
Disabled dependent member	0.06 (0.23)	0.10 (0.30)	0.11 (0.31)	0.10 (0.30)	<0.001
Single Parent	0.05 (0.22)	0.06 (0.24)	0.05 (0.21)	0.05 (0.22)	0.116
% Illegal residency	0.67 (0.40)	0.71 (0.38)	0.63 (0.42)	0.67 (0.40)	<0.001
Governorate [number (percentage)]					<0.001
Governorate 1: Akkar	426 (9.95%)	474 (10.5%)	483 (10.9%)	522 (10.5%)	
Governorate 2: Baalbek-El Hermel	333 (7.78%)	434 (9.57%)	485 (11.0%)	485 (9.79%)	
Governorate 3: Beirut	377 (8.81%)	412 (9.09%)	322 (7.27%)	471 (9.51%)	
Governorate 4: Bekaa	502 (11.7%)	477 (10.5%)	480 (10.8%)	481 (9.71%)	
Governorate 5: El Nabatieh	554 (12.9%)	537 (11.8%)	627 (14.2%)	646 (13.0%)	
Governorate 6: Mount Lebanon	847 (19.8%)	874 (19.3%)	768 (17.3%)	1009 (20.4%)	
Governorate 7: North Lebanon	823 (19.2%)	859 (18.9%)	816 (18.4%)	877 (17.7%)	
Governorate 8: South Lebanon	419 (9.79%)	467 (10.3%)	446 (10.1%)	463 (9.35%)	
Received WFP cash for food	0.65 (0.48)	0.66 (0.47)	0.65 (0.48)	0.52 (0.50)	<0.001
Received MPC	0.47 (0.50)	0.49 (0.50)	0.50 (0.50)	0.50 (0.50)	0.024
Received other monetary assistance	0.76 (0.43)	0.74 (0.44)	0.74 (0.44)	0.27 (0.45)	0.000
Child not attending school	0.28 (0.45)	0.30 (0.46)	0.29 (0.46)	0.13 (0.34)	<0.001
Cooking fuel	0.06 (0.24)	0.13 (0.34)	0.17 (0.38)	0.14 (0.35)	<0.001
Electricity	0.40 (0.49)	0.28 (0.45)	0.38 (0.49)	0.39 (0.49)	<0.001
Shelter crowdedness	0.32 (0.47)	0.29 (0.45)	0.23 (0.42)	0.20 (0.40)	<0.001
Improved sanitation	0.32 (0.46)	0.28 (0.45)	0.24 (0.43)	0.24 (0.43)	<0.001
Water	0.12 (0.32)	0.13 (0.34)	0.15 (0.35)	0.12 (0.33)	<0.001
Insecurity	0.03 (0.18)	0.13 (0.34)	0.09 (0.29)	0.15 (0.35)	<0.001

Notes: The data were taken from the Vulnerability Assessment of Syrian Refugees (VASyR) annual surveys and the Refugee Assistance Information System (RAIS). Standard errors in parentheses.

Table 2. Comparison of machines learning results across models (Lasso, Random Forest, Gradient Boosting)

Multidimensional-based PMT (MD-PMT)

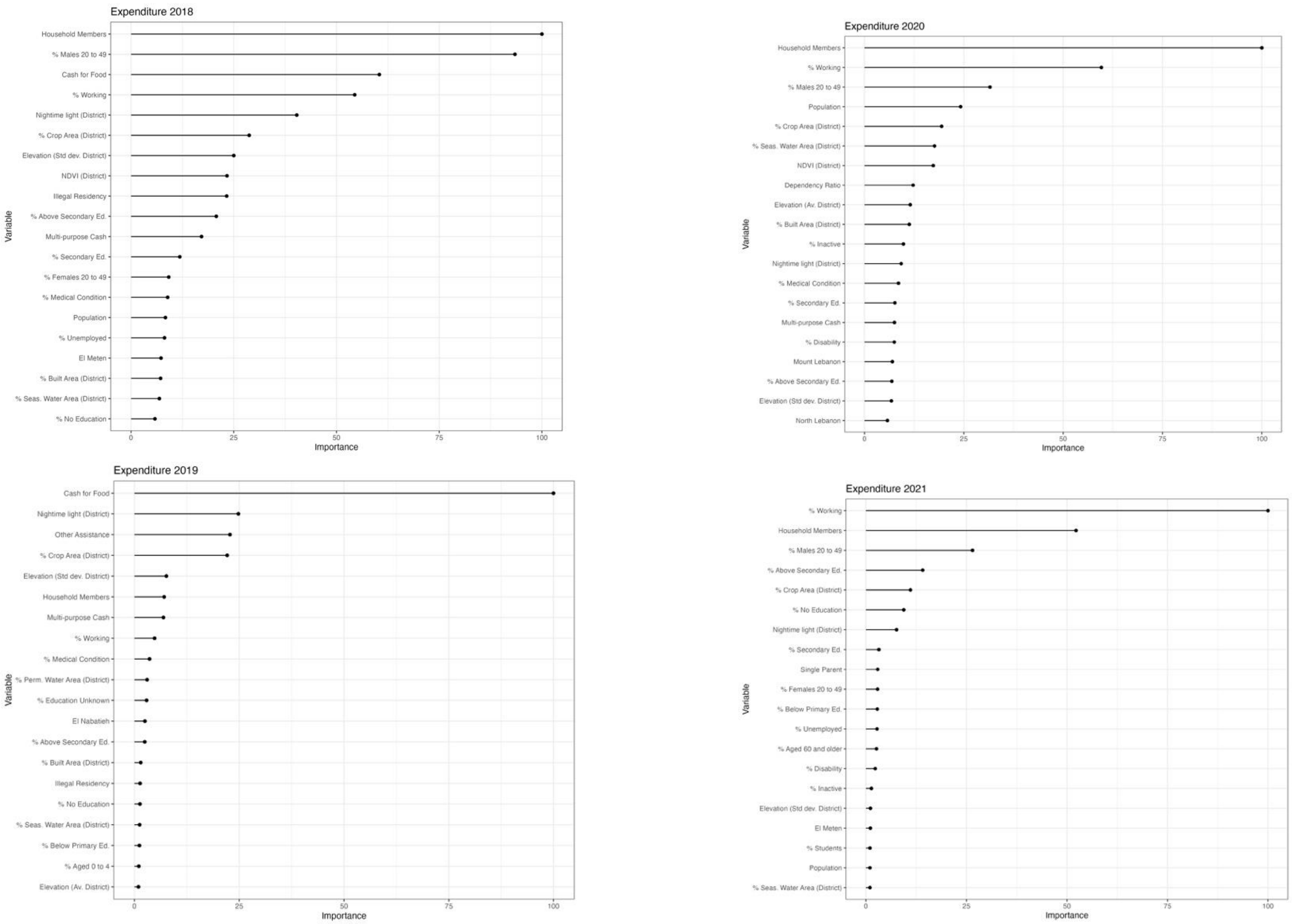
Method	Stats	2018	2019	2020	2021
Random Forest	Abs. Error	0.104	0.161	0.101	0.132
	Correlation	0.435	0.457	0.465	0.478
	MSE	0.017	0.038	0.016	0.026
	RMSE	0.132	0.196	0.125	0.162
	R-squared	0.189	0.209	0.217	0.228
LASSO	Abs. Error	0.102	0.186	0.103	0.177
	Correlation	0.429	0.463	0.452	0.451
	MSE	0.017	0.058	0.017	0.041
	RMSE	0.130	0.240	0.129	0.204
	R-squared	0.184	0.214	0.204	0.203
Gradient Boosting	Abs. Error	0.105	0.195	0.094	0.120
	Correlation	0.430	0.465	0.471	0.471
	MSE	0.018	0.065	0.014	0.022
	RMSE	0.133	0.255	0.119	0.148
	R-squared	0.185	0.216	0.222	0.222
	BEST	RF	RF	GB	GB

Expenditure-based PMT (PMT)

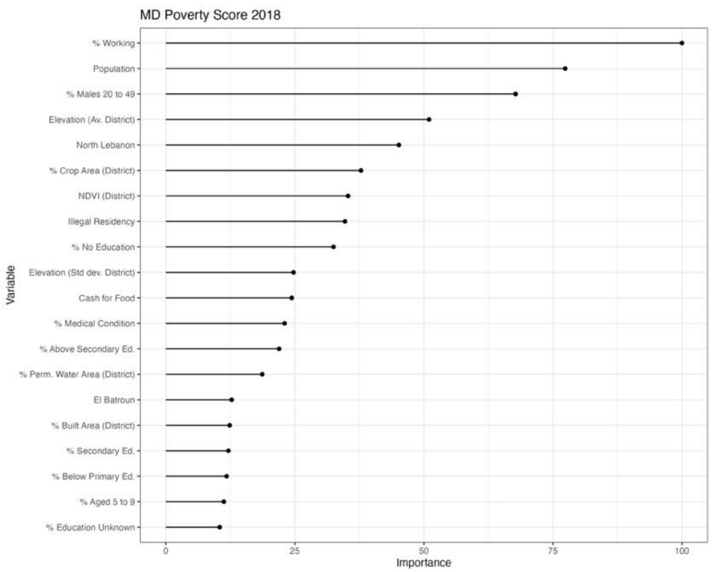
Method	Stats	2018	2019	2020	2021
Random Forest	Abs. Error	57.0	195991.9	224684.2	342812.9
	Correlation	0.616	0.430	0.647	0.564
	MSE	5716.8	18617.7	7.31E+10	1.90E+11
	RMSE	75.6	136.4	270440.8	436005.3
	R-squared	0.379	0.185	0.419	0.318
LASSO	Abs. Error	53.0	196054.1	90144.1	180792.1
	Correlation	0.609	0.467	0.669	0.574
	MSE	5733.2	5837.7	1.91E+10	8.89E+10
	RMSE	75.7	76.4	138178.1	298226.0
	R-squared	0.371	0.218	0.448	0.329
Gradient Boosting	Abs. Error	47.8	196021.2	93547.7	186893.4
	Correlation	0.630	0.426	0.688	0.560
	MSE	4700.9	14489.7	1.70E+10	8.12E+10
	RMSE	68.6	120.4	130301.2	284948.6
	R-squared	0.397	0.182	0.473	0.314
	BEST	GB	RF	GB	RF

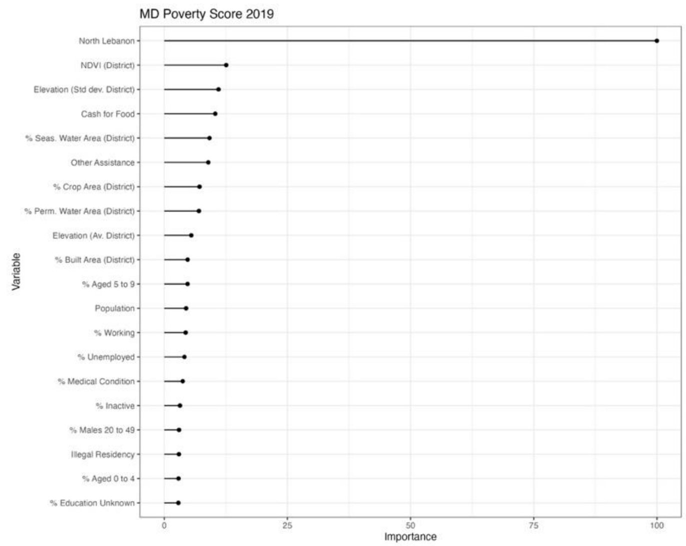
Figure 1. Poverty predictors using gradient boosting for expenditure-based PMT (PMT) versus multidimensional-based PMT (MD-PMT) by year

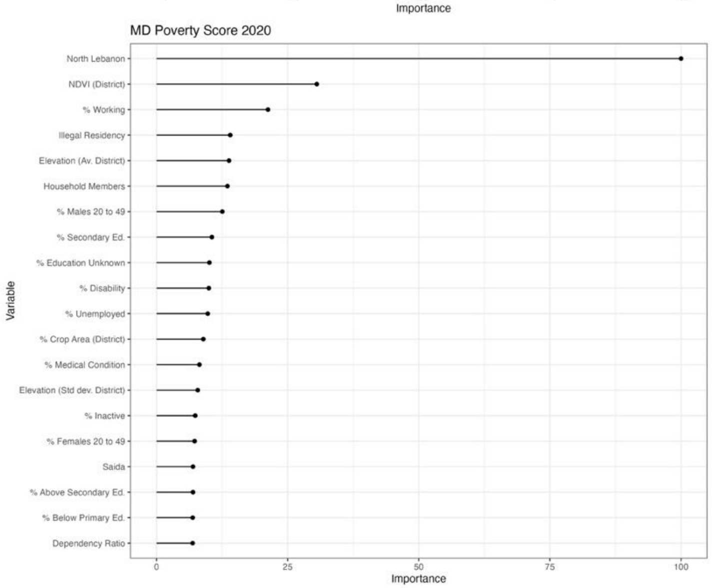
Expenditure-based PMT (PMT)



Multidimensional-based PMT (MD-PMT)







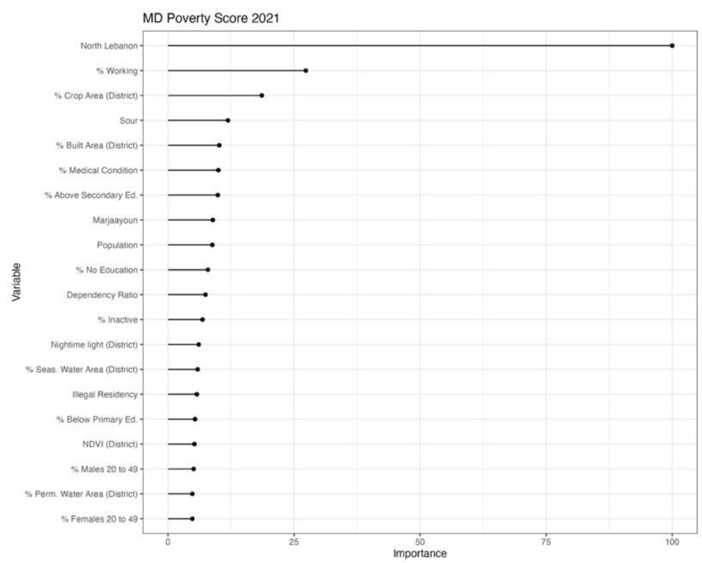


Figure 2A. Poverty based on PMT scores (bottom 30%) by district and by year

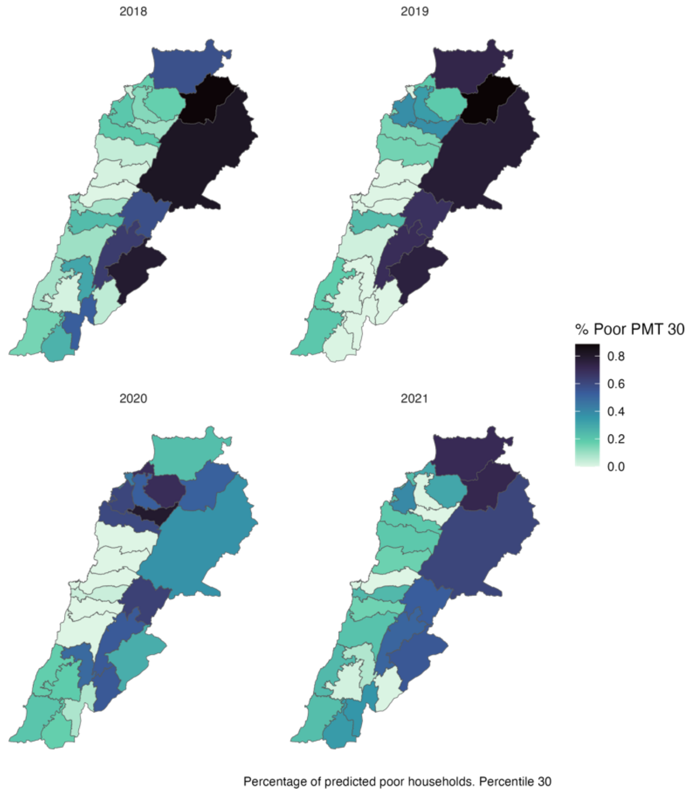


Figure 2B. Poverty based on MD-PMT scores (bottom 30%) by district and by year

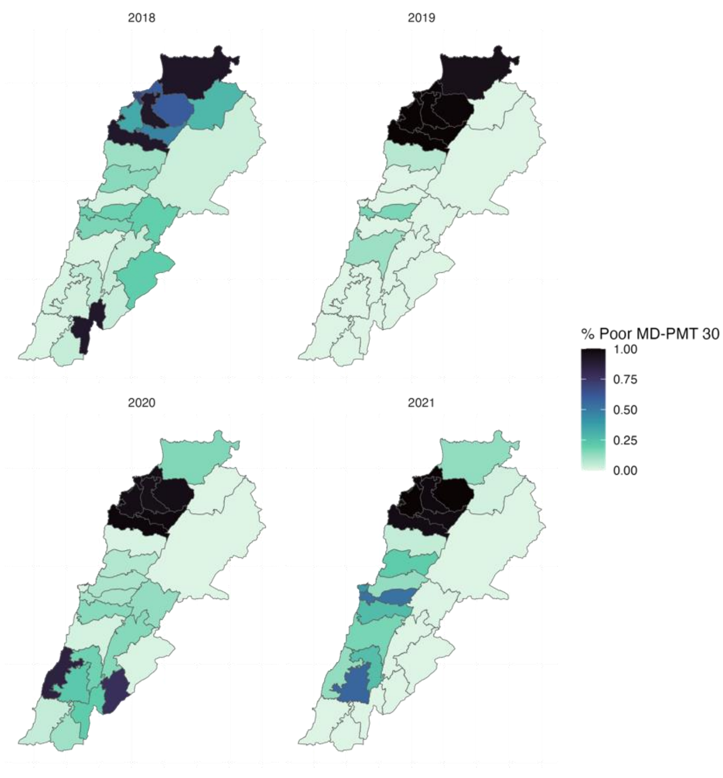


Table 3. Overlap between expenditures and MD poverty scores (real values), and between PMT and MD-PMT scores (predicted values)

Real values

Year	Perc 10	Perc 20	Perc 30	Perc 40	Perc 50
2018	29.9%	40.7%	50.5%	58.4%	66.3%
2019	18.9%	31.0%	41.4%	51.4%	61.1%
2020	24.6%	38.6%	45.2%	54.3%	62.4%
2021	18.3%	30.0%	41.3%	51.1%	59.7%

Predicted values

Year	Perc 10	Perc 20	Perc 30	Perc 40	Perc 50
2018	16.6%	33.8%	45.2%	56.8%	66.1%
2019	0.0%	14.2%	40.4%	52.5%	61.7%
2020	46.3%	50.0%	51.4%	55.4%	61.6%
2021	0.2%	8.0%	19.8%	34.8%	50.1%

Notes: Estimations are based on a distance function that assigned equal weight to each of the three dimensions (expenditures per capita, FCS, and rCSI). Percentages represent the share of households that belonged to the X^{th} percentile of the distribution of the multidimensional-based PMT scores and that were also classified in the X^{th} percentile of the distribution of the expenditure-based PMT scores.

Table 4. Relative efficiency of the MD-PMT and PMT methods at capturing other forms of deprivation

	SMEB			rCSI ≥ 19			FCS ≤ 42			All (SMEB, rCSI, FCS)		
Year	MD-PMT	PMT	Total	MD-PMT	PMT	Total	MD-PMT	PMT	Total	MD-PMT	PMT	Total
2018	64.6%	80.4%	50.8%	67.4%	38.9%	40.4%	38.2%	30.6%	31.9%	21.9%	15.9%	10.3%
2019	60.9%	79.5%	54.8%	75.5%	38.4%	43.0%	29.5%	19.0%	25.8%	14.9%	7.6%	7.5%
2020	93.2%	98.6%	87.8%	59.3%	40.1%	39.3%	69.0%	54.5%	48.3%	38.0%	24.5%	19.0%
2021	86.4%	98.0%	84.6%	78.3%	35.3%	47.3%	53.2%	38.6%	42.3%	36.1%	14.7%	18.7%

	School attendance			Cooking Fuel			Electricity			Shelter Crowdedness		
Year	MD-PMT	PMT	Total	MD-PMT	PMT	Total	MD-PMT	PMT	Total	MD-PMT	PMT	Total
2018	33.9%	43.6%	28.2%	6.7%	4.0%	6.2%	45.4%	40.6%	40.2%	34.3%	41.6%	32.2%
2019	29.3%	36.8%	29.7%	14.0%	16.5%	13.5%	29.7%	34.3%	27.7%	26.5%	37.3%	28.9%
2020	34.0%	44.8%	29.4%	22.2%	24.8%	17.4%	54.9%	47.7%	38.4%	22.4%	30.3%	23.4%
2021	14.7%	18.0%	13.0%	13.2%	16.9%	13.9%	44.3%	40.5%	39.0%	18.2%	29.9%	19.9%

	Sanitation			Water			Security		
Year	MD-PMT	PMT	Total	MD-PMT	PMT	Total	MD-PMT	PMT	Total
2018	41.0%	38.2%	31.6%	12.7%	11.5%	11.8%	2.3%	1.8%	3.2%
2019	34.8%	34.0%	27.6%	18.4%	11.2%	13.2%	10.1%	12.6%	13.0%
2020	23.9%	24.1%	24.5%	20.8%	17.3%	14.8%	10.6%	8.2%	9.3%
2021	22.9%	28.3%	24.3%	14.5%	11.4%	12.3%	16.6%	11.3%	14.7%

Notes: Households were classified as poor if their scores were in the lowest 30% of the distribution for either the multidimensional-based PMT score or the expenditure-based PMT. Percentages in columns “MD-PMT” and “PMT" represent the share of these poorest households who were deprived in other indicators of poverty or social welfare. The column “Total” measures the proportion of the whole population of refugees that was deprived in that particular indicator. Thus, it is expected that the poorest households (using both methods) have higher deprivation rates than the average population (“Total”).

Table 5. Comparison of the characteristics of refugee households predicted to be poor according to the MD-PMT and PMT

Variables	Both (N=3,596)	None (N=7,234)	Only MD-PMT (N=3,683)	Only PMT (N=3,683)	p-value
rCSI (#)	24.6 (15.0)	14.8 (12.6)	26.6 (15.0)	12.1 (10.1)	0.000
FCS (#)	47.1 (18.9)	52.5 (20.1)	45.7 (18.3)	54.1 (17.3)	<0.001
Household size (#)	5.95 (1.94)	4.33 (2.19)	4.31 (1.96)	6.25 (2.06)	0.000
Dependency ratio	0.55 (0.18)	0.39 (0.25)	0.42 (0.24)	0.54 (0.19)	0.000
Female Head	0.19 (0.39)	0.13 (0.34)	0.20 (0.40)	0.15 (0.36)	<0.001
% HH members aged 0-4	0.20 (0.18)	0.16 (0.18)	0.17 (0.19)	0.20 (0.17)	<0.001
% HH members aged 5-9	0.20 (0.16)	0.11 (0.15)	0.12 (0.17)	0.18 (0.15)	<0.001
% HH members aged 10-19	0.21 (0.21)	0.16 (0.21)	0.16 (0.21)	0.23 (0.21)	<0.001
% HH members older than 60	0.02 (0.08)	0.04 (0.15)	0.04 (0.16)	0.02 (0.08)	<0.001
% Male members aged 20-49	0.15 (0.10)	0.28 (0.25)	0.21 (0.19)	0.15 (0.10)	0.000
% Female members aged 20-49	0.19 (0.10)	0.20 (0.16)	0.22 (0.17)	0.18 (0.10)	<0.001
% HH members education unknown	0.28 (0.24)	0.21 (0.23)	0.20 (0.22)	0.25 (0.23)	<0.001
% HH members no education	0.18 (0.26)	0.13 (0.25)	0.18 (0.27)	0.22 (0.28)	<0.001
% HH members primary education	0.27 (0.24)	0.21 (0.25)	0.23 (0.26)	0.27 (0.23)	<0.001
% HH members secondary education	0.06 (0.11)	0.13 (0.21)	0.10 (0.18)	0.07 (0.12)	<0.001
% HH members above secondary education	0.02 (0.08)	0.09 (0.21)	0.06 (0.16)	0.02 (0.08)	<0.001
% HH members inactive	0.22 (0.20)	0.26 (0.25)	0.28 (0.26)	0.23 (0.18)	<0.001
% HH members studying	0.01 (0.05)	0.01 (0.06)	0.01 (0.05)	0.01 (0.06)	0.004
% HH members working	0.10 (0.12)	0.24 (0.26)	0.18 (0.20)	0.10 (0.11)	0.000
% HH members unemployed	0.09 (0.14)	0.08 (0.19)	0.09 (0.19)	0.07 (0.12)	<0.001
% HH members with disability	0.06 (0.12)	0.05 (0.15)	0.08 (0.17)	0.04 (0.10)	<0.001
% HH members with medical condition	0.14 (0.19)	0.15 (0.25)	0.21 (0.27)	0.12 (0.17)	<0.001
Disabled Head	0.11 (0.31)	0.07 (0.25)	0.11 (0.32)	0.07 (0.26)	<0.001
Disabled dependent member	0.12 (0.33)	0.07 (0.26)	0.10 (0.30)	0.10 (0.30)	<0.001
Single Parent	0.02 (0.14)	0.09 (0.28)	0.05 (0.22)	0.02 (0.14)	<0.001
% Illegal residency	0.72 (0.38)	0.62 (0.42)	0.68 (0.40)	0.69 (0.38)	<0.001
Governorate [number (percentage)]					0.000
Akkar	899 (25.0%)	285 (3.94%)	372 (10.1%)	349 (9.48%)	
Baalbek-El Hermel	179 (4.98%)	427 (5.90%)	11 (0.30%)	1120 (30.4%)	
Beirut	46 (1.28%)	1192 (16.5%)	277 (7.52%)	67 (1.82%)	
Bekaa	226 (6.28%)	552 (7.63%)	36 (0.98%)	1126 (30.6%)	
El Nabatieh	316 (8.79%)	1380 (19.1%)	280 (7.60%)	388 (10.5%)	
Mount Lebanon	334 (9.29%)	2228 (30.8%)	700 (19.0%)	236 (6.41%)	
North Lebanon	1365 (38.0%)	199 (2.75%)	1804 (49.0%)	7 (0.19%)	
South Lebanon	231 (6.42%)	971 (13.4%)	203 (5.51%)	390 (10.6%)	
Received WFP cash for food	0.85 (0.36)	0.44 (0.50)	0.49 (0.50)	0.86 (0.34)	0.000
Received MPC	0.70 (0.46)	0.32 (0.47)	0.40 (0.49)	0.72 (0.45)	0.000
Received other monetary assistance	0.76 (0.43)	0.54 (0.50)	0.55 (0.50)	0.70 (0.46)	<0.001
Child not attending school	0.37 (0.48)	0.18 (0.38)	0.21 (0.40)	0.31 (0.46)	<0.001
Cooking fuel	0.15 (0.36)	0.11 (0.31)	0.12 (0.33)	0.15 (0.36)	<0.001
Electricity	0.44 (0.50)	0.30 (0.46)	0.42 (0.49)	0.34 (0.47)	<0.001
Shelter crowdedness	0.33 (0.47)	0.22 (0.41)	0.20 (0.40)	0.33 (0.47)	<0.001
Sanitation	0.30 (0.46)	0.23 (0.42)	0.29 (0.45)	0.29 (0.45)	<0.001
Water	0.15 (0.36)	0.12 (0.32)	0.16 (0.37)	0.11 (0.31)	<0.001
Insecurity	0.09 (0.28)	0.11 (0.31)	0.12 (0.32)	0.10 0.29)	<0.001

Notes: This table compares the characteristics of the households that fall into four groups: both (meaning they were classified as poor using both methods to predict poverty; none (meaning they were not classified as poor according to the predictions of either method); and those who were classified as poor according to only one of the two methods.

Table 6. A comparison of exclusion errors across the two methods comparing the real (expenditure or MD poverty score) with the predicted values (PMT or MD-PMT)

When poverty is measured as multidimensional poverty (Real values)						
	MD-PMT (Predicted values)			PMT (Predicted values)		
Year	Perc 30	Perc 40	Perc 50	Perc 30	Perc 40	Perc 50
2018	*18.9%*	*26.8%*	*35.0%*	27.8%	36.0%	42.7%
2019	*17.6%*	*24.2%*	*32.7%*	29.8%	38.2%	47.7%
2020	*20.1%*	*26.4%*	*31.9%*	26.9%	36.1%	44.9%
2021	*17.6%*	*24.1%*	*30.6%*	32.4%	41.6%	49.5%
When poverty is measured in terms of expenditures (Real values)						
	MD-PMT (Predicted values)			PMT (Predicted values)		
Year	Perc 30	Perc 40	Perc 50	Perc 30	Perc 40	Perc 50
2018	24.8%	31.9%	39.0%	*19.9%*	*25.6%*	*28.9%*
2019	28.9%	36.2%	44.2%	*22.1%*	*27.8%*	*33.2%*
2020	22.9%	32.8%	41.5%	*20.9%*	*27.3%*	*32.2%*
2021	30.5%	40.0%	47.8%	*21.9%*	*26.9%*	*32.1%*

Notes: Assumes equal weights for each dimension included in the multidimensional-based PMT score. Percentages represent the proportion of households predicted to be non-poor while, the real value of their score (multidimensional poverty score in upper panel and expenditure level in lower panel) indicate that they are in fact poor.

Figure 3. Poverty based on MD-PMT (bottom 30%) by district and by year using 50/25/25 weighting scheme

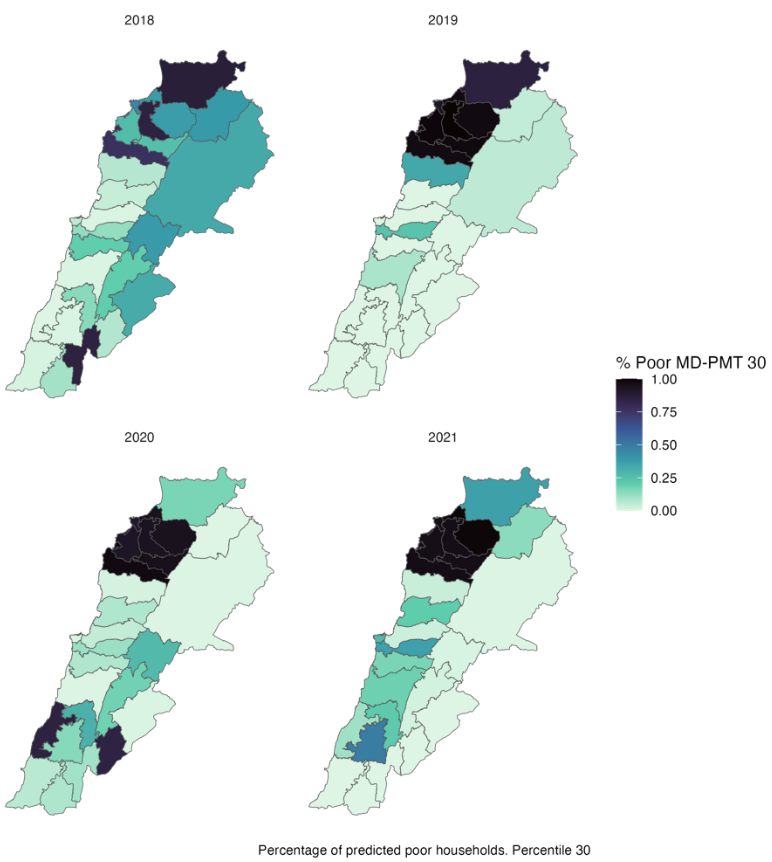


Table 7. Overlap between expenditures and MD poverty scores (real values), and between PMT and MD-PMT (predicted values) using 50/25/25 weighting scheme

Real values

Year	Perc 10	Perc 20	Perc 30	Perc 40	Perc 50
2018	38.8%	49.1%	57.6%	66.2%	73.2%
2019	25.6%	37.6%	47.8%	57.6%	68.1%
2020	27.1%	43.7%	50.6%	60.0%	66.7%
2021	21.2%	34.2%	46.8%	56.3%	64.3%

Predicted values

Year	Perc 10	Perc 20	Perc 30	Perc 40	Perc 50
2018	22.2%	44.4%	56.6%	67.9%	76.0%
2019	0.0%	27.8%	43.5%	61.9%	72.6%
2020	48.5%	52.1%	56.5%	60.5%	67.8%
2021	0.2%	10.6%	28.7%	44.4%	57.1%

Notes: Estimations are based on a distance function that assigned a weight of 50% to expenditures per capita and 25% to food consumption score (FCS) and reduced coping strategies index (rCSI).

Appendix

Figure A1. Distribution of Euclidean, Manhattan, and Minkowski distance formulas

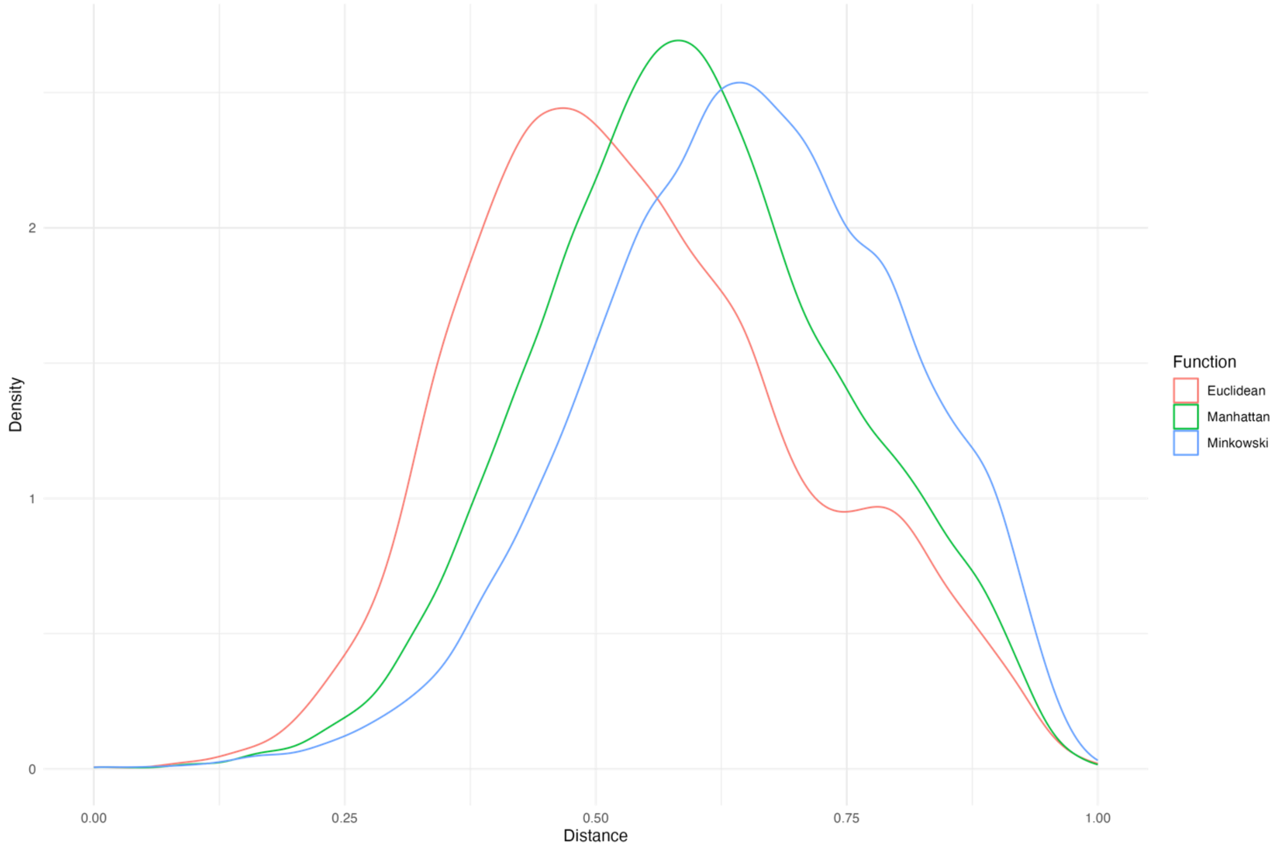
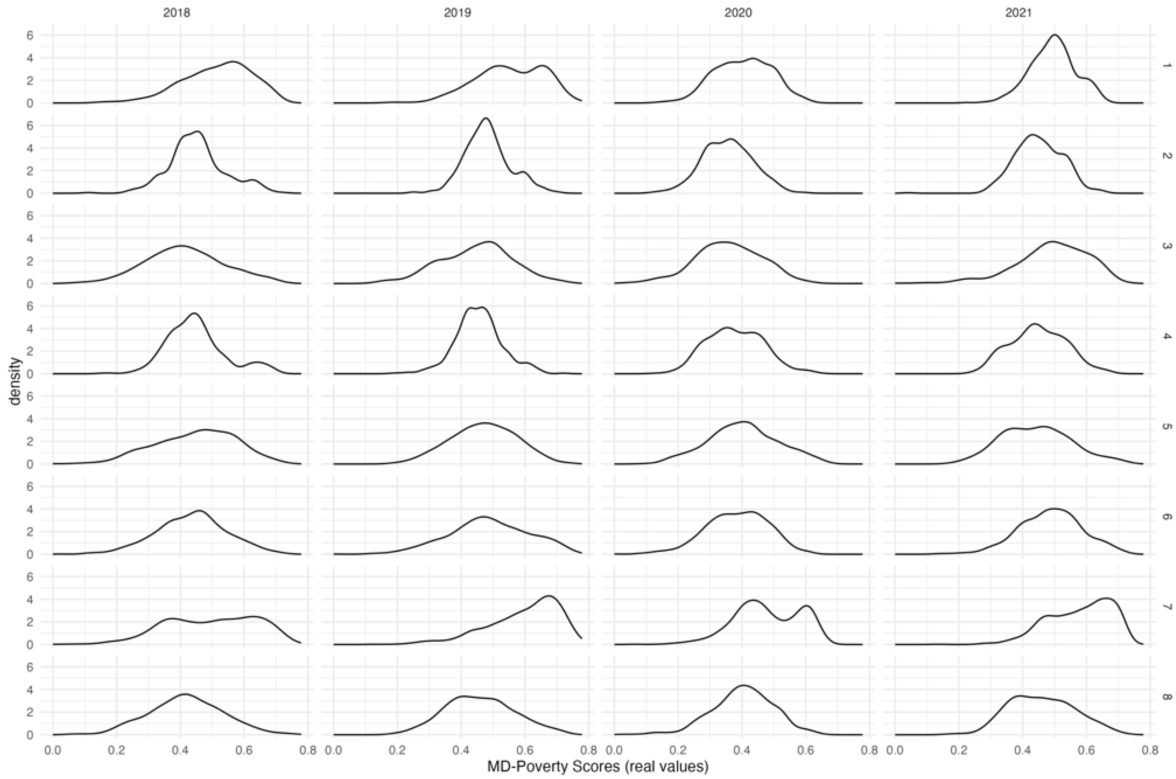


Figure A2. Distribution of the MD poverty scores and MD-PMT scores by year and governorate (real vs. predicted values)



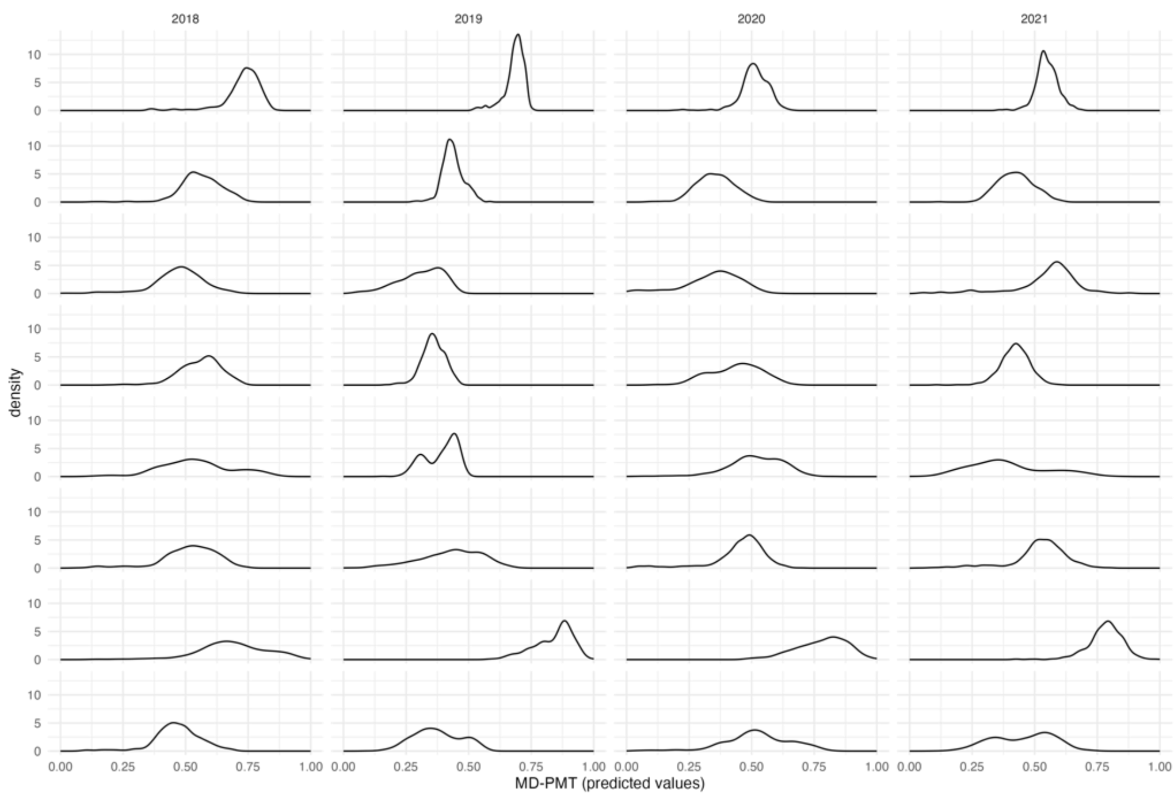


Figure A3. Distribution of the dimensions used to construct the MD poverty scores by year and governorate

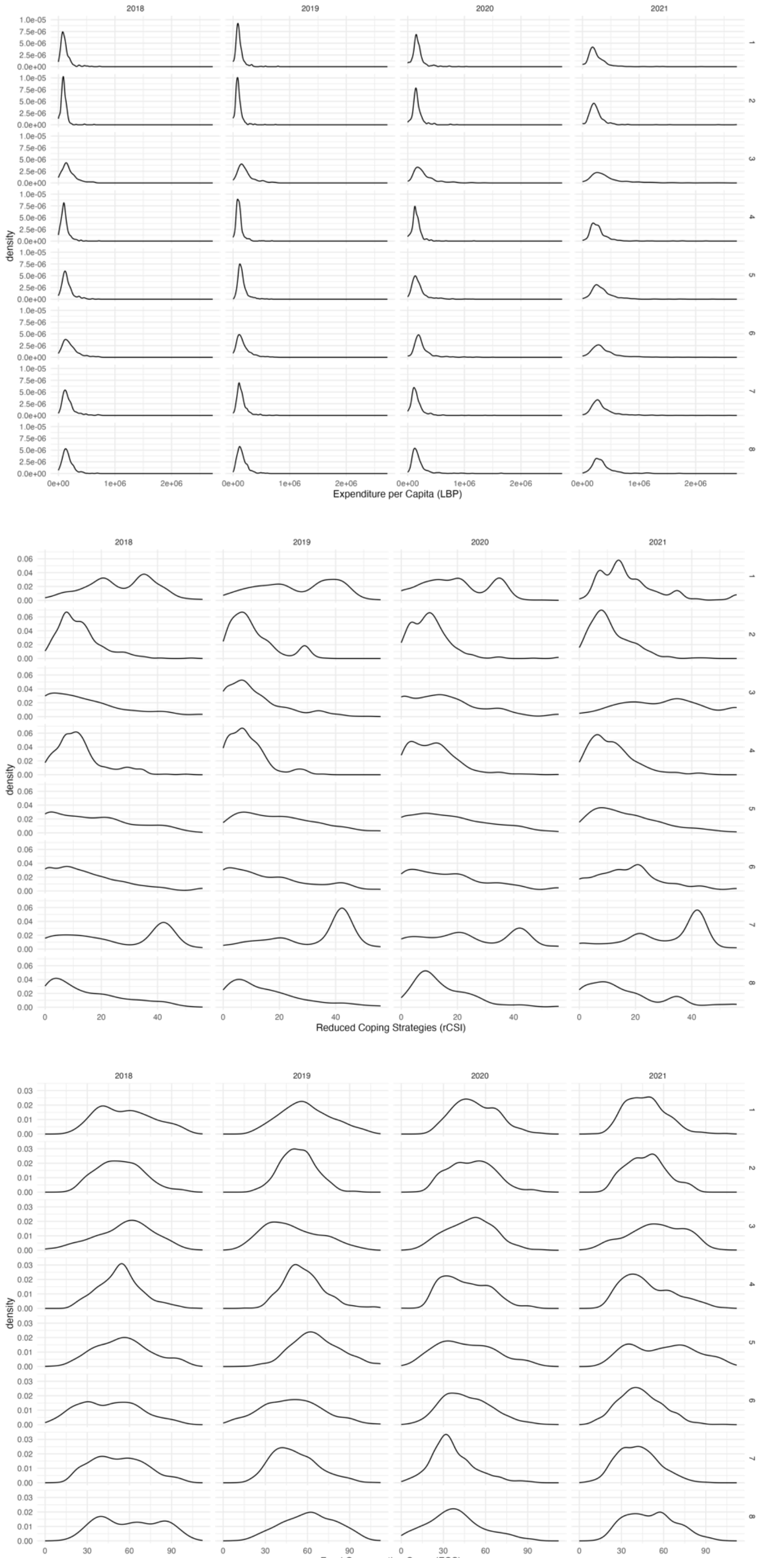


Figure A4. Poverty based on expenditures per capita (bottom 30%) by district and by year

Figure A5. Poverty based on MD poverty scores (bottom 30%) by district and by year

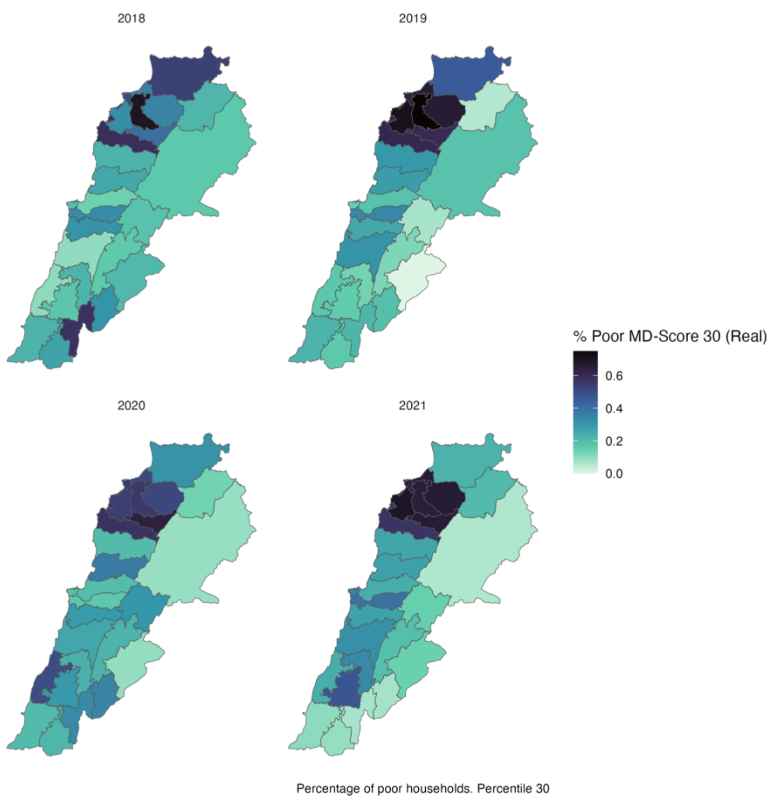


Table A1. Variable definitions

Variables	Definitions
Main variables	
Exp per capita	Expenditures per capita in Lebanese Pounds (LBP)
rCSI	Reduced food coping strategies index (rCSI) measures the strategies that households use to cope with the lack of food and the severity of the strategies used to compare the hardship faced by households due to a shortage of food. The index ranges from 0 (no coping strategies) to 56 (severe level of coping strategies), with higher scores indicating more food coping strategies are being used. Households are classified as having a low (0-3), medium (4-18), or high ($\geq$19) rCSI.
FCS	The Food Consumption Score (FCS) measures the diversity and frequency of households' diets in the week prior to the survey. Scores range from 0 to 112, with lower scores indicating less diet diversity; the FCS is grouped into three categories: acceptable (>42), borderline (28-42), and poor (<28)
Covariates	
Household size	Number of household members
Household size squared	
Dependency ratio	Ratio of dependent household members (below 15 or above 60 years of age) relative to total household members
Female Head	=1 if female headed household
% HH members aged 0-4	Percentage of children aged 0 to 4 in each household
% HH members aged 5-9	Percentage of children aged 5 to 9 in each household
% HH members aged 10-19	Percentage of household members aged 10 to 19 in each household
% Male members aged 20-49	Percentage of male adults aged 20 to 49 in the household
% Female members aged 20-49	Percentage of female adults aged 20 to 49 in the household
% HH members older than 60	Percentage of household members aged 60 and above
% HH members education unknown	Percentage of household members who do not report any educational level
% HH members no education	Percentage of household members who did not go to school
% HH members primary education	Percentage of household members who completed primary education
% HH members secondary education	Percentage of household members who completed secondary education
% HH members above secondary education	Percentage of household members with high school, technical, or college diploma
% HH members working	Percentage of household members who are working
% HH members unemployed	Percentage of household members who are unemployed
% HH members inactive	Percentage of household members who are inactive
% HH members studying	Percentage of household members who are receiving education online or going to school/university or both
% HH members with disability	Percentage of household members with any disability (seeing, hearing, walking, etc.)
% HH members with medical condition	Percentage of household members with a chronic illness or unable to care for themselves
Disabled Head	=1 if the head has a disability
Disabled dependent member	=1 if at least one member of the household other than the head has a disability
Single Parent	=1 if the household head is a single parent
% Illegal residency	Percentage of household members aged 15 or older who do not have legal residency in Lebanon
Received MPC	=1 if the household received multi-purpose cash in the 6 months prior to the survey
Received WFP cash for food	=1 if the household received cash for food in the 6 months prior to the survey
Received other monetary assistance	=1 if the household received any other cash assistance in the 6 months prior to the survey
Governorate	Fixed effects for the 8 governorates in Lebanon
District	Fixed effects for the 26 districts in Lebanon

Table A1. Variable definitions (contd.)

Other variables	
Survival Minimum Expenditure Basket (SMEB)	=1 if the household's monthly expenditures per capita is below the Survival Minimum Expenditure Basket (SMEB) cutoff. This cutoff varies by year. For 2018 and 2019, it was equivalent to 87 USD; for 2020, it was equal to 308,722 LBP; and for 2021, it was equal to 490,028 LBP
rCSI ≥ 19	=1 if the Reduced Coping Strategies Index (rCSI) is greater than or equal to 19, indicating a "high" number of food coping strategies are being used
FCS ≤ 42	=1 if Food Consumption Score (FCS) score is less than or equal to 42, indicating "poor" diet diversity that is at an unacceptable level (poor and borderline food consumption)
Child not attending school	=1 if household has a child who is of school age (5 to 14 years of age) who is not attending school
Cooking fuel	=1 if household does not have access to electric or gas stove and cooks only with dung, wood, or charcoal
Electricity	=1 household does not have access to electricity or has access for less than 16 hours
Sanitation	=1 if household does not have access to basic sanitation (i.e., no access to flushed toilets or improved pit latrines with a cement slab, and are not sharing the toilets with other households)
Shelter crowdedness	=1 if household is living in an overcrowded shelter with less than 4.5m^2 per person
Water	=1 if household does not have access to clean drinking water
Insecurity	=1 if a member of the household has experienced any form of insecurity (robbery, extortion, harassment, kidnapping, etc.)
Geospatial variables	
Elevation (Ave.)	Mean district elevation
Elevation (Std. dev)	Standard deviation of elevations in the district
Built Area	Average fraction coverage of built-up area was calculated for each district using the years 2018 and 2019
Crop Area	Average fraction coverage of crop covered area was calculated for each district using the years 2018 and 2019
Permanent Water Area	Average fraction coverage of permanent water area was calculated for each district using the years 2018 and 2019
Seasonal Water Area	Average fraction coverage of seasonal water area was calculated for each district using the years 2018 and 2019
NDVI	Normalized Difference Vegetation Index (NDVI) is a standardized measure of healthy vegetation and how sensitive vegetation in a particular area may be to drought (agriculture); the average NDVI was calculated for each district using the years 2018, 2019, 2020, and 2021.
Night Lights	Average nighttime light intensity was calculated for each district using the years 2018, 2019, 2020, and 2021.
Population	Average total population was calculated for each district using the years 2018, 2019, and 2020; based on the population counts taken from the WorldPop adjusted to match the UN estimation count

Sources: 2018, 2019, 2020, 2021 Vulnerability Assessment of Syrian Refugees (VASyR).