ERF Working Papers Series

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Economic Research Forum
منتدى البحوث الاقتصادية

Working Paper No. 1472
April 2021

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We wish to thank Jad Ghosn and Raffi Kouzoudjian, Information Management Officers of UNHCR, for their kind assistance with the data and support of this project. We also thank Andrew Greenlee (University of Illinois at Urbana-Champaign) for assistance and input on earlier work related to this project. We are grateful to Ruba Cheaib at the World Food Programme and an anonymous reviewer at the Economic Research Forum (ERF) for helpful comments. Finally, we thank the Illinois Global Institute (IGI) and the Center for South Asian and Middle Eastern Studies (CSAMES) at the University of Illinois at Urbana-Champaign for their financial support under the Migration and Refugees in Regional and Global Perspective Initiative. Any errors or omissions are the responsibility of the authors.

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First published in 2021 by
The Economic Research Forum (ERF)
21 Al-Sad Al-Aaly Street
Dokki, Giza
Egypt
www.erf.org.eg

Abstract

This study uses vulnerability assessment data collected by the UNHCR, WFP, and UNICEF from Syrian refugees in Lebanon, a country that hosts an estimated 1.5 million refugees from neighboring Syria and the highest per capita proportion of refugees in the world. The data are used to construct a multidimensional livelihood index (MLI) to identify refugee households who are currently poor. The MLI is then used to assess households' vulnerability to future poverty using a 3-stage Feasible Generalized Least Squares (FGLS) model. Our findings support the view that poverty is a dynamic phenomenon and not a static condition. The analysis allows us to identify more clearly which households and geographical locations are more vulnerable to experiencing prolonged poverty. This study is among the first to adapt the multidimensional poverty framework to the context of protracted forced displacement. It does this using a forward-looking approach to identify who, where, and how to target humanitarian assistance and development interventions more optimally, to prevent rather than simply alleviate immediate poverty.

Keywords: multidimensional poverty, poverty measurement, vulnerability, economic livelihoods, refugees, humanitarian assistance, Middle East and North Africa.
JEL Classifications: I3, I32, I38, O1, O53, R23, H1.

1. Introduction

The last decade has witnessed an exponential rise in global forced displacement as the numbers of persons fleeing conflict, violence, and persecution have almost doubled since 2010, reaching historically high levels. According to the United Nations High Commissioner for Refugees (UNHCR, 2020), there are currently close to 80 million forcibly displaced persons (FDPs) within or outside the borders of their country, with many stuck in long-lasting displacement situations. After losing assets and livelihoods, these populations face mounting socioeconomic hardships that compromise their ability to meet their basic needs. The humanitarian response to such large-scale crises has traditionally been handled by multilateral organizations such as the UNHCR, the World Food Programme (WFP), and the United Nations Children's Fund (UNICEF), which provide protection and assistance to FDPs. Despite overall increases in humanitarian funding, gaps between resources and needs have been growing, thus constraining assistance programs and challenging targeting mechanisms (ALNAP, 2018; Verme & Gigliarano, 2019).

As forced displacement has become increasingly protracted, the humanitarian system's capacity is reaching its limits both in terms of funding and action.[4] The relief response focused on alleviating suffering and addressing immediate needs, mainly through cash-based assistance, has proved insufficient to effectively tackle prolonged and complex displacements. Concerns about the development challenges posed by such crises have been on the rise, calling for more sustainable ways to support the FDPs via a longer-term perspective (OCHA et al., 2015; UNHCR, 2018; World Bank, 2017). The international community has lately placed forced displacement at the center of global priorities and emphasized the need to connect the humanitarian work with broader development and resilience-building agendas. This movement has been largely driven by the Syrian refugee crisis, one of the worst humanitarian crises of our time, which has triggered high-level policy discussions and multilateral agreements that have pushed for a paradigm shift in the humanitarian response.[5]

This study adopts a comprehensive approach that goes beyond responding to the short-term monetary needs of FDPs towards more sustainable solutions that focus on development and long-term resilience. Our analysis uses data collected from Syrian refugees in Lebanon, a country that hosts an estimated 1.5 million refugees from neighboring Syria.[6] 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 (Government of Lebanon & United Nations,

[4] The UNHCR defines the protracted refugee situation as one in which 25,000 or more refugees from the same nationality have been in exile for at least five consecutive years in a given host country. Globally, it was estimated that about 77% of refugees were in a protracted situation at the end of 2019 (UNHCR, 2020).

[5] Most actions were launched in 2016 (after the Syrian refugee crisis reached Europe) including: The *Supporting Syria and the Region* conference, the *World Humanitarian Summit*, and the *New York Declaration for Refugees and Migrants.* The latter, which was adopted unanimously by the UN member states, initiated a global commitment to refugee protection and led to the development of the *Global Compact on Refugees (GCR)* in 2018. For more information, see https://www.unhcr.org/584689257.pdf and https://www.alnap.org/system/files/content/resource/files/main/refugee-compacts-report.pdf.

[6] The massive influx of Syrian refugees has put considerable pressure on Lebanon's economy and infrastructure, weakening an already fragile country pushed recently to the brink of collapse.

2020). Over the years, humanitarian support has been primarily provided by UNHCR, WFP, and UNICEF, which have jointly set up an annual household survey to better understand the socioeconomic conditions of Syrian refugees in Lebanon. The *Vulnerability Assessment of Syrian Refugees (VASyR)* is a needs-based framework that enables these agencies to identify which of the most economically vulnerable families to target with basic cash and food assistance.[7] It is used, for instance, to construct a formula that predicts families' expenditures based on a set of demographic and socioeconomic characteristics,[8] which is in turn used to create a vulnerability score for each refugee family registered in the UNHCR's *ProGres/EfA* database.[9] Due to severe funding shortages, not all families scoring below a certain cutoff are included in the aid programs. Rather, beneficiaries are selected, starting from those with the lowest scores upward until funding limits have been reached (Chaaban et al., 2020; Government of Lebanon & United Nations, 2020).[10] Additionally, the *VASyR* data have been used as a tool for planning broader interventions in key "sectors" such as education, health, shelter, water, and sanitation, in partnership with national and international organizations and development agencies, namely the UNDP. As donors' contributions continue to fall short of the requirements for adequate support programs, it has become increasingly critical to: (1) ensure the most efficient channeling of available resources, and (2) provide stronger evidence and justification for larger funding appeals. Fundamentally, the attainment of these objectives is dependent on well-grounded targeting strategies.

In this study, we propose an approach that can serve as a guiding tool for both humanitarian actors and development partners to determine "who, where, and how to support" Syrian refugees in Lebanon and how to enhance coordination between them and with donors. So far, efforts to assess households' status and sector-specific issues have been fragmented and more emphasis has been put on refining the targeting mechanisms based on unidimensional monetary measures of current welfare.

The targeting strategy proposed in this paper adopts a multidimensional framework to measuring livelihood status, which follows the widely adopted multidimensional poverty index (MPI)

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[7] The most economically vulnerable families receive food assistance from the WFP ($27 per family member per month), along with multipurpose cash assistance ($175 per family per month) provided by the UNHCR or WFP. Other economically vulnerable families only receive food assistance. In 2018, these food and cash assistance grants were worth 40,000 LBP and 260,000 LBP, respectively.

[8] Using a proxy means test (PMT) methodology, whereby household's expenditure is considered as a proxy for economic vulnerability, the formula is constructed and annually updated by regressing expenditure on various combinations of relevant demographic and socio-economic variables from the most recent *VASyR* survey data. The best fitting model results in an equation that includes explanatory factors with their corresponding regression coefficients. The equation is in turn applied to variables from administrative data to approximate families' expenditure levels and determine their vulnerability score.

[9] The UNHCR's *ProGres/EfA* is the main case management repository used to record, verify, and update information on the Syrians who arrive in Lebanon and officially register as refugees with UNHCR, under a given case number. Thus, a "case" refers to a group of people, who are registered together as one unit in *ProGres/EfA* (usually the immediate family). It commonly represents a "household" as defined by VASyR, which is the group of people who live under the same roof, share the same expenses, and eat from the same pot. However, in some instances, a household could be composed of more than one case. It could also include members who are not registered with the UNHCR.

[10] While both WFP and UNHCR adopt a bottom-up approach, UNHCR adds a geographical layer, whereby funding is allocated by region and selection focuses on the most vulnerable families up until the region's quota has been reached.

methodology proposed by Alkire and Foster (2011). We use micro-level data from the 2018 *VASyR* survey to construct a multidimensional livelihood index (MLI) to identify which Syrian refugee households are currently poor. We test the scope and reliability of our measure to various specifications. We then use our MLI to predict refugees' vulnerability to poverty using a forward-looking, cross-sectional approach suggested by Chaudhuri, Jalan, and Suryahadi (2002). Specifically, we estimate a 3-stage Feasible Generalized Least Squares (FGLS) model to predict which households are expected to "fall into" or "out of" multidimensionally poverty in the future. Our findings support the view that poverty is a dynamic phenomenon and not a static condition. The analysis allows us to identify more clearly which households and geographical locations are more vulnerable to experiencing prolonged poverty. This study is among the first to adapt the multidimensional poverty framework to the context of protracted forced displacement. It also is among the first to use a forward-looking approach to identify who, where, and how to target humanitarian assistance and development interventions more optimally, to prevent rather than simply alleviate immediate poverty.

The remainder of this paper is structured as follows. Section 2 discusses the relevant literature and major contributions of this study. It is followed by Section 3, which provides an overview of the data and a description of the demographic and socioeconomic profiles of Syrian refugees in Lebanon. Section 4 focuses on the construction and analysis of the multidimensional livelihood index (MLI). Section 5 describes the empirical methodology used to predict vulnerability to multidimensional poverty. The estimation results are then presented in Section 6. The final section summarizes the key findings and highlights implications for humanitarian and development actors and policymakers involved specifically in the Syrian refugee crisis, and in forced displacement crises in general.

2. Literature Review

2.1 Measuring poverty

Previous studies have looked at the determinants of welfare-related outcomes to measure current poverty levels for households in general and for FDPs such as Syrian refugees in Lebanon and Jordan (Altindag et al., 2020; Chaaban, Ghattas, Irani & Thomas, 2018; Verme et al., 2016; Verme & Gigliarano, 2019). In the broad poverty literature, there are two standard approaches to measure poverty – unidimensional and multidimensional. Most of the studies that have used a unidimensional approach compare a household's consumption expenditures to a poverty line cutoff, which is the lowest cost for a bundle of goods that satisfies a household's most basic needs. Unidimensional instruments are less difficult to construct. They often use assets and proxy means tests, which are relatively easy metrics to collect data and identify which households are most in need of assistance. In the context of FDPs, namely that of Syrian refugees in Lebanon, unidimensional metrics such as consumption and expenditure are used to target recipients of assistance (Altindag et al., 2020). These measures of monetary poverty do not provide sufficient policy guidance with regards to deprivations in other dimensions and can lead to misallocating limited public funds (Alkire & Foster, 2009; Azeem, Mugera, & Schilizzi, 2018). Other approaches have moved beyond monetary measures to include non-monetary measures such as food, housing, and crowding to determine current poverty levels (Chaaban, Ghattas, Irani & Thomas, 2018; Verme et al., 2016; Verme & Gigliarano, 2019). However, even in these cases, using measures that focus on the lack of material resources are not always good proxies of living standards, because individuals often have different needs and face different costs in trying to achieve the same living standards (Hick, 2012). More flexible approaches considering other deprivation factors, besides the lack of resources, are key to developing a better understanding of the multifaceted nature of poverty.

A large and growing body of research now uses multidimensional measures of poverty, particularly in the form of the Multidimensional Poverty Index (MPI) (Alkire & Foster, 2011; Alkire & Santos, 2014). The multidimensional approach, which follows the Townsend (1979) and Sen's capability approach, classifies as poor those households who are deprived in different dimensions of human life, such as health and education, among others. Within this framework, poverty is thus a *"multidimensional"* problem in which poor households are not able to satisfy a minimum level of basic capabilities or opportunities. Further, the multidimensional approach includes only those deprivations that restrict human lives and does not include voluntary restrictions (Hick, 2012). More importantly, it identifies how severe those deprivations are relative to the population, revealing which deprivations are more prevalent amongst the poor relative to the non-poor. As such, the index captures both the *incidence* and *intensity* of poverty and allows for decomposition to show the contribution of each dimension. In certain cases, such as rural areas where information about consumption expenditures is not accurately measured (i.e., when households receive in-kind assistance and do not report this assistance as an expenditure), the multidimensional approach can also provide more accurate measures of poverty (Feeny & McDonald, 2016).

This methodology is currently used by the Oxford Poverty & Human Development Initiative (OPHI) and the UNDP's Human Development Report (HDR) to assess multidimensional poverty in more than 100 countries (UNDP, 2019a, 2019b; UNDP & OPHI, 2020). It also has been adjusted to capture the needs of various countries as an instrument of public policy (Alkire, Kanagaratnam, & Suppa, 2020; OPHI, 2018). Because of its flexibility, the MPI can be decomposed by region or group, which is useful for making comparisons and identifying which segments of the population require specific interventions, especially within the context of FDPs. However, few, if any, studies have applied multidimensional poverty analysis within the context of FDPs.

2.2 Measuring poverty versus vulnerability within the context of FDPs

Assessing poverty and vulnerability among refugees is at the core of the humanitarian response. The aim is to provide protection and assistance on the basis of need. Agencies develop and refine their targeting approaches to efficiently identify "vulnerable" refugees. In this context, "vulnerability" is commonly operationalized as an ex-post measure of welfare and widely used as an eligibility criterion for assistance in anti-poverty programs. With regards to the Syrian refugee crisis in Lebanon, WFP and UNHCR have established cash assistance programs that target the most economically vulnerable households, identified via a proxy means test (PMT) that approximates household expenditures using the most updated administrative data.[11] Despite several practical advantages of PMT methodologies, they have limited accuracy in measuring households' status and do so at only a specific point in time (Kidd & Wylde, 2011). Poverty, however, is not a static phenomenon. In effect, households can fall into poverty and move out of poverty.

Some researchers have suggested alternative models to enhance targeting and distribution of assistance to the Syrian refugees. These studies tend to focus on assessing the current welfare of households and rarely address the long-term needs and development challenges posed by large-scale and protracted displacements. Using data from Lebanon, Chaaban, Ghattas, Irani and Thomas (2018) used current food security status and per capita expenditure to identify the refugee households who were most in need of cash-based food assistance to minimize under-coverage and leakage. Similarly, Verme and Gigliarano (2019) sought to optimize coverage and leakage and improve the targeting and efficiency of a food aid program in Jordan by using Receiver Operating Characteristics (ROC) curves to select the optimal probability threshold for classifying households as currently poor or non-poor. Another study used our same dataset to look at the targeting of a multipurpose cash (MPC) assistance program in Lebanon (Altindag et al., 2020). They proposed a low-cost methodology that used limited administrative data to predict household expenditures with accuracy comparable to that of survey-based models that have used PMT. Despite the valuable contributions of these studies, they remain concentrated on measuring current poverty and none have addressed the long-term concerns associated with the prolonged nature of the refugee crisis.

The only study that we are aware of, which has looked into Syrian refugees' *vulnerability to poverty* as the ex-ante risk of becoming or staying poor, was a joint effort by the World Bank and the UNHCR to "bridge the historical divide between humanitarian and development work" (Verme et al., 2016). Using administrative and survey data from Jordan, Verme et al. (2016) followed the methodology of Chaudhuri, Jalan and Suryahadi (2002) to measure vulnerability to monetary poverty of refugee households, based on the common expenditure indicator. They then considered non-monetary indicators that captured the basic needs of food and housing. Their results showed how non-monetary aspects relate differently with monetary vulnerability and emphasized the partial overlap between monetary poverty and vulnerability, suggesting that measures to alleviate monetary poverty are not equally adequate to address vulnerability to poverty nor non-monetary aspects of vulnerability.

In the development literature, "vulnerability" has been subject to various definitions within different contexts, such as low expected utility, uninsured exposure to risk, or also expected poverty (e.g., Calvo & Dercon, 2013; Feeny & McDonald, 2016; Gaiha & Imai, 2008; Ligon & Schechter, 2003; Ozughalu, 2016; Verme et al., 2016). Within the FDP context, we focus on the latter and define households' vulnerability to future poverty as the ex-ante risk (or probability) of being poor in the future. This definition implies that both poor and non-poor households can be vulnerable. It contrasts with other measures of vulnerability, such as the one used by the OPHI, which classifies households

[11] This mechanism has been adopted by key humanitarian agencies in Lebanon since 2014, in an effort to standardize the targeting system (Battistin, 2016). Recall the PMT methodology these agencies adopted, as explained in Footnote 9.

as vulnerable if their current deprivation scores are between 0.2 and the poverty cutoff of 0.33 (Feeny & McDonald, 2016).

Chaudhuri et al. (2002) and others have more rigorously predicted a household's vulnerability to future poverty. They use a common cross-sectional data approach to predict the probability that households will be poor in future using their characteristics and the volatility of deprivations within the population of households. Their methodology assumes that current measures of poverty can be used to provide reliable estimates of vulnerability to future poverty. The methodology was originally used by Chaudhuri et al. (2002) to estimate vulnerability using a unidimensional measure of poverty – consumption expenditures. However, it has since been applied to measuring vulnerability to food security and food expenditures (Bogale, 2012; Ozughalu, 2016) and more recently to measuring vulnerability to multidimensional poverty (Feeny & McDonald, 2016; Azeem et al., 2018).

Our study belongs to existing literature that combines: (1) the multidimensional approach to poverty outlined by Alkire and Foster (2011) that measures current poverty and (2) the forward-looking approach used by Chaudhuri et al. (2002) that assesses vulnerability to future poverty. We are among the first researchers to fuse these two methodological approaches and apply them to the case of forced displacement, and specifically to the case of the Syrian refugees in Lebanon. There are several advantages to this approach. First, it allows us to identify which refugee households are multidimensionally poor or non-poor, providing a more comprehensive alternative to that of the unidimensional approach, or at a minimum, a reliable complement. Second, it allows us to develop a deeper understanding of the specific deprivations facing refugee populations (i.e., food insecurity, poor health, lack of education, inadequate living standards, social inclusion) and their distribution across geographical locations. Third, we are able to identify the characteristics that are most likely to influence vulnerability and which refugees are vulnerable to future poverty. In this respect, our multidimensional, dynamic approach can assist humanitarian and development agencies in designing and implementing more effective targeting strategies that address both immediate humanitarian needs and longer-term development goals, especially when resources are limited.

3. Data

3.1 Overview of VASyR data

Since 2013, the UNHCR, WFP, and UNICEF have jointly conducted an annual survey that provides an understanding of the socioeconomic conditions and vulnerabilities of Syrian refugees in Lebanon. These UN agencies, actively involved in providing humanitarian support to the refugee families, have implemented the *Vulnerability Assessment of Syrian Refugees (VASyR)* as a needs-based framework to inform interventions and assistance. The *VASyR* is the only nationally representative household survey collecting observed and self-reported data on various dimensions of the livelihoods of the refugees, including food consumption, health, shelter, education, financial resources, and personal security, among others (UNHCR, UNICEF, & WFP, 2017, 2018).

This study uses micro-level data from the sixth wave of the *VASyR* survey, which was the most recent data available to us at the time this study was initiated. Between April and May of 2018, survey data were collected from Syrian refugee households who were randomly selected from the 26 administrative districts across the eight governorates of Lebanon.[12] 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.[13] 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) for a complete overview of the sampling and survey methodology.

We conducted our analysis at the governorate and household levels, with the latter referring to both nuclear and extended family compositions with an average of five members per household.[14] The initial sample included 4,444 households. We focused exclusively on Syrian households, dropping households where the head's nationality was not Syrian. We also dropped from the sample households with heads who were less than 15 years old or who had heads with missing information about their educational attainment. In the end, the final sample size consisted of 4,358 households.

The *VASyR* questionnaires collected detailed information on both individual-level and household-level characteristics. Core survey topics consisted of: (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 (5) coping strategies; and (6) assistance. The latter refers to self-reported information on certain types of assistance received by the household. Given the tendency of survey respondents to underreport assistance to increase the likelihood of being eligible for further assistance, we resorted to a more reliable data source for this information. The *2018 VASyR* data were thus supplemented with data from the *Refugee Assistance Information System (RAIS)* linked to the UNHCR's *ProGres/EfA* database.[15] These two centralized systems compile information on the types, amounts, and duration of assistance provided to registered cases by the different humanitarian agencies.

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[12] See the map of Lebanon in Figure 1 for a visualization of the country's administrative divisions. Note that each of the eight governorates includes two or more districts, except for Beirut and Akkar governorates, with only one district. To ensure larger sample sizes, Beirut and Akkar were divided each into three sub-areas that were treated as "districts." In total, the sample for the *2018 VASyR* was selected from 30 districts covering the 26 administrative districts (shown on the country's map) plus two additional "districts" for each of Beirut and Akkar (UNHCR, UNICEF, & WFP, 2018).

[13] Recall that the UNHCR classifies refugees according to case numbers, where a "case" refers to the group of people registered together as one unit in *ProGres/EfA*. It contains demographic and socio-economic characteristics on the registered refugees and assists the UNHCR in providing protection and assistance services. Once selected to be included in the VASyR, cases are visited by UNHCR's partner organizations, who interview the adult member (usually the household head) who can provide the most accurate information about the entire household.

[14] Recall also the definition for a "household," as defined in Footnote 10.

[15] *RAIS* is used by UNHCR, but also other humanitarian partners and donors, to enhance effectiveness in the tracking of assistance overall, including distribution, coordination, and accountability. To this end, RAIS includes information on other cash and non-cash assistance received by the refugees. The following link provides an overview of the UNHCR's

We used the merged data to construct our multidimensional livelihood index (MLI) and to identify households who were currently in poverty at the time of the survey. A description of all the variables included in our study and how they were constructed is presented in Appendix A1.

3.2 Descriptive profile of refugees

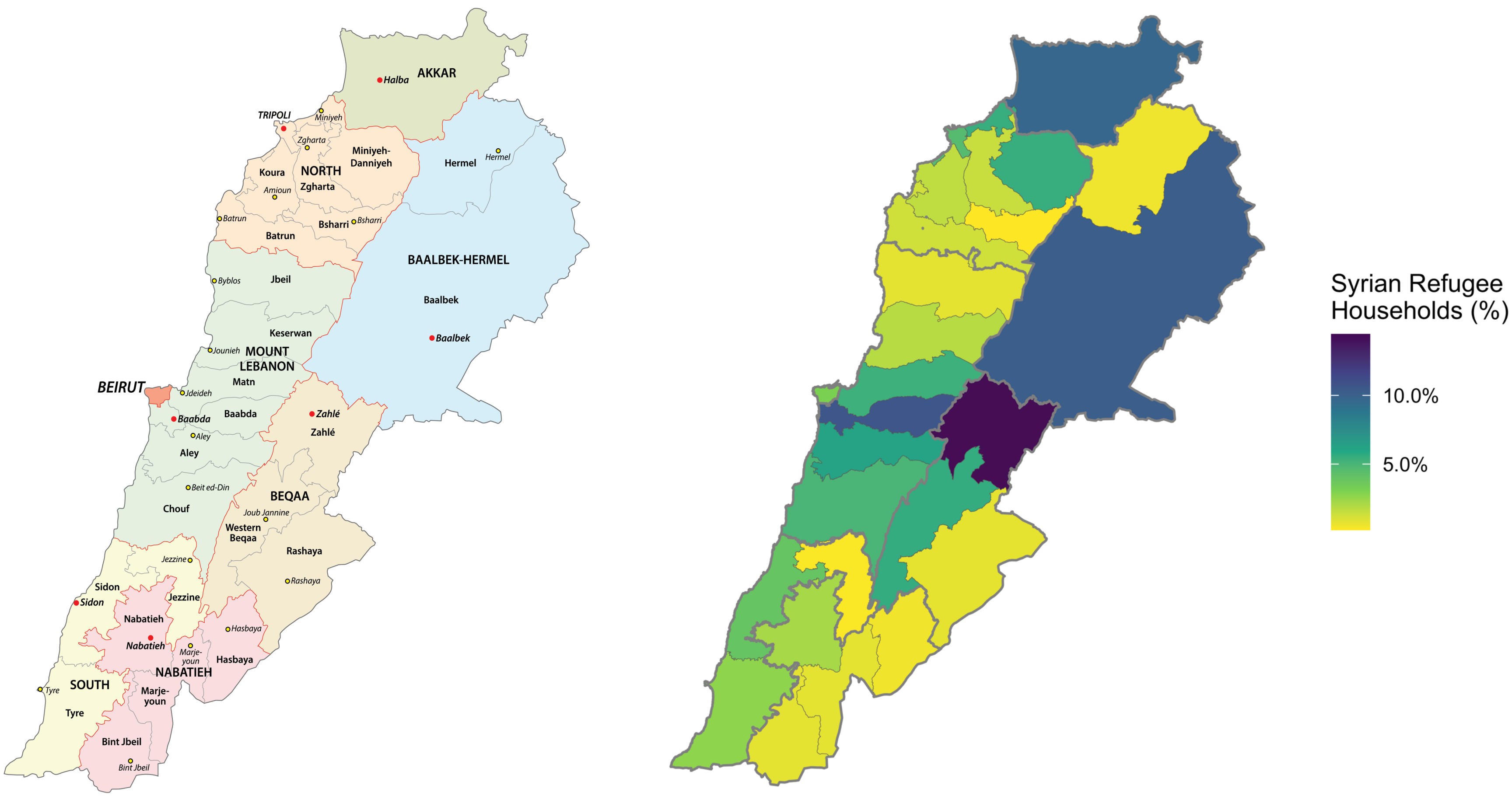
Table 1 presents a demographic and socioeconomic profile of the Syrian refugee households for Lebanon as a whole and for each of the eight governorates. The top row indicates how the sample of 4,358 households was spread across the governorates. However, these numbers do not accurately reflect the distribution of the Syrian refugee population in Lebanon, due to the sampling methodology adopted which results in larger sample sizes for governorates with higher numbers of districts. A more consistent overview of the geographical distribution of the population is therefore presented in Figure 1, showing the percentages of Syrian refugees per district after assigning the weights.

Note that Lebanon's Syrian refugee population is split by several major geographic features of the country. Two major mountain ranges run north-south through the middle of the country separating a western coastal region from the Bekaa valley, which is then separated from eastern Lebanon, portions of which border Syria. Lebanon's regions are characterized by stark economic and social disparities. While development efforts have been concentrated in the capital city of Beirut and its suburbs, the northern, eastern and southern areas of the country remain marginalized and underdeveloped. These peripheral regions tend to have weak infrastructure and limited access to opportunities, resulting in highest levels of unemployment and poverty.[16] Administratively, the country is split into eight governorates. Three governorates – Akkar, Baalbek-El Hermel, and Bekaa – border Syria. The confluence of this physical and administrative geography results in the Syrian refugee population being primarily split between heavily urbanized Greater Beirut and remote rural areas that abut the Syrian border. At the governorate level, the Mount Lebanon governorate, which surrounds Beirut, contained the highest proportion of Syrian refugees (30.0%) in 2018. Looking at the district level, a sub-geography of the governorates, the highest concentrations of Syrian refugees were found in Zahlé (major district of the Bekaa governorate) which hosted around 14.5% of the Syrian refugee population in Lebanon. Other districts with high concentrations of Syrian refugees included Baabda, Baalbek-El Hermel, and Akkar, which each contained between 9.7% and 10.6% of the Syrian refugee population. These districts are rural and border Syria. The exception is Baabda, which is the major district of the Mount Lebanon governorate, which abuts Beirut. The high proportion of refugees in the Baabda district were characterized primarily by refugees who lived in and around the urban municipalities of

entire *Population Registration and Identity Management Ecosystem (PRIMES)*: https://www.unhcr.org/registration-guidance/chapter3/registration-tools/.

[16] The most recent data on the distribution of poverty based on a 2011/2012 budget survey of Lebanese households reveal that those living in poverty represented 38.0% of the population in the Bekaa region (covering the Bekaa and Baalbek-El Hermel governorates), 36.0% in North Lebanon (including Akkar governorate), and 31.0% in South Lebanon, compared to 16.0% in Beirut and 22.0% in Mount Lebanon (Lebanon Central Administration of Statistics & World Bank, 2015).

Figure 1. Percentage of Syrian Refugees in Lebanon by governorate and district (2018 VASyR, N=4,358)



Sources: *World Atlas (2020)*. Retrieved from https://www.worldatlas.com/maps/lebanon; *2018 Vulnerability Assessment of Syrian Refugees* (VASyR), https://data2.unhcr.org/en/documents/details/67380

Table 1. Descriptive profile of Syrian refugees in Lebanon by governorate (N=4,358)

Variables	**Lebanon N=4,358**	Akkar n=424	Baalbek-Hermel n=333	Beirut n=397	Bekaa n=503	El Nabatieh n=568	Mount Lebanon n=882	North Lebanon n=832	South Lebanon n=419
Head characteristics									
Age of household head (years)	**38.09**	39.67	40.65	37.71	38.53	37.39	37.29	37.87	37.37
Age 15-24	**7.62**	8.96	6.61	5.54	6.96	8.27	7.14	9.38	6.44
Age 25-34	**35.27**	33.02	25.23	37.28	32.21	39.79	39.00	33.29	37.23
Age 35-44	**33.50**	28.07	34.23	34.26	35.19	32.04	32.54	33.53	39.62
Age 45-54	**14.96**	15.33	21.02	15.87	17.69	11.27	14.63	15.14	10.98
Age ≥ 55	**8.65**	14.62	12.91	7.05	7.95	8.63	6.69	8.65	5.73
Education of household head									
Educ: Illiterate	**12.12**	14.62	22.52	9.32	14.51	11.62	8.62	10.22	12.89
Educ: Less than primary	**61.13**	57.78	61.56	52.90	62.03	58.45	63.83	63.58	63.96
Educ: Primary	**16.96**	17.45	9.91	21.91	13.32	20.25	17.35	17.19	15.99
Educ: Secondary to some tertiary	**5.53**	6.60	4.50	8.56	4.37	6.16	5.33	5.29	3.82
Educ: University	**4.27**	3.54	1.50	7.30	5.77	3.52	4.88	3.73	3.34
Female-headed household	**16.13**	21.70	26.73	14.86	20.08	14.08	14.29	13.10	11.22
Married	**86.42**	85.14	79.28	84.13	85.29	88.03	87.98	87.14	89.98
Worked in the last week	**52.64**	46.23	33.33	49.87	35.39	67.78	51.70	58.05	68.50
Household characteristics									
Share of dependents	**43.84**	44.69	45.26	40.16	47.06	45.89	41.75	42.01	46.75
Household's highest education level									
Educ: Illiterate	**3.92**	6.84	7.81	4.03	4.77	3.87	1.81	2.88	3.34
Educ: Less than primary	**51.63**	51.18	61.86	41.31	55.27	50.35	49.21	52.04	55.37
Educ: Primary	**26.32**	24.29	16.82	29.47	22.07	29.75	27.10	28.85	26.73
Educ: Secondary to some tertiary	**11.34**	11.56	8.41	15.37	9.74	10.21	14.63	10.22	8.35
Educ: University	**6.79**	6.13	5.11	9.82	8.15	5.81	7.26	6.01	6.21
Household size (#)	**4.92**	5.04	5.24	4.81	5.10	4.98	4.65	4.82	5.11
% HH members working (15-64 yrs of age)	**57.55**	54.82	39.49	49.37	38.24	73.24	56.32	63.44	75.26
Household resources									
Main income source: Employment	**39.90**	17.22	4.80	76.07	9.54	40.67	60.88	39.54	48.45
Main income source: Assistance	**21.84**	41.98	70.87	2.02	52.88	22.89	0.45	12.86	5.49
Main income source: Borrowing	**15.51**	20.75	19.52	8.56	30.82	7.39	7.26	20.07	14.56
Borrowed money or received credit	**82.31**	71.93	89.79	60.20	91.25	88.20	75.06	89.78	89.50
Expenditures and poverty									
Below SMEB (< $87)	**50.57**	69.10	78.98	37.53	73.56	50.35	34.69	43.15	42.48
SMEB – MEB ($87-$113)	**16.66**	12.50	16.22	16.88	12.72	18.31	15.53	18.75	21.72
MEB – 125% MEB ($114-$142)	**10.95**	8.96	3.00	12.09	5.96	13.20	12.47	13.70	12.41
≥ 125% MEB (≥ $143)	**21.82**	9.43	1.80	33.50	7.75	18.13	37.30	24.40	23.39
Below poverty line (< $3.84/day)	**67.83**	82.55	95.50	55.16	86.68	69.01	50.68	62.62	65.16
Humanitarian assistance									
Received cash for food only	**17.00**	31.84	15.32	17.38	21.87	15.85	7.03	19.47	14.80
Received multipurpose cash (MPC)	**16.50**	18.63	58.26	8.56	35.19	26.41	2.95	5.65	2.86
Received no cash assistance	**66.50**	49.53	26.43	74.06	42.94	57.75	90.02	74.88	82.34
Livelihood coping strategies									
Emergency level coping strategies	**4.82**	3.77	1.20	16.12	0.80	2.46	7.71	2.52	4.53
Crisis level coping strategies	**36.69**	35.85	27.93	35.26	26.24	29.58	45.46	39.06	44.87
Stress level coping strategies	**50.50**	49.06	64.26	37.78	69.18	60.74	34.58	52.52	46.30
No coping strategies needed	**7.99**	11.32	6.61	10.83	3.78	7.22	12.24	5.89	4.30
Expectations about the future									
Hopeless	**20.35**	13.21	14.41	15.87	15.71	23.94	25.85	26.32	13.84
Frequently feeling negative	**30.38**	19.58	46.85	19.65	55.86	26.76	21.88	30.53	30.31
Neutral	**34.44**	54.72	25.53	45.09	20.68	26.58	34.35	31.01	45.11
Optimistic	**14.82**	12.50	13.21	19.40	7.75	22.71	17.91	12.14	10.74

Note: The data were taken from the 6th round of the *2018 Vulnerability Assessment of Syrian Refugees* (VASyR).

Greater Beirut,[17] although they were enumerated within Baabda and other districts in the Mount Lebanon governorate.

With respect to the Syrian refugees' characteristics, Table 1 shows that 68.8% of household heads were between 25 and 44 years of age at the time of the survey, 73.3% had less than a primary level of education, and 86.4% were married. In Akkar, Baalbek-El Hermel, and Bekaa, more than one-fifth of households were headed by women (compared to less than 15.0% in other governorates), and less than one-half of household heads reported having worked in the last week. Across these three governorates, employment income was least likely to be reported as the main source of income. Instead, households reported that assistance and borrowing were their main sources of income. This is in stark contrast to governorates such as Beirut and Mount Lebanon, where 76.1% and 60.9% of households, respectively, reported that their main income source was from employment. Akkar, Baalbek-El Hermel, and Bekaa also had the highest percentages of households (approximately 70.0% or more) reporting that their monthly expenditures per capita were below the threshold for the Survival Minimum Expenditure Basket (SMEB < \$87 USD per month per capita, which was equivalent to 130,000 LBP in 2018 at the time of the survey). On average, about one-half of Syrian refugee households in Lebanon spent less than the SMEB. In Beirut and Mount Lebanon, more than one-third of households appeared in the upper expenditure group, with spending exceeding \$143 USD per month per capita (≥ 125% MEB). In addition, 67.8% of the refugee households were below the poverty line such that household members were living on less than \$3.84 USD per day. Given consumption expenditures and the poverty line statistics, it is not surprising that the percentages of households receiving cash-for-food assistance or multipurpose cash assistance (MPC) were highest for Akkar, Baalbek-El Hermel, and Bekaa when compared to more urbanized governorates such as Beirut and Mount Lebanon. Information was also included in the survey to capture coping strategies used to deal with their current situation. The unfortunate news is that the vast majority of refugees were utilizing some type of coping strategies. Stress level coping strategies (such as spending, savings, selling goods, buying on credit, or incurring debt) were commonly reported in almost all governorates, followed by crisis level strategies (such as the sale of productive assets, the withdrawal of children from school, the reduction of non-food expenses, or the marriage of children under 18 years of age). The percentage of households who had to resort to emergency coping strategies (such as selling house or land, accepting high-risk jobs, involving school children in income activities, or begging) was fairly low except for Beirut, where about 16.1% household reported taking emergency actions. In terms of expectations about the future, the majority of refugee households reported that they frequently felt negative or hopeless (50.7% on average). Only 14.8% reported feeling optimistic, while 34.4% were neutral.

[17] Beirut is the capital of Lebanon. It is the main city of the country and a governorate on its own. Greater Beirut, however, represents the urban agglomeration comprised of the Beirut governorate and several adjacent municipalities from the Mount Lebanon governorate.

4. Construction of the multidimensional livelihood index (MLI)

To construct our multidimensional livelihood index (MLI) within the context of FDPs, we adopted the framework that Alkire and Foster (2011), Alkire, Kanagaratnam, and Suppa (2020), OPHI (2018), and others have used to construct multidimensional poverty indices (MPI) to measure poverty amongst populations in general. As mentioned in the literature review, the MPI provides a more holistic approximation to poverty by calculating a set of indicators that measure deprivations in different dimensions of welfare. The MPI initially proposed by Alkire and Foster (2011) encompasses 3 dimensions (education, health, and living standards) and 12 indicators. Each indicator measures a specific deprivation (e.g., not having access to electricity), which makes the MPI easily interpretable and calculable, as it transforms each variable into a binary response. The MPI calculates how many households are poor or "deprived" (usually known as the headcount ratio), as well as the intensity or severity of the poverty.

We expanded on the MPI proposed by Alkire and Foster (2011) and others previously cited by incorporating and modifying some dimensions and indicators to better suit the case of Syrian refugees in Lebanon. In particular, we added a specific dimension for employment since under- and unemployment are critical to refugees' ability to create sustainable livelihoods for themselves and their families. We also included a dimension to account for personal security and social inclusion that includes indicators for legal residency status, area/settlement conditions, communications access, movement and mobility, and community interaction. We also expanded the health dimension to encompass indicators for healthcare access, households with special health care needs, and food security such as diet diversity. Factors such as food diversity, social inclusion, and connectivity to mobile phones and social networks have been documented as being particularly important to households' resiliency and their capacity to cope with and recover from negative shocks, especially households who have been forcibly displaced (Gerlitz et al. 2017; Hahn, Riederer & Foster, 2009; Lyons & Kass-Hanna, 2020a, 2020b; Khawaja et al., 2020; Rajesh, Jain & Sarma, 2018).

To calculate our index, we followed the steps described in Alkire and Santos (2014).[18] First, we defined the dimensions, indicators, and the cutoffs to measure deprivation for each indicator (see Table 2). Our index included 21 indicators that spanned five dimensions: (1) health and food security, (2) education, (3) living standards, (4), employment, and (5) security and social inclusion. We assigned weights using two weighting schemes. In our first and primary weighting scheme, we assigned equal weights to the five dimensions (0.2000 x 5 = 1.000). The weight of each dimension was then divided equally across the indicators included in each dimension. In the second weighting scheme, the 21 indicators were given equal weighting (0.0476 x 21 = 1.000). Next, we calculated the deprivation score for each household, which ranged from 0 to 1. Households with a deprivation score of 0.33 or higher were classified as multidimensionally poor. Although some estimations of the MPI

[18] Since 2014, some minor adjustments have been made to the Alkire and Foster (2011) and Alkire and Santos (2014) method. For example, see the revised global MPI (OPHI, 2018; Alkire, Kanagaratnam, & Suppa, 2020). However, these adjustments still rely on the original methodology proposed by Alkire and Foster (2011) and Alkire and Santos (2014).

Table 2. Deprivation cutoffs using dimensions, indicators, and weights (N=4,358)

Dimensions/Indicators	Deprivation Cutoffs (Household is deprived if…)	Percentages	Weighting Schemes: Dimensions equal weights	Weighting Schemes: Indicators equal weights
Health and Food Security Indicators			**0.2000**	**0.1905**
1. Special needs	at least one household member had special needs, including chronic disease, serious/life-threatening medical condition, disability, mental illness, and/or an older person unable to care for themselves.	**51.95**	0.0500	0.0476
2. Healthcare access	at least one household member was unable to access primary health care assistance or be hospitalized when needed.	**9.29**	0.0500	0.0476
3. Food coping strategies	household's rCSI was greater than 20 (i.e., rCSI > 20). This index measures 5 food-consumption-based coping strategies in the previous seven days. The index ranges from 0 (no use of coping strategies) to 56 (use of all coping strategies).	**37.38**	0.0500	0.0476
4. Diet diversity	household's weekly diet diversity was not adequate such that the household consumed less than 9 food groups during the last week (HWDD < 9 food groups). The index ranges from 0 to 12 (the total number of food groups). A score lower than 6 is considered as low diversity, 7-8 borderline, and 9 or higher acceptable.	**31.71**	0.0500	0.0476
Education Indicators			**0.2000**	**0.0952**
1. Child school attendance	at least one child in the household (aged 6-14) was not attending school.	**19.62**	0.1000	0.0476
2. Adult years of schooling	all household members (≥ 10 years of age) had less than 6 years of education.	**15.63**	0.1000	0.0476
Living Standards Indicators			**0.2000**	**0.3810**
1. Electricity	household did not have access to electricity or had less than 16 hrs of electricity.	**40.13**	0.0250	0.0476
2. Basic sanitation	household did not have access to basic sanitation (i.e., no access to flushed toilets or improved pit latrines with a cement slab, and was not sharing the toilets with other households).	**31.64**	0.0250	0.0476
3. Drinking water	household did not have access to clean drinking water.	**11.59**	0.0250	0.0476
4. Cooking fuel	household's cooking fuel was dung, wood, or charcoal. Household did not have access to electric or gas stove, or other cooking fuels.	**15.53**	0.0250	0.0476
5. Basic assets	household did not have access to ALL of the following basic assets in usable condition to cover household needs: mattress, blankets, winter clothes, small gas stove, refrigerator, and heater.	**70.45**	0.0250	0.0476
6. Crowdedness of shelter	household was living in an overcrowded shelter with less than 4.5m^2 per person.	**32.12**	0.0250	0.0476
7. Shelter conditions	household was living in a non-residential or non-permanent structure.	**30.50**	0.0250	0.0476
8. Housing stability	household moved in the past 6 months or planned to move due to high rent or eviction.	**17.30**	0.0250	0.0476
Employment Indicators			**0.2000**	**0.0952**
1. Unemployment	50% or more of household members (aged 15-64) were unemployed in the past week.	**22.69**	0.1000	0.0476
2. Underemployment	All household members who were working (aged 15-64) reported working irregularly or working less than 10 days in the past month.	**46.44**	0.1000	0.0476
Security and Social Inclusion Indicators			**0.2000**	**0.2381**
1. Legal residency	no household members (≥ 15 yrs of age) were legal residents in Lebanon.	**55.00**	0.0400	0.0476
2. Area/settlement conditions	at least one of the following conditions was present in the area/settlement in which the household was living: physical security threats, high population density, low standard living conditions, far from essential basic services, environmentally sensitive area, and/or poor sanitation conditions.	**16.06**	0.0400	0.0476
3. Communications access	household did not have a mobile phone or access to a social media platform such as WhatsApp.	**10.28**	0.0400	0.0476
4. Movement and mobility	there was an imposed curfew in the household's refugee community.	**24.76**	0.0400	0.0476
5. Community interaction	household reported "never" or "rarely" interacting with the host community.	**20.93**	0.0400	0.0476

Notes: The indicators were constructed using data from the 6th round of the *2018 Vulnerability Assessment of Syrian Refugees* (VASyR).

have used a different cutoff, the standard in the literature has been 0.33 (e.g., OPHI, 2018).[19] The percentage of multidimensionally poor households within the sample is known as the headcount ratio (*H*). In the final step, we calculated our multidimensional livelihood index (MLI) as the product of $H \times A$, where H was the incidence of poverty (the headcount ratio) as defined above, and A was the average deprivation score, but only for those who were classified as poor (the average intensity of poverty).[20] Hence, the MLI score is the proportion of weighted indicators in which multidimensionally poor refugees were deprived, out of all the potential deprivations the whole refugee population could have experienced.[21]

4.1 Baseline MLI and robustness checks

The top of Table 3 presents some descriptive statistics for the baseline MLI, which assumes equal weights for each dimension. All five dimensions and 21 indicators were included in the baseline model. Each indicator counted as a deprivation. Refugee households had an average of 6.1 deprivations. The deprivation score was calculated as the weighted sum of deprivations for the total sample, including both poor and non-poor households.[22] The average deprivation score was 0.2827. The cutoff of 0.33 was used to identify the percentage of households who were poor, while the cutoff of 0.50 was used to identify those who were extremely poor. Accordingly, about 36.5% of households were classified as currently poor (*H*) and 7.3% as extremely poor. The highest rate of poverty was found for Baalbek-El Hermel (50.8%), while the lowest rates were found for Beirut and El Nabatieh (both 23.9%). The average intensity of poverty (*A*) was 0.4323. Note that the intensity of poverty had low variance among the governorates, with the lowest value being 0.4099 for Beirut and the highest value being 0.4566 for Baalbek-El Hermel. Multiplying $H \times A$, we found that the baseline MLI on average for Syrian refugees in Lebanon was 0.1585, ranging from 0.0981 for Beirut to 0.2317 for Baalbek-El Hermel. In this case, refugees classified as multidimensionally poor were experiencing on average 15.9% of the total potential deprivations possible.

We tested the robustness of our results to various specifications for the MLI. In addition to our *baseline model*, we reran our calculations for four additional models. The first was a *basic* index, which was constructed utilizing the dimensions for health, education, and living standards only – the

[19] The standard cutoff used by other researchers when constructing traditional MDP indices with 3 dimensions (education, health, living standards) is 0.33. This cutoff identifies households who are poor in at least 1 of the 3 dimensions. Alkire and Santos (2014) and OPHI (2018) found that the relative scores of the MPI did not vary across countries when the cutoffs ranged between 0.20 and 0.40. In our analysis, we have 5 dimensions. We identify households as multidimensionally poor if they are deprived in at least one-third of the indicators (more than 7 of the 21 indicators). Sensitivity analysis revealed that small changes in our cutoff resulted in fairly small changes in the headcount ratio (H).

[20] When calculating the MLI, H was equal to P/N, where P was the number of refugee households who were deprived in more than 33.3% of the total deprivations and N was the total number of refugee households, which included both those who were multidimensionally poor and those who were not. The intensity of poverty (A) was equal to $A = \sum_i^P \sum_k^K w_k D_{ik} / P$ for $k=\{1, \ldots, K\}$ indicators in the index and $i=\{1, \ldots, P\}$ multidimensionally poor households. In this equation, w_k denotes the weight of the k^{th} indicator, and D_{ik} is a binary indicator that is equal to 1 if the i^{th} refugee household who was multidimensionally poor was deprived in the k^{th} indicator and 0 otherwise.

[21] http://www.ophi.org.uk/wp-content/uploads/MPI-interpretation-decompositions.pdf

[22] See Appendix A2 for the probability distribution for the baseline deprivation score, as compared to the normal distribution.

Table 3. Multidimensional Livelihood Index (MLI) for Syrian refugees living in Lebanon by governorate

Variables (Means/Percentages)	**Lebanon N=4,358**	Akkar n=424	Baalbek-Hermel n=333	Beirut n=397	Bekaa n=503	El Nabatieh n=568	Mount Lebanon n=882	North Lebanon n=832	South Lebanon n=419
Baseline Multidimensional Livelihood Index (MLI)									
Ave tot number of deprivations	**6.11**	6.37	7.05	4.98	6.16	5.46	6.21	6.75	5.53
Deprivation score	**0.2827**	0.2966	0.3364	0.2353	0.3033	0.2493	0.2841	0.3044	0.2452
Incidence of poverty - headcount (H)									
Poor: Deprivation score > 0.33	**0.3653**	0.4127	0.5075	0.2393	0.4354	0.2394	0.3719	0.4231	0.2816
Extreme poverty: Deprivation score ≥ 0.50	**0.0730**	0.0542	0.1441	0.0227	0.0915	0.0563	0.0692	0.0938	0.0501
Ave intensity of poverty (A)	**0.4323**	0.4137	0.4566	0.4099	0.4374	0.4397	0.4326	0.4396	0.4219
MLI – Dimensions equal weights (all 5 dimensions) (H x A)	**0.1585**	0.1708	0.2317	0.0981	0.1905	0.1053	0.1609	0.1860	0.1188
Other MLI Specifications									
Incidence of poverty (H) for deprivation score > 0.33									
Basic (health, education, and living standards)[a]	**0.3561**	0.3868	0.4685	0.2317	0.3499	0.2641	0.3379	0.4651	0.3079
Basic + Employment[a]	**0.3905**	0.4646	0.5315	0.2846	0.4950	0.2535	0.3776	0.4435	0.2864
Basic + Security and social inclusion[a]	**0.3098**	0.2995	0.4234	0.1788	0.3042	0.2218	0.3243	0.3990	0.2721
Indicators equal weights (all 5 dimensions)	**0.4199**	0.4646	0.5586	0.2544	0.4612	0.2887	0.4286	0.5216	0.3294
MLI using deprivation score > 0.33 (H x A)									
Basic (health, education, and living standards)[a]	**0.1579**	0.1694	0.2160	0.0983	0.1570	0.1176	0.1493	0.2071	0.1331
Basic + Employment[a]	**0.1775**	0.2026	0.2560	0.1222	0.2272	0.1143	0.1708	0.2060	0.1251
Basic + Security and social inclusion[a]	**0.1332**	0.1282	0.1890	0.0713	0.1293	0.1006	0.1377	0.1713	0.1159
Indicators equal weight (all 5 dimensions)	**0.1734**	0.1882	0.2430	0.0955	0.1872	0.1190	0.1760	0.2198	0.1367
Health and Food Security Indicators (%)									
1. Special needs	**51.95**	54.95	62.46	45.59	57.65	49.12	42.86	61.06	44.63
2. Healthcare access	**9.29**	1.65	7.51	15.11	6.56	9.86	14.63	7.69	7.40
3. Food coping strategies	**37.38**	73.58	12.61	29.22	15.71	40.14	28.91	56.85	29.59
4. Diet diversity	**31.71**	32.55	24.02	23.43	21.47	29.75	40.02	40.75	24.34
Education Indicators (%)									
1. Child school attendance	**19.62**	11.56	29.43	16.37	22.27	15.32	24.15	19.83	15.75
2. Adult years of schooling	**15.63**	17.45	26.43	12.59	21.27	15.14	10.88	13.34	16.47
Living Standards Indicators (%)									
1. Electricity	**40.13**	24.53	62.76	13.10	21.87	35.21	49.43	55.89	41.29
2. Basic sanitation	**31.64**	53.30	42.94	26.70	44.33	19.19	18.71	35.70	26.25
3. Drinking water	**11.59**	6.13	15.62	4.53	12.52	18.13	6.46	18.15	8.35
4. Cooking fuel	**15.53**	7.08	17.72	2.27	24.85	16.90	14.63	18.39	18.14
5. Basic assets	**70.45**	65.57	72.67	75.82	55.67	69.72	77.66	68.39	76.13
6. Crowdedness of shelter	**32.12**	33.49	35.74	46.10	35.79	11.62	42.18	28.13	24.82
7. Shelter conditions	**30.50**	51.89	51.65	8.82	45.13	14.44	19.05	37.98	26.01
8. Housing stability	**17.30**	12.50	15.62	20.15	16.50	19.72	22.00	15.38	12.41
Employment indicators (%)									
1. Unemployment	**22.69**	20.28	26.73	26.95	33.60	14.61	25.62	19.95	15.04
2. Underemployment	**46.44**	57.08	69.37	34.76	65.21	36.09	40.48	46.03	33.41
Security and Social Inclusion Indicators (%)									
1. Legal residency	**55.00**	75.00	58.56	50.88	61.63	31.34	62.24	59.98	34.84
2. Area/settlement conditions	**16.06**	8.73	14.11	26.20	5.96	13.38	29.02	8.65	18.62
3. Communications access	**10.28**	14.62	30.33	5.79	14.91	8.80	6.80	6.25	5.97
4. Movement and mobility	**24.76**	1.18	4.50	0.50	11.73	52.11	30.61	28.73	46.06
5. Community interaction	**20.93**	13.68	23.72	13.10	20.87	25.53	14.29	27.88	27.45

Note: The data were taken from the 6th round of the *2018 Vulnerability Assessment of Syrian Refugees* (VASyR).
[a] Specification assumes each dimension received equal weight (0.2000)

three standard MPI dimensions included in Alkire and Foster (2011). Our basic index varied somewhat from theirs as our data did not allow us to construct some indicators related to child mortality, undernourishment, and shelter characteristics. Also, some indicators needed to be adapted or added given the refugee context (e.g., assets, crowdedness of shelter, housing stability). The second index added the employment dimension to the *basic* index, while the third index added the security and social inclusion dimension. A fourth additional model used our original *baseline* index, but equal weights were assigned to each indicator instead of equal weights to each dimension, which increased the weighting of those dimensions with more indicators, such as living standards. Table 3 presents for each model the incidence of poverty (H) and the MLI values using the deprivation score cutoff of 0.33. The results show that the values for our original baseline model fall somewhere in between the other four specifications.

The basic model that includes the security and social inclusion dimension generates the lowest percentage of poor households (MLI = 0.1332), while the one that uses the basic index plus the employment dimension generates the highest (MLI = 0.1775).

Figures 2a and 2b present additional information about the distribution of the deprivation scores for the various MLI specifications. Figure 2a shows the cumulative distribution of the Syrian refugees in Lebanon who are poor according to different cutoffs or deprivation scores and using various specifications and weighting schemes. This figure shows that increasing the cutoff decreases the percentage of poor households (the headcount ratio), and that these changes are gradual for the different specifications, but particularly for our baseline specification. The behavior of the five different specifications appear to follow a similar pattern when it comes to classifying households according to their deprivations, and this pattern remains even after using cutoffs higher than 0.33 to identify those households who are currently poor. Figure 2b provides similar information, but at the governorate level, using our baseline specification only. The results show that changes in the deprivation score cutoff do not alter the ordering of governorates in terms of the relative percentage of the population classified as poor. Thus, Baalbek-El Hermel remains as the governorate with the highest percentage of poor households, independent of the specified cutoff, whereas Beirut, El Nabatieh, and South Lebanon are the governorates with the lowest percentages of poor households.

4.2 Dimensions and indicators

The bottom of Table 3 presents a closer look at the percentage of refugees who were classified as deprived according to each indicator, for Lebanon as a whole and across governorates. For the health and food security dimension, we find that over half of the households (52.0%) had at least one household member with special needs (e.g., a chronic disease, a serious/life threatening medical condition, a disability, mental illness, and/or an older person unable to care for themselves). Approximately 37.4% had a food coping strategy index greater than 20, which implies these

Figure 2a. Headcount ratio for different index specifications and deprivation cutoffs

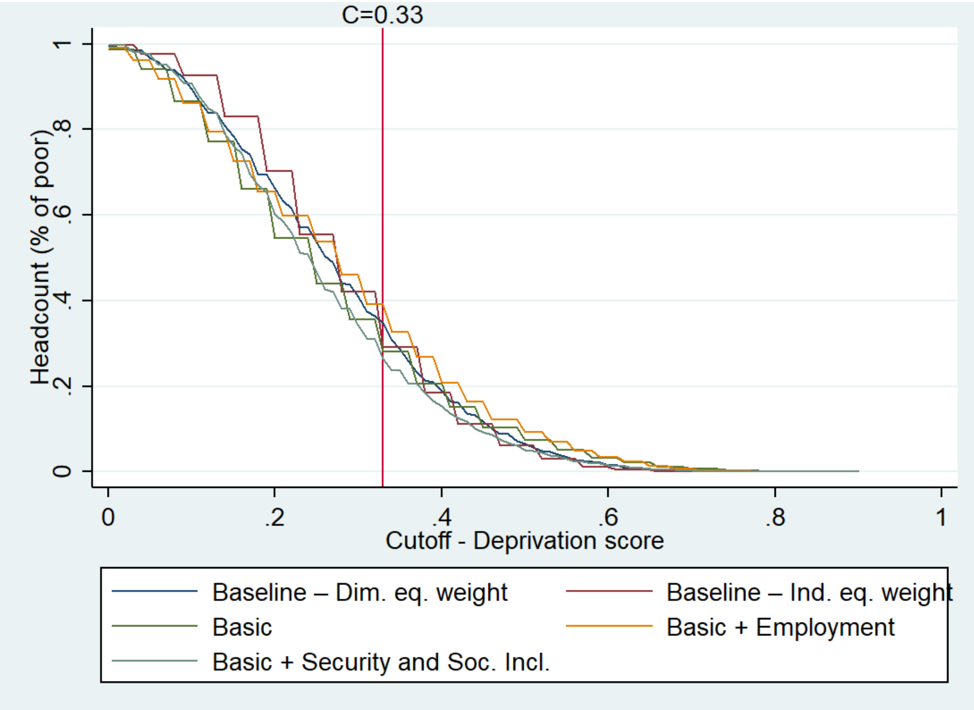
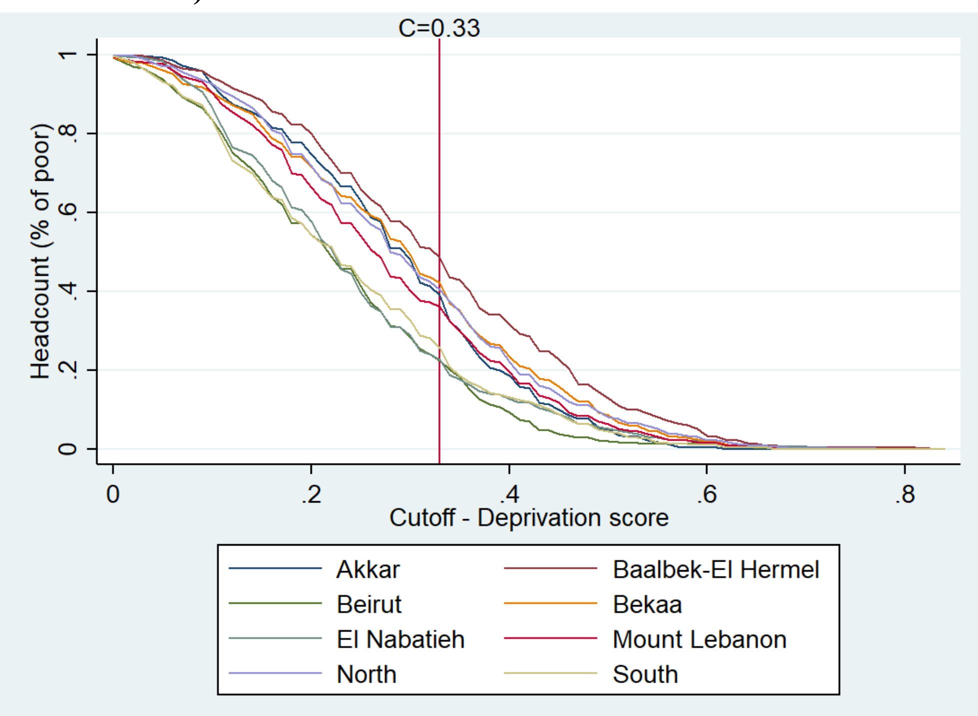


Figure 2b. Headcount ratio for different governorates and deprivation cutoffs (using the baseline index)



households had to adopt more severe strategies to deal with food insecurity.[23] Besides the basic strategies of relying on less expensive food or borrowing food from friends or relatives, households were also adopting more severe strategies like reducing the size of meals, spending days without eating, or restricting the consumption of household members. The use of food coping mechanisms was particularly acute in Akkar (73.6%), North Lebanon (56.9%) and El Nabatieh (40.1%). Moreover, around one-third of households (31.7%) were consuming diets that were inadequately diversified, such that the households had consumed less than 9 out of 12 key food groups.[24] In terms of access to primary or secondary health care, only 9.3% of households reported being unable to access primary health care assistance to hospitalization services if needed. Although Beirut had the lowest poverty rate, it was the governorate that reported the highest rate of limited access to health services (15.1%).

For the dimensions related to education and employment, 19.6% had at least one child in the household (aged 6-14) who was not attending school. For 15.6%, all household members (≥ 10 years of age) had less than 6 years of education. Baalbek-El Hermel and Bekaa had the highest levels of deprivation when it came to education. In terms of employment, 22.7% reported that 50% or more of working-age household members were unemployed among all the refugees on average, while 46.4% of those who were working were working irregularly or had worked less than 10 days in the past month. The highest rates of unemployment were found for Bekaa (33.6%), followed by Beirut (27.0%) and Baalbek-El Hermel (26.7%). Not surprisingly, underemployment rates were higher in the governorates with the highest poverty rates. Even so, lack of employment opportunities was a major problem for all governorates, as the lowest reported rate of underemployment was only 33.4% for South Lebanon.

The living standards dimension captured deprivations related to lack of access to electricity, basic sanitation, clean drinking water, cooking fuel, and basic assets. This dimension also included the crowdedness of the shelter in which the household was living, the conditions of the shelter, and the stability of the current housing arrangement. On average, 40.1% of refugee households had inadequate access to electricity, 31.6% lacked access to basic sanitation, and over 30.0% were living in overcrowded shelters and structures that were non-residential or non-permanent. Only 11.6% did not have access to clean drinking water, and only 15.5% did not have access to cooking fuels and instead were using dung, wood, or charcoal. Most (70.5%) did not have access to the following basic assets: a mattress, blankets, winter clothes, small gas stove, refrigerator, and a heater. Geographically, some of the worst living conditions were again found for governorates such as Baalbek-El Hermel and Bekaa.

Regarding the dimension for security and social inclusion, the main problem facing the refugees was the lack of legal residency, which could affect their ability to find stable employment. On average,

[23] This index captures the extent to which households were using coping strategies to specifically deal with the lack of food or money to purchase food during the week prior to the *VASyR* survey. The index included eight strategies that, when multiplied by the seven days of the week, resulted in values ranging from 0 to 56.

[24] The 12 food groups included: cereals (bread, rice, pasta, etc.), tubers (potatoes), roots and legumes, dairy, sea food, eggs, vegetables, fruits, oils (including butter and other fats), sugars and sweets, spices (including coffee, tea, sauces, etc.), and meat (chicken, beef, lamb, etc.).

55.0% reported that no household members (≥ 15 years of age) had obtained legal residency in Lebanon. In addition, 16.1% reported living in an area/settlement which had at least one of the following conditions: physical security threats, high population density, low standard living conditions, located far from essential basic services, environmentally sensitive area, and/or poor sanitation conditions. Area/settlement conditions were notably poorer in Beirut and Mount Lebanon, the most densely populated areas in Lebanon. Not surprisingly, a higher percentage of refugees in these governorates reported that they were living in areas or settlements with higher population densities. Only 10.3% of households reported having no access to a mobile phone or social media platform such as WhatsApp. One of the exceptions was Baalbek-El Hermel, where 30.3% reported not having access to these type of communication services. Further, in some governorates, refugees were more restricted by movement and mobility than others. Specifically, households living in refugee communities in the governorates of El Nabatieh, South Lebanon, North Lebanon, and Mount Lebanon were considerably more likely to have curfews than the other governorates. On average, 20.90% of refugee households also reported having very little, if any, interaction with the host community; percentages varied across the governorates, ranging from 13.1% for Beirut to 27.9% for North Lebanon. Including this dimension in the overall livelihood index is particularly important when it comes to FDPs such as the Syrian refugees in Lebanon. Factors such as legal residency, communication access, ability to move about, and to interact with the host community can have a significant impact on employment, education, and training outcomes, as well as access to other resources that could impact their current situation and future economic security (Lyons & Kass-Hanna, 2020a, 2020b).

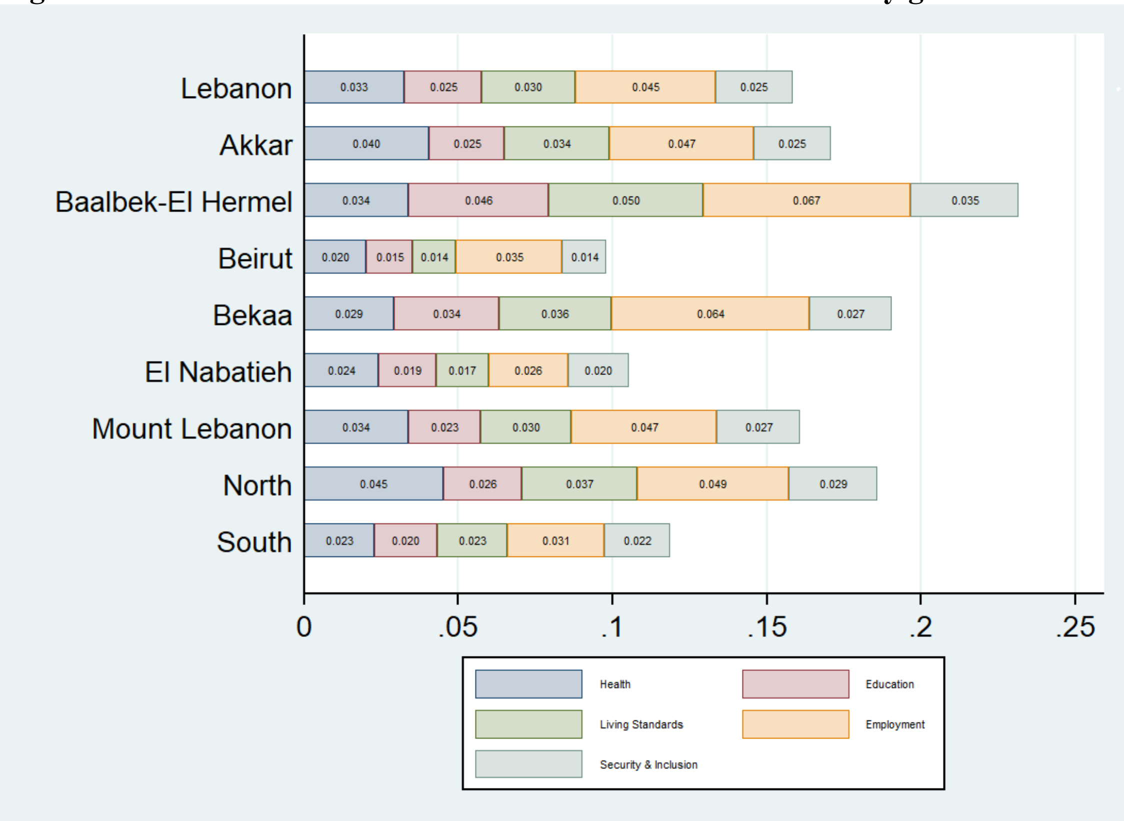
4.3 Contributions of each dimension to the MLI

Figures 3a and 3b reveal the absolute and relative contribution of each dimension to the MLI for Lebanon as a whole and for each of the eight governorates[25]. These figures help one to visualize the critical challenges that poor refugees are facing in each governorate, and hence identify the pressing areas where interventions need to be prioritized. For example, employment appears to be an issue at the national level. It is the main contributor to livelihood, both in absolute and relative terms, in all governorates. This suggests the strong need for interventions that improve access to employment not only through enhancing employability of refugees (via job training and matching), but also by setting short- and long-term strategies for employment creation. Given the legal constraints impacting refugees' ability to work,[26] and the high levels of unemployment among host communities, wider development programs that surpass humanitarian action are needed. These require close coordination

[25] Within each governorate, the relative contribution of the k^{th} indicator was calculated as $RCont_k = w_k CR_k / MLI$, where $CR_k = \sum_i^P \sum_k^K w_k D_{ik} / N$ is defined as the censored ratio or the sum of the total deprivations for those who are multidimensionally poor relative to the total population in that governorate. The absolute contribution to the total MLI is calculated as $ACont_k = w_k CR_k$.

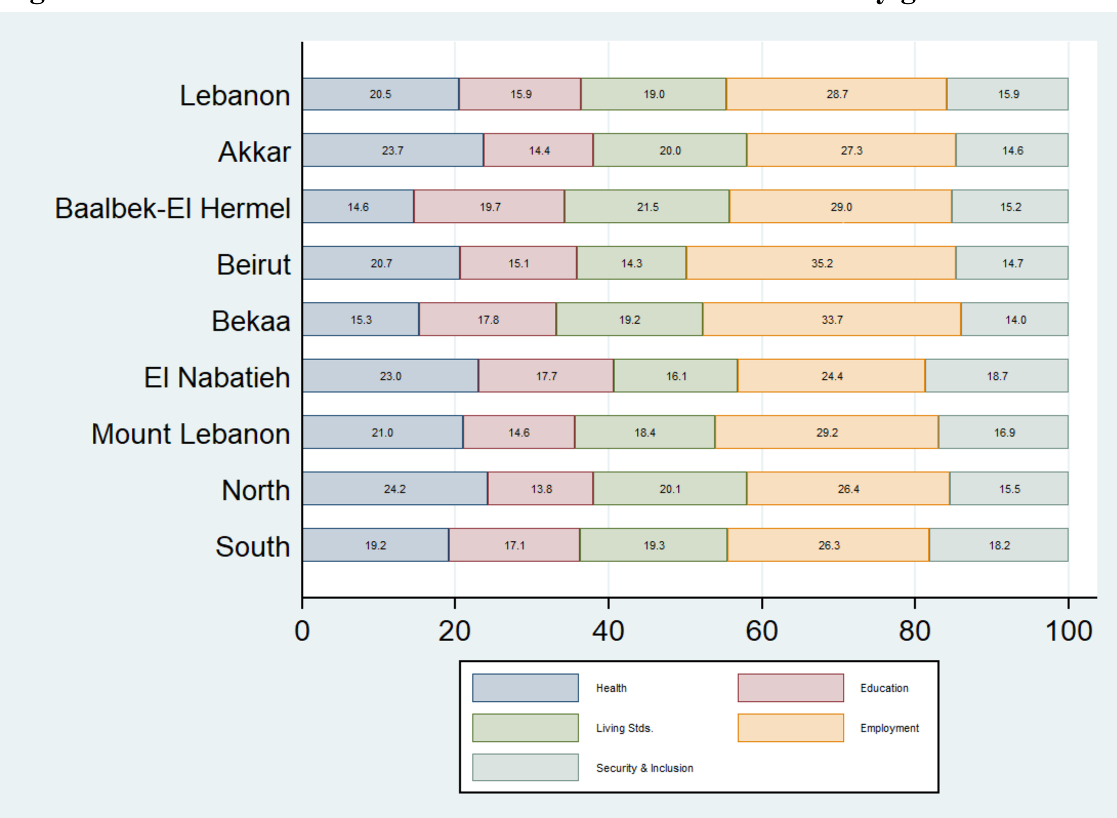
[26] According to the Lebanese law, Syrian refugees are only permitted to work in those sectors in which Syrians were traditionally engaged before the crisis, namely agriculture, construction, and environment. Moreover, most of the refugees in 2018 (55.0%) did not have legal residency, which complicates their search for formal employment. This situation has led to high concentrations of informal employment among the refugees, which has put them in direct competition with many low-skilled, low-income Lebanese workers, worsening the job quality and working conditions for both. A recent report by Dempster et al. (2020) estimates that around 95.0% of Syrian refugees in Lebanon have informal jobs. The 2018 VASyR data do not include direct measures for informal employment. We indirectly measure labor conditions via our indicators for un- and underemployment.

Figure 3a. Absolute contribution of each dimension to the MLI by governorate



Note: Assumes equal weight for each dimension (weight=0.2000).

Figure 3b. Relative contribution of each dimension to the MLI by governorate



Note: Assumes equal weight for each dimension (weight=0.2000).

between development actors and Lebanese government to develop legal frameworks, as well as initiatives that stimulate local economic development and support the creation of income-generating opportunities for both refugees and local communities.[27]

Also, health and food security seem to be critical issues in Akkar and North Lebanon governorates, which display above-average levels of deprivation in terms of their absolute contributions (second-highest relative contributor to the MLI). In Baalbek-El Hermel and Bekaa, living standards and education appear to be the most salient deprivations (second and third-highest relative contributors to the MLI). Addressing these problems might entail projects that enhance community infrastructures such as electricity, sanitation, and water networks, as well as public health and schools. These also exceed the operational and financial ability of humanitarian agencies and call for development organizations that are better positioned to ensure medium to long-term funding and support for national government and municipalities to undertake them. By identifying the locations where such projects could have the most significant impact on improving the conditions of multidimensionally poor refugees, our proposed framework offers guidance as to where to start/focus specific interventions to foster efficient use of limited funds. This framework also allows decompositions by indicator and by district, which can provide even more detailed insights about *how* and *where* to target the multidimensionally poor in the refugee communities.

5. Empirical framework for predicting vulnerability to future poverty

5.1 Assessing vulnerability using cross-sectional data

So far, the MLI we calculated provides insight into which refugee households are currently poor. However, it does not consider that certain characteristics can result in households being more or less vulnerable to being poor in the future, independent of whether they are poor in the present. Thus, our current analysis does not consider the probabilistic aspect of vulnerability. For example, households whose incomes come from highly risky activities might not be poor in the present, but they could be highly vulnerable to becoming poor in the future. To show this, we would ideally need longitudinal data, which is often not readily available when studying highly vulnerable and mobile populations whose situations are fluid and constantly changing. To this end, we follow the approach proposed by Chaudhuri et al. (2002) that uses cross-sectional data to measure vulnerability to future poverty.[28] This framework assumes that the socioeconomic and geographic characteristics which explain current poverty can be used to estimate vulnerability to future poverty. With a large enough sample size, Chaudhuri et al. (2002) asserts that cross-sectional data that exhibit variations in observable determinants of current poverty across different types of households can provide a reliable indication of intertemporal variations in poverty over time. As pointed out in the literature review, this methodology has also been used by Azeem et al. (2018), Feeny and McDonald (2016), and others.

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[27] The UNDP has been engaged in such programs to enhance economic participation opportunities for refugees and disadvantaged local communities in Lebanon (Government of Lebanon & UN, 2020). Still, efforts and funding are needed to implement larger programs, especially in the current context of the acute economic crisis of Lebanon. Lessons can be learned from initiatives carried out in Jordan and Turkey. See the Regional Refugee and Resilience Plans (3RPs) for 2017 and 2018 (UNDP & UNHCR, 2017, 2018).

[28] Chaudhuri et al. (2002) defines vulnerability to poverty as the risk of being poor in the near future, where the "near future" typically refers to 1-2 years.

Since we only have data for 2018, this approach seems to be an appropriate second-best alternative to longitudinal analysis.[29]

Note also that our methodology varies from Chaudhuri et al. (2002) in that we use the deprivation score of the MLI (a multidimensional measure) as the indicator of poverty instead of household consumption expenditures. The deprivation score resembles a continuous variable, as it takes 126 different values between 0 and 1 in a sample of less than 4,400 households. We also improve upon Chaudhuri et al. (2002) by attempting to capture heterogeneities across refugee communities by controlling for fixed effects by governorate. This is similar to the improvement made by Günther and Harttgen (2009), who separated household characteristics that affected vulnerability (idiosyncratic risk) from community characteristics (covariate community risk) using a multi-level analysis, where the coefficients for the household characteristics varied by community.

5.2 Three-stage FGLS using deprivation scores

To calculate vulnerability to future poverty, we follow the 3-step feasible generalized least squares (FGLS) approach used by Chaudhuri et al. (2002). In Stage 1, we express the stochastic process generating household's current poverty as follows:

$$DS_{ij} = X_{ij}\beta + e_{ij}, \tag{1}$$

where DS_{ij} is the deprivation score for the i^{th} refugee household in the j^{th} governorate. The factors that determine DS_{ij} are represented by X_{ij}, which includes the characteristics of the household head (age, education, gender, marital and employment status), as well as household-level characteristics (share of dependents, highest attained education level, household size, percentage of household members who are working). Also included is information about the household's coping strategies, expectations about the future, and available resources such as the household's main sources of income, consumption expenditures, and whether the household has received humanitarian assistance. Geographical indicators are also included to account for governorate fixed effects. In this model, β is the vector of parameters and e_{ij} represents the random error term.

We use ordinary least squares (OLS) to estimate Equation (1) and predict the residuals (e_{ij}), which are stored so that they can be used in Step 2. The residuals, e_{ij}, in this equation are critical to our estimation, as they capture idiosyncratic shocks to deprivation that are assumed to be identically and *independently* distributed *over time* for each household. Because we are using a single cross-section of data, we also need to assume structural changes in the economy are relatively stable over time and

[29] However, to estimate the probability of vulnerability to future poverty, we need to assume normality for the distribution of the deprivation scores. This assumption stems from Chaudhuri et al. (2002), who also impose normality for the logarithm of expenditure to measure unidimensional vulnerability. Within the context of our study, this assumption seems reasonable, as the distribution of the deprivation scores appear to exhibit tendencies toward a normal distribution. See again Appendix A2.

that any uncertainty about future poverty arises solely from the uncertainty related to the idiosyncratic shocks, e_{ij}, that the household may experience in the future.[30]

In Step 2, the estimated residuals ($\hat{e}_{OLS,ij}$) are squared and regressed on the same explanatory variables included in Equation (1) using OLS:

$$\hat{e}^2_{OLS,ij} = X_{ij}\theta + \eta_{ij}. \tag{2}$$

The predicted values are obtained and used to transform Equation (2) as follows:

$$\frac{\hat{e}^2_{OLS,ij}}{X_{ij}\hat{\theta}_{OLS}} = \left(\frac{X_{ij}}{X_{ij}\hat{\theta}_{OLS}}\right)\theta + \frac{\eta_{ij}}{X_{ij}\hat{\theta}_{OLS}}. \tag{3}$$

Equation (3) is the re-estimation of equation (2) but using FGLS with $X_{ij}\hat{\theta}_{OLS}$ as the weight. This step results in an asymptotically efficient FLGS estimate of the parameters, $\hat{\theta}_{FGLS}$, such that $X_{ij}\hat{\theta}_{FGLS}$ is now a consistent estimate of $\hat{\sigma}^2_{e,ij}$, the variance of the idiosyncratic component of the deprivation score.

In Step 3, the transformed standard deviation:

$$\hat{\sigma}_{e,ij} = \sqrt{X_{ij}\hat{\theta}_{FGLS}} \tag{4}$$

is then used as the weight to obtain FGLS estimates for Equation (1):

$$\frac{DS_{ij}}{\hat{\sigma}_{e,ij}} = \left(\frac{X_{ij}}{\hat{\sigma}_{e,ij}}\right)\beta + \frac{e_{ij}}{\hat{\sigma}_{e,ij}}. \tag{5}$$

The OLS estimation of Equation (5) now yields consistent and asymptotically efficient estimates of the parameters ($\hat{\beta}_{FGLS}$). Now that we have consistent estimations of $\hat{\beta}_{FGLS}$ from Equation (5) and $\hat{\theta}_{FGLS}$ from Equation (3), we are able to obtain consistent estimations of the expected deprivation scores:

$$\hat{E}[DS_{ij} \mid X_{ij}] = X_{ij}\hat{\beta}_{FGLS} \tag{6}$$

and the variance of the deprivation scores:

[30] Chaudhuri et al. (2002) point out that without longitudinal data we are unable to identify the parameters (β) driving unobservable persistence in deprivation. Even if we have repeated cross-sections, we would need a fairly lengthy time series worth of data to identify the stochastic process generating β.

$$\hat{V}[DS_{ij} \mid X_{ij}] = \hat{\sigma}^2{}_{e,ij} = X_{ij}\hat{\theta}_{FGLS} . \tag{7}$$

Using equations (6) and (7), we can calculate the probability that a refugee household with characteristics X_{ij} will be deprived in the future. Assuming our poverty cutoff of 0.33 and a normal distribution, the i^{th} household is vulnerable (v_{ij}) if the probability of being poor in the future (i.e., the household has a deprivation score greater than 0.33) is greater than or equal to 0.5 such that:

$$\widehat{v_{ij}} = \widehat{Pr}(DS_{ij} > 0.33 \mid X_{ij}) = \Phi\left(\frac{X_{ij}\hat{\beta}_{FGLS} - 0.33}{\sqrt{X_{ij}\hat{\theta}_{FGLS}}}\right) \geq 0.5 . \tag{8}$$

Here we use the 0.5 cutoff for vulnerability used by Chaudhuri et al. (2002). This implies that a household is vulnerable if it has a higher chance of being poor in the future than of not being poor.[31]

6. Empirical results

6.1 Estimations and determinants of vulnerability to poverty

Table 4 presents the results for the 3-stage FGLS model using the deprivation scores that were constructed from our MLI. We focus on discussing the results from the final stage, which are presented in Column 3 and highlight the key determinants of vulnerability to future poverty. In terms of household expenditures, the results show that lower expenditures per capita were associated with a higher likelihood of being vulnerable to future poverty. This is not surprising since consumption expenditures is a common unidimensional metric used by Chaudhuri et al. (2002) and others to predict future poverty. In terms of other resources, households whose main source of income was from employment were significantly less likely to be vulnerable, as were those whose head had worked in the past week or who had a greater share of household members working. In fact, those whose main source of income was from employment were 3.5% less vulnerable. Interestingly, households who reported borrowing, especially those who were using borrowing as their main source of income, were more likely to be susceptible to future poverty. In terms of education, Table 4 shows that those living in refugee households where the head was illiterate or where the highest level of household education was only primary education or less were also significantly more likely to be vulnerable.

[31] Chaudhuri et al. (2002) defined as highly vulnerable those households whose probability of being poor in the future was greater than or equal to 0.5. Similarly, those households with probabilities higher than the poverty line, but lower than 0.5 were defined as transient vulnerable. In this study, we only use the 0.5 cutoff. However, sensitivity analysis was conducted. The results showed that movements in the vulnerability estimations close to the cutoff value (more specifically, between 0.40 and 0.60) follow a linear pattern. This means that increasing (decreasing) the threshold by 1.0% reduces (increases) the percentage of vulnerable households by around 1.0%. Thus, moving the cutoff up or down a bit produces similar results and does not significantly alter our conclusions. More recently, Gallardo (2020) proposed a methodology to calculate vulnerability based on the MPI proposed by Alkire and Foster (2011) called VMPI. The main advantage of his methodology is that the probability of vulnerability can be calculated separately for each dimension instead of using only an aggregated measure like the MPI. However, the disadvantages of this method are that the cutoffs for vulnerability are not easy to calculate as they are based on a complicated mathematical procedure. Also, since the cutoffs are based on a mathematical produce, they do not have as intuitive of an interpretation, as the 50.0% threshold used by Chaudhuri et al. (2002).

Table 4. Determinants of vulnerability to poverty using deprivation score constructed from multidimensional poverty index (N=4,358)

	3-Stage FGLS		
	Stage 1: OLS	Stage 2: FGLS	Stage 3: 3-stage FGLS
Variables	Deprivation score	Variance of deprivation score	Deprivation score $\widehat{Pr}(DS_{ij} > 0.33 \mid X_{ij}) \geq 0.5$
Expenditures			
Below SMEB (< $87 USD)	0.0449***	0.0022***	0.0448***
	(0.0044)	(0.0006)	(0.0043)
SMEB – MEB ($87-$113 USD)	0.0118**	0.0006	0.0114**
	(0.0052)	(0.0007)	(0.0050)
Household resources			
Main income source: Employment	-0.0345***	-0.0015**	-0.0347***
	(0.0045)	(0.0006)	(0.0044)
Main income source: Assistance	-0.0128*	-0.0003	-0.0141**
	(0.0070)	(0.0010)	(0.0068)
Main income source: Borrowing	0.0171***	-0.0004	0.0168***
	(0.0058)	(0.0009)	(0.0058)
Borrowed money or received credit	0.0162***	-0.0013**	0.0162***
	(0.0046)	(0.0007)	(0.0045)
Humanitarian Assistance			
Received cash for food only	-0.0174***	-0.0024***	-0.0165***
	(0.0056)	(0.0008)	(0.0055)
Received multipurpose cash (MPC)	-0.0211***	-0.0022**	-0.0199***
	(0.0069)	(0.0010)	(0.0067)
Livelihood Coping Strategies			
Crisis-level coping strategies	0.0211***	0.0001	0.0212***
	(0.0036)	(0.0005)	(0.0035)
Emergency-level coping strategies	0.0550***	0.0029***	0.0549***
	(0.0065)	(0.0010)	(0.0067)
Expectations about the future			
Hopeless	0.0414***	0.0009	0.0409***
	(0.0057)	(0.0008)	(0.0056)
Frequently feeling negative	0.0186***	-0.0003	0.0184***
	(0.0054)	(0.0008)	(0.0053)
Neutral	0.0100*	-0.0007	0.0101**
	(0.0052)	(0.0007)	(0.0050)
Head characteristics			
Age 15-24	0.0413***	-0.0017	0.0392***
	(0.0087)	(0.0012)	(0.0084)
Age 25-34	0.0368***	-0.0007	0.0357***
	(0.0070)	(0.0010)	(0.0070)
Age 35-44	0.0398***	-0.0012	0.0372***
	(0.0071)	(0.0010)	(0.0071)
Age 45-54	0.0255***	0.0002	0.0242***
	(0.0073)	(0.0011)	(0.0074)
Educ: Illiterate	0.0949***	0.0028**	0.0958***
	(0.0094)	(0.0013)	(0.0090)
Educ: Less than primary	0.0147*	0.0006	0.0152**
	(0.0079)	(0.0010)	(0.0074)
Educ: Primary	-0.0078	-0.0016	-0.0065
	(0.0086)	(0.0011)	(0.0079)
Female-headed household	0.0156***	-0.0001	0.0143**
	(0.0057)	(0.0008)	(0.0056)
Married	-0.0147**	0.0007	-0.0138**
	(0.0059)	(0.0008)	(0.0057)
Worked in the last week	-0.0262***	0.0001	-0.0258***
	(0.0065)	(0.0009)	(0.0064)
Household characteristics			
Share of dependents	0.0555***	0.0023*	0.0526***
	(0.0095)	(0.0014)	(0.0094)
Highest education: Primary or less	0.0188***	0.0022***	0.0189***

	(0.0060)	(0.0008)	(0.0057)
Household size	-0.0010	0.0003*	-0.0010
	(0.0010)	(0.0002)	(0.0010)
% HH members working (15-64 yrs of age)	-0.0981***	-0.0011	-0.0985***
	(0.0066)	(0.0009)	(0.0065)
Governorates			
Akkar	-0.0042	-0.0020*	-0.0011
	(0.0084)	(0.0012)	(0.0084)
Beirut	-0.0312***	-0.0009	-0.0278***
	(0.0094)	(0.0014)	(0.0093)
Bekaa	-0.0316***	-0.0010	-0.0307***
	(0.0078)	(0.0012)	(0.0079)
El Nabatieh	-0.0183**	-0.0019	-0.0168**
	(0.0081)	(0.0012)	(0.0081)
Mount Lebanon	0.0095	-0.0004	0.0127
	(0.0084)	(0.0013)	(0.0085)
North Lebanon	0.0231***	-0.0010	0.0252***
	(0.0080)	(0.0012)	(0.0080)
South Lebanon	-0.0204**	-0.0002	-0.0179**
	(0.0090)	(0.0014)	(0.0091)
R-squared	0.4181	0.0397	0.4234

Note: Omitted categories include: MEB ≥ $114 USD; Received no cash assistance; No coping strategies or stress-level coping strategies needed; Optimistic; Age ≥55; Educ: More than Primary; Governorate: Baalbek-El Hermel.
*** p<0.01, ** p<0.05, * p<0.1

How can these initial findings assist humanitarian organizations in better targeting existing resources? We know from Table 4 that employment and education are strong predictors of vulnerability to future poverty, regardless of current poverty status. We also know from Figures 3a and 3b that certain governorates in Lebanon have refugee populations which exhibit higher levels of deprivation when it comes to the dimensions related to employment and education. In these refugee locations, humanitarian organizations may want to consider shifting available resources towards skill-building and job training programs and partnering with development agencies and national authorities to create viable employment opportunities and career paths for both the refugees and the host communities. If we had used only one measure of poverty such as consumption per capita, we would not have captured the additional insights revealed by the multidimensional analysis.

Table 4 identifies additional groups of refugees who are more likely to be poor in the future based on other sociodemographic characteristics. Specifically, households with heads who were younger, female, and non-married were more likely to be vulnerable, as were households with a higher share of dependents (younger than 15 years of age or older than 64). These vulnerable refugees are likely to need more targeted programs, services, and resources that address their specific needs. Household size was not a significant factor in explaining vulnerability, most likely because the share of household dependents and working household members were also controlled for in the model.

Additionally, Table 4 shows that the impacts of humanitarian assistance also mattered. Receiving cash for food or multi-purpose cash (MPC) assistance in the 6 months prior to the survey were both associated with a lower likelihood of being poor in the future, compared to not having received any cash assistance. Related factors such as those pertaining to the severity of livelihood strategies used by refugees to cope with their current situation were positively associated with vulnerability to future poverty. Not surprisingly, households who were implementing emergency level strategies were on average 5.5 percentage points more likely to be vulnerable than those who were using no strategies or only stress level strategies.

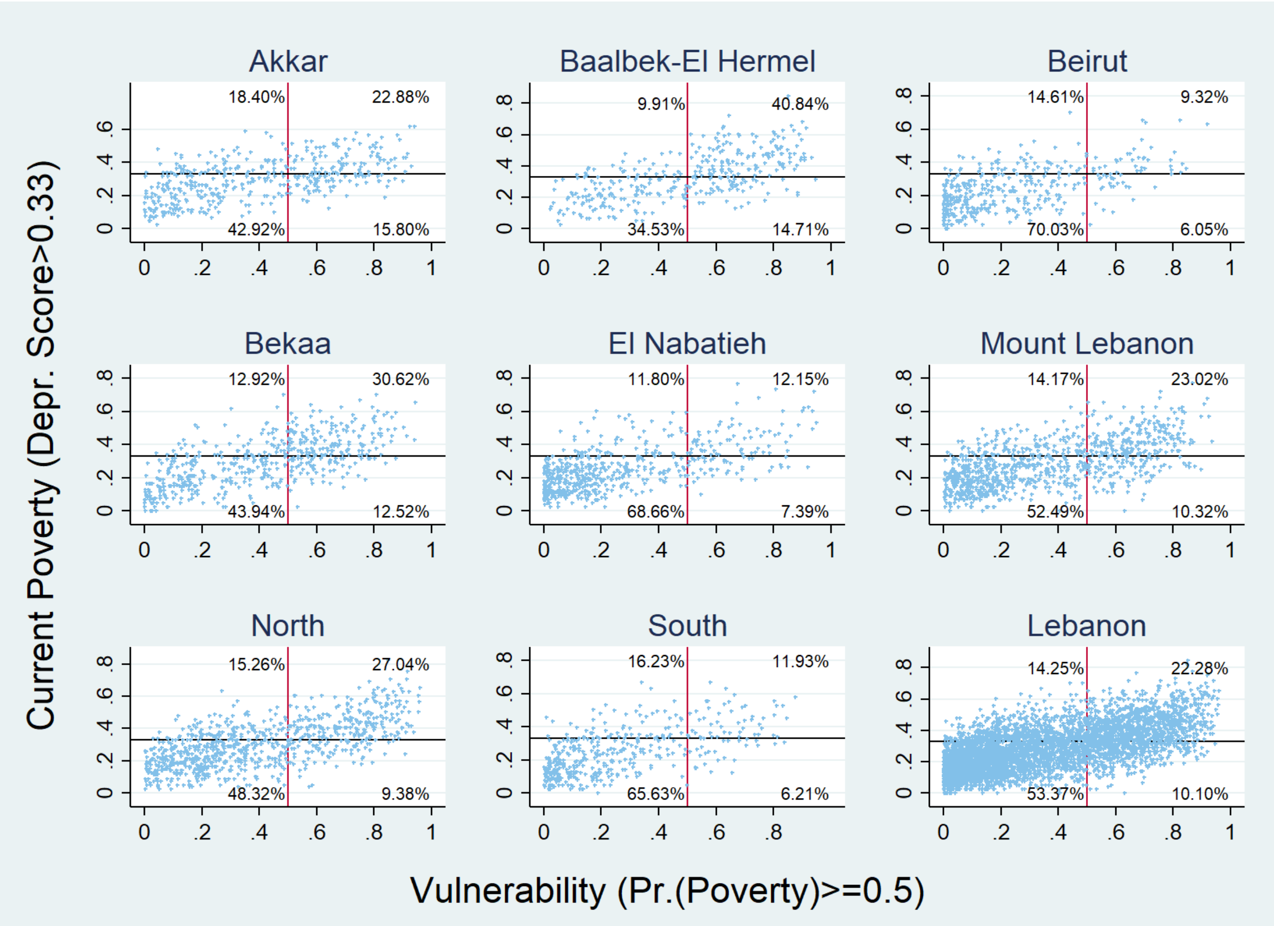
Interestingly, households' perceptions about the future were also relevant. Households who reported feeling hopeless or frequently negative about their future were significantly more likely to be vulnerable in the future compared to those who reported feeling optimistic. The use of these types of psychometric and behavioral measures have been rarely used to target assistance. Yet, these variables may provide valuable insights into how one's perception of their situation and the world around them might also impact their ability to escape poverty, regardless of the amount of humanitarian aid and other types of assistance received. In this way, psychometric measures of welfare, such as those related to one's future expectations, could be a useful diagnostic tool when assessing which populations and geographical areas are most in need. However, agencies also need to be cautious in using more subjective measures such as these, as some refugees might communicate a more negative outlook if they believe it could increase their likelihood of receiving assistance.

Finally, Table 4 shows that the governorates of Beirut, Bekaa, El Nabatieh, and South Lebanon were less likely to have refugee populations that were more vulnerable to future poverty compared to Baalbek-El Hermel (the reference group). Relative to Baalbek-El Hermel, refugees living in North Lebanon were more likely to be vulnerable to future poverty. Recall that Baalbek-El Hermel had the highest current poverty rate, whether it was measured using the poverty line, the headcount ratio, or the MLI (see again, Table 3). How might these geographical findings be used to better inform which refugees to target and where? Figures 3a and 3b show that the highest deprivation scores for refugees living in Baalbek-El Hermel were related to employment and living standards, and employment and health for those living in North Lebanon. Thus, future resources and assistance which support programs and services aimed at improving employment and health outcomes, as well as the living conditions of the refugee settlement areas and communities, may be particularly effective at improving longer-run resiliency outcomes. The next section shows yet another way in which these findings can be used to better target assistance across the refugee population and geographically.

6.2 Comparison of current poverty and vulnerability to future poverty

Using the results from the 3-stage FGLS model presented in Table 4, we can empirically calculate the proportion of Syrian refugees who are likely to be poor in the future using Equation (8) from the empirical framework. We calculate the predicted probability of being poor ($\widehat{Pr}\left(DS_{ij} > 0.33 \mid X_{ij}\right)$) using the results from Column 3 in Table 4. We then identify the households with probabilities of being poor in the future greater than or equal to 0.5 ($\widehat{Pr}\left(DS_{ij} > 0.33 \mid X_{ij}\right) \geq 0.5$). Figure 4 presents a series of scatterplots by governorate and for Lebanon as a whole. Each dot in the scatterplot represents a household according to their current poverty classification (y-axis) and their vulnerability

Figure 4. Scatterplot comparing current poverty and vulnerability to future poverty by governorate



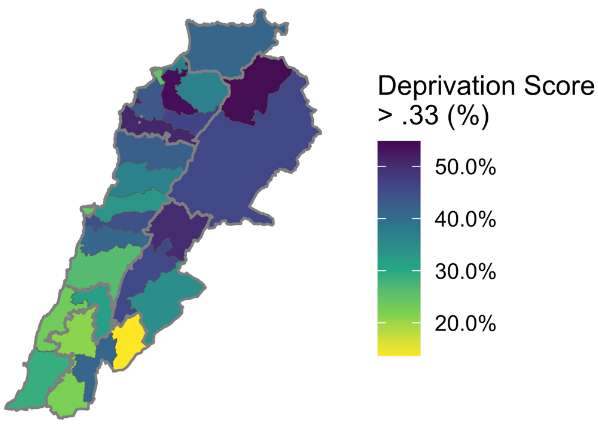
Note: The percentages were generated using data from the *2018 Vulnerability Assessment of Syrian Refugees* (VASyR) and the estimates from the 3-stage FGLS model presented in Table 4. Each of the four quadrants denotes a different group. Specifically, the North-West (NW) quadrant denotes "Poor and non-vulnerable," the North-East (NE) quadrant denotes "Poor and vulnerable," the South-West (SW) quadrant denotes "Non-poor and non-vulnerable," and the South-East (SE) quadrant denotes "Non-poor and Vulnerable."

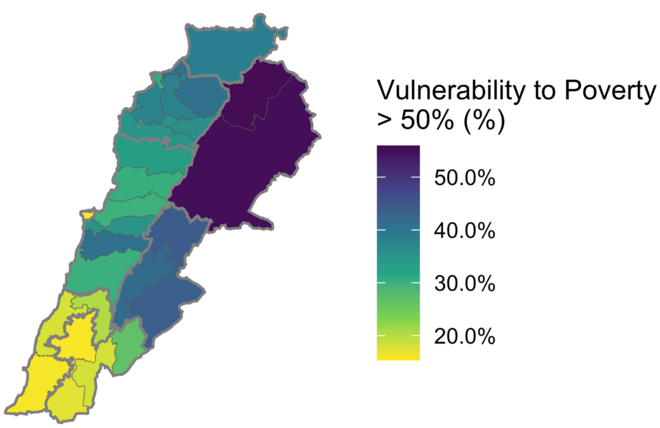
to future poverty (x-axis) as determined by the 3-stage FGLS estimation. Each scatterplot has four quadrants. The south-west (SW) quadrant denotes those refugee households who were not poor in 2018 and not vulnerable to being poor in the future (0,0). The north-east (NE) quadrant denotes households who were poor in 2018 and vulnerable to still being poor in the future (1,1). Most of the refugee households fell into one of these two quadrants. However, a considerable number of households also fell into the remaining quadrants, along the opposite diagonal. The north-west (NW) quadrant identifies households who were poor in 2018, but not vulnerable to being poor in the future (1,0). These households could have a better chance, than others who are currently poor, of breaking out of the cycle of poverty and being able to build sustainable livelihoods. In contrast, the south-east (SE) quadrant identified households who were not currently poor but vulnerable to falling into poverty in the future. These are refugee households who often slip through the cracks, because humanitarian organizations place emphasis on awarding aid to those who are currently poor. From these simple scatterplots, one can easily see the additional value to identifying heterogeneities related to poverty among FDPs. This additional information can be helpful in better knowing *which households* to target with available assistance and other resources.

Figure 5 presents a geographical mapping of both current poverty and vulnerability to future poverty. The middle map presents, by governorate and district, the share of Syrian refugee households whose deprivation scores were greater than 0.33, denoting current poverty. High deprivation scores, indicative of greater current poverty, were largely concentrated in the remote rural regions of Baalbek-El Hermel and Bekaa, which are predominately rural and abut Syria. These governorates contained high shares of Lebanon's Syrian refugee population, with many of these refugees living either in the very east of the country, or the agricultural areas of the Bekaa valley. Comparatively speaking, the country's western coastal regions contained Syrian refugees with lower levels of current poverty. Some exceptions were the Zgharta and Batroun districts of North Lebanon, which contained a greater share of refugees with high deprivation scores.

The bottom map presents the share of refugee households in each governorate and district who were predicted to be vulnerable to poverty in the future. In comparing the two maps, we can begin to identify geographical areas where poverty is more likely to increase in the near future, as well as areas that are more likely to experience reductions in poverty. Most notably, we see that the north-east governorate of Baalbek-El Hermel, bordering Syria, is most likely to not only see an increase in poverty amongst refugees, but to experience the highest level of future poverty of all the governorates. The districts of Rashaya in Bekaa and Hasbaya in El Nabatieh, which similarly abut the Syrian border and are more rural, are also likely to see increases in future poverty. With this said, we note the comparatively low rates of future poverty predicted for the more prosperous and opportunity-rich area of Beirut. The surrounding and urbanized districts of Baabda and Matn in Mount Lebanon, although predicted to have higher poverty rates than Beirut, are likely to see improvements as well. The southernmost governorates of South Lebanon and El Nabatieh are most likely to have the lowest levels of future poverty. Some districts that had currently high levels of poverty such as the northeast district of Zgharta in North Lebanon and the western district of Zahlé in Bekaa are also likely to experience improvements in poverty, but the rates are still likely to remain relatively high compared to the other districts. The districts of Zgharta and Zahlé include the capital cities for their respective governorates, which are more urbanized areas and could explain why they are more likely to see some recovery, albeit less than other areas of Lebanon. From these mappings, one can see again how applying a multidimensional approach, which looks at both current and future poverty, can provide additional information to assist humanitarian and development organizations in better identifying *which geographical areas* to target.

Figure 5: Map of current poverty and vulnerability to poverty by governorate and district





Note: Data for these mappings were taken from the *2018 Vulnerability Assessment of Syrian Refugees* (VASyR) and generated using the estimates from the 3-stage FGLS model presented in Table 4.

7. Conclusions

This study used two important methodologies from the poverty literature to make important contributions to the existing research related to the targeting of FDPs. Recall that most targeting efforts have focused on identifying "who is poor," mostly through unidimensional metrics. Our approach merged multidimensional and forward-looking methodologies to determine "who is multidimensionally poor" and "who is vulnerable to future multidimensional poverty." We used data from the *2018 Vulnerability Assessment of Syrian Refugees* in Lebanon to construct a multidimensional livelihood index (MLI), so as to better understand the complex needs of FDPs and assess their poverty levels based on a set of indicators that measured deprivations in different dimensions of welfare, including social inclusion. We then used this MLI to predict which households were expected to stay in poverty or become multidimensionally poor in the future. We found – and visually showed – that across all governorates, non-trivial shares of households were either "poor but not vulnerable" or "not poor but vulnerable," confirming the dynamic nature of poverty.

These findings are particularly important for both humanitarian and development organizations that are on the frontlines responding to global and protracted humanitarian crises. Humanitarian and development organizations can use our findings to better optimize the mobilization of funding and the targeting mechanisms used to allocate resources. Thus, our approach offers these organizations additional information to identify households who are more in need of assistance, especially when resources are limited. For example, an additional criterion to supplement traditionally used PMT formulas would be to prioritize those households who are also multidimensionally poor. Likewise, our approach shows that, although multidimensional and unidimensional measures of poverty are correlated, monetarily "poor" households could experience different needs and face different costs to fulfill those needs. In this way, a multidimensional approach is a good complement, at a minimum, to assist humanitarian and development organizations in identifying "who" to target with assistance.

Our analysis also provides valuable insights into "where" and "how" to target by identifying which dimensions and indicators should be prioritized given the budgetary constraints and development goals of each refugee community and settlement area. For instance, our analysis highlighted the locations where improved access to services such as electricity, basic sanitation, and clean drinking water are likely to be more critical. Actions to support municipalities in these governorates so that they can improve infrastructure and service provision could reduce the deprivations for the entire refugee community and could have a significant impact on those who are multidimensionally poor. Likewise, in locations where education or healthcare access are problematic, investments in programs that expand the capacity and reach of schools and healthcare institutions (via rehabilitation or construction) and support capacity building amongst teachers and healthcare workers are likely to be key. Employment also appears to be an important issue across Lebanon, calling for coordination with authorities to improve economic participation opportunities and promote self-reliance among refugees and host communities, along with skill-building and job training programs.

In this way, we have shown how improving poverty outcomes, especially for FDPs, is not just about identifying who is intrinsically poor based on a single characteristic, or even set of characteristics. It is also that they may be living in areas that are fundamentally poor with limited resources and low productivity rates (Klein & Pritchett, 2021). From this viewpoint, it is important to think about addressing *poor places* in conjunction with *poor people*. As this study has pointed out, a multidimensional approach can help aid organizations to more easily identify which dimensions and geographical areas need to be prioritized. In the case of Lebanon, this point is particularly important, as the daily living conditions of the Lebanese people continue to worsen due to deepening economic, financial, and political crises. Syrian refugees, thus, have migrated to a location that is already struggling with limited resources, low growth, and high unemployment, making it that more difficult to create sustainable livelihoods for themselves and their families.

Thus, our work has immediate and timely implications for humanitarian actors, as well as development partners and donors, involved in the Syrian refugee crisis in Lebanon, and beyond. This is particularly critical given persistent funding shortages and the need to ensure the most efficient channeling of available resources.

With this said, we acknowledge that our analysis has some limitations. First, our MLI index is limited to the variables provided by *VASyR* 2018. These variables exclude some information used to calculate the indicators found in the standard MPI, which limits our ability to compare our findings for the Syrian refugees to other previous studies which have focused on measuring poverty among more general populations. Our data, though, did allow us to include additional measures such as those related to social inclusion, which are receiving growing international attention among multilateral organizations.

Second, the use of panel data would provide better estimations of vulnerability to future poverty. However, panel data is rarely available especially when investigating highly vulnerable and mobile populations such as refugees. To this end, we turned to a standard cross-sectional methodology commonly used and widely recognized by other researchers.

Third, our MLI index requires the use of cutoffs to classify households as deprived according to each indicator. Households are then classified as poor or vulnerable depending on the number of deprivations (i.e., the percentage of total possible deprivations). We followed the standard approach to define cutoffs for poverty using Alkire and Foster (2011) and cutoffs for vulnerability using Chaudhuri et al. (2002). However, there were other approaches we could have taken to define these cutoffs, including a recent approach proposed by Gallardo (2020), which uses assumptions about risk aversion to establish cutoffs. As a starting place for examining poverty among FDPs, we chose a more established and conventional approach.

Finally, we acknowledge that there could be strong associations and correlations amongst the indicators in our index. The indicators are not likely to be completely independent of each other.

Further, the relationships are likely to vary among households. For example, the lack of access to clean drinking water can have negative effects on the health indicators. Identifying and incorporating these relationships into the analysis poses significant challenges.

Regardless, this study provides a useful foundation to address these and other challenges and from which future research and policy examining poverty among refugees and other FDPs can build upon. The scale and duration of forced displacement is expected to intensify globally in the coming decades due to population growth, climate change, economic inequality, and ensuing disasters and conflicts. Our work offers a targeting strategy to support more coordinated and collaborative humanitarian-development action and resource mobilization, leading to a more integrated response that goes beyond alleviating immediate hardships to preventing future ones.

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Appendix A1. Variable definitions

Variables	Definitions
Expenditure and poverty indicators	
Below SMEB (< $87)	=1 if the household's total monthly expenditure per capita was less than US $87, as defined by the Survival Minimum Expenditure Basket (SMEB). The SMEB is calculated based on the cost of food and non-food items needed by a Syrian refugee household of 5 members over a one-month period. Food items involve quantities containing 2,100 kcal per day, regardless of nutrients, while non-food items include : (1) cleaning and hygiene supplies; (2) clothes; (3) communication; (4) rent (informal tented settlements); (5) water (15 liters per day); (6) transportation; and (7) debt repayment.
SMEB – MEB ($87-$113)	=1 if the household's total monthly expenditure per capita was between US $87 and US $113, as defined by the SMEB and MEB. The Minimum Expenditure Basket (MEB) set at US $114 is calculated based on methodology and composition similar to that used for SMEB with the following differences: (1) the cost of food accounts for the same caloric intake of 2,100 but includes all nutrients; (2) higher rent (considered regardless of shelter type); (3) higher water consumption (35 liters per day); (4) additional expenses including health and education; (5) debt repayment is excluded.
MEB – 125% MEB ($114-$142)	=1 if the household's total monthly expenditure per capita was between US $114 and US $142, as defined by the MEB.
≥ 125% MEB (≥ $143)	=1 if the household's total monthly expenditure per capita was equal to or higher than US $143, as defined by the MEB.
Below poverty line (< $3.84/day)	=1 if the household had reported expenditures less than $3.84 USD per person per day, which is the national poverty line applied to all residents in Lebanon, below which people are considered poor.
Humanitarian assistance	
Received cash for food only	=1 if the household received cash for food assistance in the last 6 months (between November 2017 and April of 2018). Eligible family/case (household or part of a household) receives US $27 per member per month.
Received multipurpose cash (MPC)	=1 if the household received multipurpose cash (MPC) assistance for essential needs in the last 6 months (between November 2017 and April of 2018). A family/case eligible for MPC receives US $175 per month that are provided by WFP or UNHCR. All families/cases receiving MPC assistance also received food assistance, except for 21 cases.
Received no cash assistance	=1 if no one in the household (i.e., no family/case) received cash for food or multi-purpose cash (MPC) assistance between November 2017 and April of 2018.
Livelihood coping strategies	
Emergency level coping strategies	=1 if the household adopted severe coping strategies such as involving school children in income activities, begging, accepting high-risk jobs, and selling house or land.
Crisis level coping strategies	=1 if the household adopted coping strategies such as the sale of productive assets, the withdrawal of children from school, the reduction of non-food expenses, and the marriage of children under 18.
Stress level coping strategies	=1 if the household adopted coping strategies such as spending savings, selling goods, buying on credit, and incurring debt.
No coping strategies needed	=1 if the household did not adopt any coping strategies as listed below.
Expectations about the future	
Hopeless	= 1 if the respondent reported feeling "hopeless" about the situation and future of their household.
Frequently feeling negative	= 1 if the respondent reported feeling "frequently negative" about the situation and future of their household.
Neutral	= 1 if the respondent reported feeling "neither positive nor negative" about the situation and future of their household.
Optimistic	= 1 if the respondent reported feeling "optimistic" or "somewhat optimistic" about the situation and future of their household.

Appendix A1. Variable definitions (conti.)

Variables	Definitions
Head characteristics	
Age of the HH head	Average age of the household head in years.
Age 15-24	=1 if age of household head was between 15-24.
Age 25-34	=1 if age of household head was between 25-34.
Age 35-44	=1 if age of household head was between 35-44.
Age 45-54	=1 if age of household head was between 45-54.
Age $\geq$ 55	=1 if household head was age 55 or older.
Education of household head	
Educ: Illiterate	=1 if the household head cannot read and write.
Educ: Less than primary	=1 if the household head had completed less than 9 years of education (primary education).
Educ: Primary	=1 if the household head completed 9 years of education (primary education) but did not finish secondary education (studied up to 10th or 11th grade), including incomplete TVET.
Educ: Secondary to some tertiary	=1 if the household head completed at least some secondary education (including TVET). This includes household heads with at least 12 years of education.
Educ: University	=1 if household head had completed some college/university.
Female-headed household	=1 if household head was female.
Married	=1 if household head was married.
Worked in the last week	=1 if household head had worked for pay in the last week.
Household Characteristics	
Share of dependents	Ratio of dependent household members (aged below 15 or above 65) relative to total household members.
Household's highest education level	Highest level of education attained by the household:
Educ: Illiterate	=1 if all household members were unable to read and write.
Educ: Less than primary	=1 highest level was less than primary education.
Educ: Primary	=1 highest level completed was primary education.
Educ: Secondary to some tertiary	=1 highest level completed was at least some secondary or tertiary education (including TVET).
Educ: University	=1 highest level completed was some college/university.
Household size (#)	Average number of household members.
% HH members working (15-64 yrs of age)	Share of household members between the ages of 15-64 who were working.
Household Resources	
Main income source: Employment	= 1 if the household's main source for cash or income in the last 30 days was from employment (in agriculture, construction, manufacturing, concierge, hotel, restaurant, transport and personal services, professional services, and wholesale and retail trade).
Main income source: Assistance	= 1 if the household's main source for cash or income in the last 30 days was from assistance from humanitarian and charitable organizations.
Main income source: Borrowing	= 1 if the household's main source for cash or income in the last 30 days was from borrowing (formally from banks or informally from shops or friends).
Borrowed money or received credit	= 1 if the household reported borrowing money or receiving credit in the past year.

Source: 2018 Vulnerability Assessment of Syrian Refugees (VASyR) – 6th round. Note that our measures for SMEB and MEB supplement the VASyR survey data as they are based on secondary data on expenditures collected by 17 agencies, then consolidated and analyzed by Handicap International during the second quarter of 2014. See UNHCR, UNICEF, and World Food Programme (2018) for more details.

Appendix A2. Probability distribution for the baseline deprivation score compared to the normal distribution